Improving Future U.S. Drought Assessment (2026)

DETAILS

221 pages | 7 x 10 | PAPERBACK
ISBN 978-0-309-99526-9 | DOI 10.17226/29217

CONTRIBUTORS

Committee on the Future of Drought in the United States; Earth Systems and Resources Program Area; Center for Health, People, and Places; National Academies of Sciences, Engineering, and Medicine

SUGGESTED CITATION

National Academies of Sciences, Engineering, and Medicine. 2026. *Improving Future U.S. Drought Assessment*. Washington, DC: The National Academies Press. https://doi.org/10.17226/29217.

NATIONAL ACADEMIES *Sciences Engineering Medicine*

NATIONAL ACADEMIES PRESS
Washington, DC

Improving Future U.S. Drought Assessment

Committee on the Future of Drought in the United States

Earth Systems and Resources Program Area

Center for Health, People, and Places

Consensus Study Report

PREPUBLICATION COPY

NATIONAL ACADEMIES PRESS 500 Fifth Street, NW Washington, DC 20001

This study was supported by a contract between the National Academy of Sciences and the National Oceanic and Atmospheric Administration (contract number 1305M322DNRMA0003 / 1305M324F0183), and funding from the Interstate Council on Water Policy, the National Academy of Sciences Arthur L. Day Fund, and the National Academy of Sciences Maurice Ewing and Planetary Sciences Fund. Any opinions, findings, conclusions, or recommendations expressed in this publication do not necessarily reflect the views of any organization or agency that provided support for the project.

International Standard Book Number-13: 978-0-309-XXXXX-X
Digital Object Identifier: https://doi.org/10.17226/29217

This publication is available from the National Academies Press, 500 Fifth Street, NW, Keck 360, Washington, DC 20001; (800) 624-6242; https://nap.nationalacademies.org.

The manufacturer's authorized representative in the European Union for product safety is Authorised Rep Compliance Ltd., Ground Floor, 71 Lower Baggot Street, Dublin D02 P593 Ireland; www.arccompliance.com.

Printed in the United States of America.

Suggested citation: National Academies of Sciences, Engineering, and Medicine. 2026. *Improving Future U.S. Drought Assessment*. Washington, DC: National Academies Press. https://doi.org/10.17226/29217.

The **National Academy of Sciences** was established in 1863 by an Act of Congress, signed by President Lincoln, as a private, nongovernmental institution to advise the nation on issues related to science and technology. Members are elected by their peers for outstanding contributions to research. Dr. Marcia McNutt is president.

The **National Academy of Engineering** was established in 1964 under the charter of the National Academy of Sciences to bring the practices of engineering to advising the nation. Members are elected by their peers for extraordinary contributions to engineering. Dr. Tsu-Jae Liu is president.

The **National Academy of Medicine** (formerly the Institute of Medicine) was established in 1970 under the charter of the National Academy of Sciences to advise the nation on medical and health issues. Members are elected by their peers for distinguished contributions to medicine and health. Dr. Victor J. Dzau is president.

The three Academies work together as the **National Academies of Sciences, Engineering, and Medicine** to provide independent, objective analysis and advice to the nation and conduct other activities to solve complex problems and inform public policy decisions. The National Academies also encourage education and research, recognize outstanding contributions to knowledge, and increase public understanding in matters of science, engineering, and medicine.

Learn more about the National Academies of Sciences, Engineering, and Medicine at **www.nationalacademies.org**.

Consensus Study Reports published by the National Academies of Sciences, Engineering, and Medicine document the evidence-based consensus on the study's statement of task by an authoring committee of experts. Reports typically include findings, conclusions, and recommendations based on information gathered by the committee and the committee's deliberations. Each report has been subjected to a rigorous and independent peer-review process and it represents the position of the National Academies on the statement of task.

Proceedings published by the National Academies of Sciences, Engineering, and Medicine chronicle the presentations and discussions at a workshop, symposium, or other event convened by the National Academies. The statements and opinions contained in proceedings are those of the participants and are not endorsed by other participants, the planning committee, or the National Academies.

Rapid Expert Consultations published by the National Academies of Sciences, Engineering, and Medicine are authored by subject-matter experts on narrowly focused topics that can be supported by a body of evidence. The discussions contained in rapid expert consultations are considered those of the authors and do not contain policy recommendations. Rapid expert consultations are reviewed by the institution before release.

For information about other products and activities of the National Academies, please visit www.nationalacademies.org/purpose.

COMMITTEE ON THE FUTURE OF DROUGHT IN THE UNITED STATES

JONATHAN T. OVERPECK, (*Chair*), University of Michigan
AMIR AGHAKOUCHAK, University of California, Irvine
CLARA DESER, National Science Foundation - National Center for Atmospheric Research
TRENT W. FORD, Illinois State Water Survey, University of Illinois, Urbana-Champaign
KRISTIANA M. HANSEN, University of Wyoming
RICHARD R. HEIM, JR., National Oceanic and Atmospheric Administration (retired)
JENNIFER HENDERSON, Texas Tech University
ZACHARY H. HOYLMAN, Montana Climate Office, University of Montana
YUSUKE KUWAYAMA, University of Maryland, Baltimore County
VENKATARAMAN LAKSHMI, University of Virginia
JUSTIN MANKIN, Dartmouth College
KAREN MCKINNON, University of California, Los Angeles

Study Staff

DEBORAH GLICKSON, Senior Program Director, Earth Systems and Resources Program Area
STEVEN STICHTER, Senior Program Officer, Earth Systems and Resources Program Area, *Study Director*
CHARLES R. BURGIS, Program Officer, Earth Systems and Resources Program Area
DOMINIQUE JENKINS, Senior Program Assistant, Earth Systems and Resources Program Area

Reviewers

This Consensus Study Report was reviewed in draft form by individuals chosen for their diverse perspectives and technical expertise. The purpose of this independent review is to provide candid and critical comments that will assist the National Academies of Sciences, Engineering, and Medicine in making each published report as sound as possible and to ensure that it meets the institutional standards for quality, objectivity, evidence, and responsiveness to the study charge. The review comments and draft manuscript remain confidential to protect the integrity of the deliberative process.

We thank the following individuals for their review of this report:

ANDREW AYRES, University of Nevada, Reno
MARK BRUSBERG, USDA Chief Meteorologist (Former, Retired)
BENJAMIN I. COOK, Columbia University
AMANDA E. CRAVENS, U.S. Geological Survey
PAOLO D'ODORICO, University of California, Berkeley
MICHAEL HAYES, University of Nebraska-Lincoln
RUTH LANGRIDGE, University of California, Santa Cruz
JOHN NIELSEN-GAMMON, Texas A&M University
DONALD ORT, University of Illinois, Urbana-Champaign
GABRIELA PEREZ-QUESADA, University of Tennessee
JESSE TACK, Kansa State University

Although the reviewers listed above provided many constructive comments and suggestions, they were not asked to endorse the conclusions or recommendations of this report nor did they see the final draft before its release. The review of this report was overseen by **JAMES S. (JAY) FAMIGLIETTI,** Arizona State University, and **JAY R. LUND,** University of California, Davis. They were responsible for making certain that an independent examination of this report was carried out in accordance with the standards of the National Academies and that all review comments were carefully considered. Responsibility for the final content rests entirely with the authoring committee and the National Academies.

Acknowledgments

The committee wishes to thank Britt Parker, Veva Deheza, Elizabeth Ossowski, Joel Lisonbee, and Andrew Hoell, from the National Oceanic and Atmospheric Administration (NOAA) National Integrated Drought Information System, who were liaisons to the study. They oversaw the contract and provided helpful information to the committee.

Additionally, the committee thanks Beth Callaway and Danny Johnson from the Interstate Council on Water Policy (ICWP), who were also liaisons to the study, providing information from the perspectives of ICWP member groups.

The study committee met as a full group four times in person and three times virtually over approximately 12 months to gather information for the study, deliberate on the charge in the statement of task, and write the report. The committee thanks the following individuals for presentations during these meetings and for submitted materials:

From State Climatology Offices: John Nielsen-Gammon, Texas; Laura Edwards, South Dakota; Russ Schumacher, Colorado

From Regional Climate Centers (RRCs) and Climate Adaptation Partnerships (CAPs): Beth Hall, Midwestern RCC; Tim Brown, Western RCC; Michael Crimmins, Southwest CLIMAS CAP; Rick Thoman, Alaska Center for Climate Assessment and Policy

From other organizations: Brian Fuchs, National Drought Mitigation Center, University of Nebraska–Lincoln; Chris Milly, U.S. Geological Survey, emeritus; Upmanu Lall, Arizona State University; Benjamin Cook, Columbia University; Sujay Kumar, NASA; Michael Dettinger, Scripps; Robert S. Webb, former NOAA Physical Sciences Lab; Andy Wood, Colorado School of Mines; Balaji Rajagopalan, University of Colorado; Mark Brusberg, former U.S. Department of Agriculture; Terry Fulp, former U.S. Bureau of Reclamation; Michael Anderson, California Department of Water Resources, and California State Climatologist; Elizabeth Kerby, Missouri Department of Natural Resources; Seth Shanahan, Southern Nevada Water Authority

Project Management

Steven Stichter managed the study and assisted the committee in drafting the report with support from Charles R. Burgis, under the guidance of Deborah Glickson. Dominique Jenkins provided administrative and logistical support. Lauren Everett managed the report review process.

Contents

Boxes, Figures, and Tables

BOXES

FIGURES

TABLES

Preface

Droughts of the twenty-first century have been unprecedented, less a reflection of what has come before than a harbinger of what is ahead. Reflected in record low spring snowpack and record high temperatures, the United States is now 27 years into the first multidecadal "megadrought" in the nation's history. In less than three decades, the megadrought has highlighted how warming temperatures across the West can intensify soil moisture declines, forest mortality, and wildfire impacts, including wildfires that destroyed lives and livelihoods. During the same twenty-first century period, the United States has seen other unusually devastating droughts across the Great Plains, in the Southeast, and in Hawaii. Even my home state of Michigan has seen typical summer dry spells become persistent and costly droughts.

These intensifying drought conditions spurred this report, which was commissioned by federal and state leaders who work hard to provide society's decision-makers with assessments of ongoing droughts and information for dealing with these and future droughts, even as the job gets more challenging due to nonstationarity. Their work includes collaboration with scientists, modelers, observing systems, and perhaps most visibly, the individuals and organizations across the country and continent who produce regular updates to the U.S. Drought Monitor, the North American Drought Monitor, and other regular products essential for decision-making in every state of the country. The job of this National Academies study team and this report is to recommend how to build on the solid foundation of drought assessment that already exists in the United States, and in doing so increase our nation's resilience to nonstationarity as it responds to worsening drought and its impacts across the country.

The present report does two things. First, it shows the ways in which current drought assessment practices can be impacted by nonstationarity, including in ways that might make droughts more difficult to manage, and thus more costly. Second, this report provides tractable strategies to update the nation's current strong foundation of drought assessment to become more robust and helpful in the context of nonstationarity. We are on the cusp of a new era of drought assessment innovation and resilience that we hope will be sparked by this report and involve the collaborative efforts of federal and state experts, the broader scientific research community, and all those in society who have a stake in lessening the impacts and costs associated with the increasing challenge of drought.

This report is the work of a dozen scientific experts who volunteered their time and expertise to study how to help this country and its people become more resilient to the worsening impacts of drought under a changing climate—to these colleagues I wish to extend my deepest thanks. I also want to thank those from around the country who answered the committee's call for information on the execution and use of drought assessments. And importantly, on behalf of the whole team, I want to extend my great appreciation to the excellent professional staff of the National Academy of Sciences, particularly Steven Stichter, Charles Burgis, and Dominique

Jenkins, as well as to all those who helped with the peer review of this work. This report was a team effort, and we were lucky to have had such a great team.

Jonathan Overpeck, *Chair*

Committee on the Future of Drought in the United States

June 2026

Acronyms and Abbreviations

AED	Atmospheric Evaporative Demand
AI	Aridity Index
AI/ML	Artificial Intelligence/Machine Learning
AMS	American Meteorological Society
ASCAT	Advanced Scatterometer
CE	Common Era
CHIRPS	Climate Hazards Group InfraRed Precipitation with Stations
CHIRTS	Climate Hazards Center Infrared Temperature with Stations
CMI	Crop Moisture Index
CMOR	Condition Monitoring Observer Report
CONUS	Contiguous United States
CRP	Conservation Reserve Program
DMI	Dipole Mode Index
DMDU	Decision Making under Deep Uncertainty
DSCI	Drought Severity Coverage Index
ECMWF	European Centre for Medium-Range Weather Forecasts
EDO	European Drought Observatory
ENSO	El Niño–Southern Oscillation
ERA5	Fifth Generation ECMWF Reanalysis
ESA	European Space Agency
ESA-CCI	European Space Agency Climate Change Initiative
ESMI	Empirical Standardized Soil Moisture Index
ET_o	Reference Evapotranspiration
FIRO	Forecast-Informed Reservoir Operations
GAMLSS	Generalized Additive Models in Location, Scale and Shape
GEV	Generalized Extreme Value
GHG	Greenhouse Gases
GLDAS	Global Land Data Assimilation System
GLEAM	Global Land Evaporation Amsterdam Model
GNN	Graph Neural Network
GPM	Global Precipitation Measurement
GPM-IMERG	Integrated Multi-satellitE Retrievals for GPM
GRACE	Gravity Recovery and Climate Experiment
GRACE-FO	GRACE-Follow On
IPCC	Intergovernmental Panel on Climate Change
IQR	Inter-Quartile Range
ITCZ	Intertropical Convergence Zone
KDE	Kernel Density Estimation

LLMs	Large Language Models
LULC	Land Use and Land Cover
MODIS	Moderate Resolution Imaging Spectroradiometer
NASA	National Aeronautics and Space Administration
NCEI	National Centers for Environmental Information
NDVI	Normalized Difference Vegetation Index
NIDIS	National Integrated Drought Information System
NDMC	National Drought Mitigation Center
NLDAS	North American Land Data Assimilation System
NOAA	National Oceanic and Atmospheric Administration
NSPEI	Nonstationary Standard Precipitation Evapotranspiration Index
NSPI	Nonstationary Standardized Precipitation Index
NWS	National Weather Service
PDO	Pacific Decadal Oscillation
PET	Potential Evapotranspiration
PDSI	Palmer Drought Severity Index
SAM	Southern Annular Mode
SMAP	Soil Moisture Active Passive
SMI	Soil Moisture Index
SMOS	Soil Moisture and Ocean Salinity
SMVI	Soil Moisture Volatility Index
SPI	Standardized Precipitation Index
SPEI	Standardized Precipitation Evapotranspiration Index
SST	Sea Surface Temperatures
TEK	Traditional Ecological Knowledge
TWS	Terrestrial Water Storage
UNEP	United Nations Environment Programme
USBR	United States Bureau of Reclamation
USCRN	United States Climate Reference Network
USDA	United States Department of Agriculture
USDA/RMA	United States Department of Agriculture Risk Management Agency
USDM	United States Drought Monitor
USGS	United States Geological Survey
VPD	Vapor Pressure Deficit
WGA	Western Governors' Association
WMO	World Meteorological Organization

Summary

Drought[1] has become seared into the history of the United States, most notably thanks to the Dust Bowl drought of the 1930s. Nearly a decade of meteorological drought (driven by precipitation deficits and high temperatures), combined with poor land management practices, led to widespread crop failures in the Great Plains states and mass migration of people from the affected regions as they escaped desiccated landscapes and clouds of dust searching for better livelihoods elsewhere. Fast-forward to the early twenty-first century and the country is weathering an even worse drought in the U.S. Southwest, the first multidecadal "megadrought" in the nation's history and the most severe of many such droughts over the past 1,200 years. The nation has adapted to recent droughts and become more resilient to drought in multiple ways. Despite that progress, droughts and drought impacts are becoming more severe, as evidenced most clearly by a growing water crisis in the Southwest, groundwater running dry in parts of western Kansas, and declining more broadly across the High Plains, and unprecedented hot drought and wildfire affecting an ever-increasing swath of the nation.

Among billion-dollar weather and climate disasters in the United States, drought is the third most costly in terms of economic loss behind hurricanes (tropical cyclones) and severe weather (e.g., tornadoes). Between 1980 and 2025 in the United States, the economic cost of each of the largest droughts has averaged over $11 billion per event, with consequent wildfire events adding to this toll, averaging nearly $9 billion each. In terms of human lives lost, drought and extreme heat combined are responsible for over 100 deaths per year, ranked behind only the human toll associated with hurricanes. Human deaths related to extreme heat events are on the rise as well, as record heat and drought both become more common and often combine to make impacts worse.

The United States needs an expanded capability for drought assessment to support efforts that ensure resilience and thriving in the face of the changing (nonstationary) nature of drought and drought impacts. Conducted at the request of the National Oceanic and Atmospheric Administration (NOAA), with support of the Interstate Council on Water Policy, this report proposes a framework for incorporating nonstationary considerations into drought assessment, addressing drought characterization, research, data sources, indicators, and impact tracking. Critical to advancing this framework, this report includes recommendations on the development and implementation details that need to be determined jointly by the partners involved in the National Integrated Drought Information System (NIDIS) and the nation's broader drought research, assessment, and response enterprise.

Before the twenty-first century, droughts were thought of as climate extremes that slowly developed and eventually ended. In the twenty-first century, there is a whole new array of drought behaviors that include droughts that are faster to intensify, are more severe, and that may even morph into long-term aridification in some parts of the country. Increasingly, these

[1] This summary does not include references. Citations for the information presented herein are provided in the main text.

changing drought behaviors may include a wide array of severe consequences for crop production, water security, healthy ecosystems, and successful livelihoods, among many others, in more and more parts of the U.S.

THE NATION'S DROUGHT ASSESSMENT ENTERPRISE

The United States' success and resilience in the face of drought stems from advances in the scientific understanding of drought and partnerships that help turn scientific understanding into action and resilience. The nation's response to drought has also evolved over the last two centuries as severe droughts created significant impacts to the economy, especially agriculture. Major droughts of the 1890s, 1930s, and 1950s in the Great Plains; the 1960s in the Northeast; and the 1970s, 1980s, and 1990s in the West prompted changes in water system infrastructure and operations, farm policies, and insurance and aid programs to reduce drought vulnerability. Drought response shifted from a focus on reactive crisis management policies to proactive responses to build resilience. Drought monitoring tools co-evolved during this time from simple indices that incorporated basic measures of precipitation or streamflow to more sophisticated model-based indices addressing water supply (precipitation), atmospheric evaporative demand, soil moisture, and other hydrological (snowpack, streamflow) and biophysical (satellite vegetative data) components. The proliferation of drought indices in the last decades of the twentieth century gave rise to a convergence-of-evidence methodology that integrated the indices into a composite product, with the U.S. Drought Monitor being developed in 1999.

The federal government took the lead in managing drought response, recovery, and assessment efforts during the twentieth century. The creation of state drought response plans accelerated in the 1980s and 1990s. During this time, regional, state, and local agencies and organizations coordinated drought response, planning, and assessment with federal entities. This work ultimately led to the creation of the National Integrated Drought Information System, which coordinates drought monitoring, forecasting, planning, and information across all government levels.

This report and its analysis encompass the five primary drought types—meteorological drought (including flash drought), agricultural drought, hydrological drought, socioeconomic drought, and ecological drought—each of which have their own characteristic timescales, impacts, level of scientific understanding, and opportunities for resilience-based decision-making and management.

Drought assessment is ultimately designed to assist with making decisions in response to, or in preparation for, droughts. In the context of drought assessment, important decisions include those made over shorter time frames, such as emergency response and water resource operations, as well as those that relate to longer-term planning and preparedness. Traditional drought assessment generally comprises five key components: prediction, early warning, monitoring, post-event analysis, and projection (see Figure 2-7). All five components require accurate and actionable information plus clear and effective risk communication. To focus its work and recommendations, the study committee adopted a decision-centered approach to its charge. This decision framing is tied closely to risk framing in that risk mitigation systems—including government programs, insurance systems, and infrastructure—involve decision-making that buffers risk or unintentionally sustains vulnerability by discouraging adaptation.

Key decision-makers include federal, Tribal and Native, state, and local entities and universities, resource managers, stakeholders, and citizens; these groups, and partnerships between them, help turn science and understanding into action and resilience. The creation of the NOAA-led NIDIS, an interagency, multipartner approach to drought monitoring, forecasting, and early warning, established a strong foundation for the U.S. to be resilient in the face of drought.

Drought Assessment

Droughts are characterized along multiple dimensions, including duration, intensity, spatial coverage, magnitude, severity, frequency (return period), and in the case of flash droughts, the rapidity of onset and intensification. Drought assessment evaluates available water and climate information within these multiple dimensions and turns it into decision-relevant information. Drought assessment informs a wide variety of decisions made by governments, communities, firms, and individuals; these assessments often function either as a trigger mechanism for taking action or as one component of a broader convergence-of-evidence approach to decision-making, in which multiple indicators, indices, models, and impact reports are evaluated together by human experts to inform assessments about drought severity.

For example, drought assessments are explicitly embedded in federal disaster and emergency programs targeted at the agricultural sector. Several major U.S. Department of Agriculture (USDA) programs are triggered in response to U.S. Drought Monitor (USDM) severity levels listed in Box S-1. USDA Secretarial Disaster Designations are automatically "fast-tracked" when counties meet specified USDM intensity thresholds, which in turn makes producers eligible for Farm Service Agency Emergency Loan assistance.

Drought assessments also inform municipal water management decisions. For example, the South Florida Water Management District cites rainfall deficits compared to historical averages when issuing landscape irrigation restrictions for residents and businesses in its service area (SFWMD, 2026). In Texas, the Green Valley Special Utility District imposes staged water use restrictions, including limits on landscape irrigation, vehicle washing, and pool filling, based on drought response triggers tied to levels in the Edwards Aquifer.

BOX S-1
The U.S. Drought Monitor

The U.S. Drought Monitor (USDM) is a composite product that incorporates drought and climate indices and indicators, output from numerical models, and drought impact reports provided by regional and local field experts from around the country. The indices, indicators, and model data are first converted to a standard percentile-based form using the history (reference period) of the input dataset. The percentile-based data are then merged manually by a cadre of USDM authors into the map product using a convergence-of-evidence methodology. The USDM expresses drought intensity in percentile-based "Dx" categories, each corresponding to a specific range of return-period rarity (see Table S-1 for the USDM categories and Table 6-1 for the corresponding percentile ranges). The USDM has become the de facto standard for U.S. drought monitoring. Numerous states make drought response decisions, and federal agencies allocate drought relief funds, based on the drought severity as depicted on the USDM. Currently, the USDM is used as a source to inform understanding of both drought severity (for drought relief) and drought rarity.

TABLE S-1 USDM Drought Monitor Categories

Category	Description
	Normal or wet conditions
D0	Abnormally Dry
D1	Moderate Drought
D2	Severe Drought
D3	Extreme Drought
D4	Exceptional Drought

SOURCE: USDM, n.d., https://droughtmonitor.unl.edu/About/AbouttheData/DroughtClassification.aspx, accessed December 7, 2025.

THE CHANGING NATURE OF DROUGHT

Along with the first multidecadal megadrought in the United States, the twenty-first century has opened with the realization that the changing nature of drought threatens the nation's resilience to drought. In many regions, droughts are becoming hotter and thus more severe. Flash droughts, defined by unusually rapid onset and intensification, are becoming more common. Droughts are also becoming more frequent and longer-lasting, occurring against a backdrop of long-term regional drying (aridification) trends.

The regional expressions of this drought transformation vary considerably. In the West, a marked increasing trend in temperatures is drying soils faster and stressing ecosystems through enhanced evapotranspiration, coupled with low precipitation. Higher temperatures have altered regional hydrology, shifting a greater fraction of winter precipitation from snow to rain and reducing mountain snowpack that serves as an essential natural reservoir, sustaining streamflow during the melt season. In the Midwest, conditions have generally trended wetter overall, yet the region has simultaneously experienced an increase in the frequency and intensity of flash droughts—rapid-onset events capable of inflicting severe agricultural and ecological damage. Notable examples include the 2012 drought that struck during the agricultural growing season and the 2017 drought centered in the Northern Great Plains. The Northeast (including, as used in this report, the states extending from Maryland and Delaware to Maine), not traditionally associated with significant drought risk, has experienced historic drought conditions in 2000, 2016, 2020, and 2022, levels not seen since the 1960s.

This report identifies three broad categories of processes that can generate drought nonstationarity, each potentially operating on a number of timescales that can act through different mechanisms: (1) climate variability internal to the climate system (i.e., over decadal and longer timescales); (2) forced climate change, both natural (e.g., due to changing volcanic forcing) and anthropogenic (i.e., due to emissions of greenhouse gas and aerosol pollution into the atmosphere); and (3) land surface (e.g., vegetation) and human water and land management changes (e.g., over-allocation of river flows and groundwater depletion, crop changes and land fallowing). Whereas the solutions to each factor could differ by mechanism, all share the same consequence of undermining accurate drought assessment due to the resulting nonstationarity.

DESIGNING A TWO-PRONGED APPROACH FOR INCORPORATING NONSTATIONARITY

Given the steadily increasing impact of human-caused climate change, as well as human water and land management changes that can exacerbate drought conditions, the nation's drought assessment enterprise must incorporate nonstationarity into drought assessment, decision-making, and action to ensure future resilience to drought. Nonstationarity challenges drought classification and assessment because drought is traditionally defined based on static thresholds relative to a baseline climate; when the baseline changes, the same physical conditions can be misclassified and consequently provide inaccurate information for operational decision-making or long-term planning.

The concepts of *period of record* and *reference period*, used to refer to the temporal span over which data are available and deemed representative for analysis, lies at the heart of drought assessment methodologies. Traditionally, drought assessment has relied on long-term historical records to establish baselines and characterize the rarity of conditions, often drawing on the longest available period (e.g., 60+ years). While 30-year climate normals established by the World Meteorological Organization (WMO) are widely used in climatology and have been applied in some drought contexts, longer records have generally been preferred where available, assumed to better capture extremes. However, under increasing nonstationarity, these long-term historical baselines may no longer provide a stable reference for assessing current-day drought conditions and risk. Specifically, fixed reference periods risk masking secular trends (i.e., long-term trends not attributed to a cause), failing to capture the increasing spread of drought extremes now emerging under climate change, and systematically misinterpreting contemporary drought risk, including under- and overestimating drought risk in some areas. The challenge is particularly significant because the selection of baseline period fundamentally shapes drought detection, classification, and communication. A baseline drawn from earlier decades may classify current conditions as more anomalous than one drawn from recent decades, yet neither fully captures the trajectory of ongoing change.

The report's authoring committee concludes that a framework for incorporating nonstationarity in drought assessment to inform decision-making should be designed around a two-pronged drought analysis framework that delineates and addresses the specific needs of (1) short-term operational assessments for activities like emergency management and (2) long-term planning assessments for activities like adaptation, depending on the application (see Figure S-1).

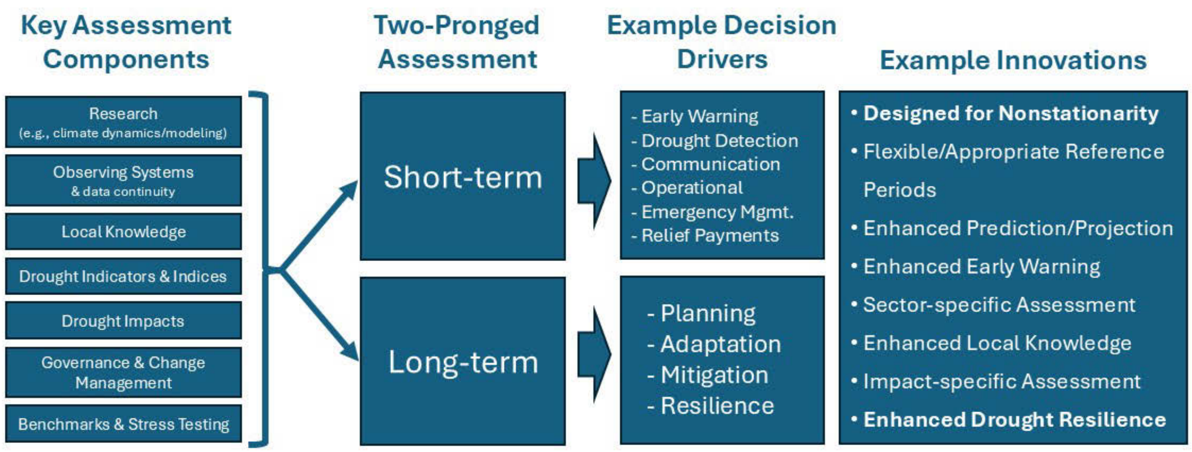


FIGURE S-1 Elements of the proposed two-pronged assessment framework.
NOTE: This schematic highlights key components to be provided by the recommended assessment consortium, example decision drivers, and examples of the innovations that would yield improved drought assessments.

In this framework, short-term operational assessments aimed at predicting subseasonal-to-seasonal changes in drought conditions (prediction and early warning), characterizing current drought conditions (monitoring), analyzing the characteristics of a recent drought event (post-event assessment), or assessing potential changes in regional to local drought characteristics under the current climate (projection) require that the community should employ an updated stationary approach based on contemporary baselines (e.g., 30 years ± 10 years, depending on the type of drought assessment, systems of interest, and decision frameworks), with clear rules for baseline refreshing, documentation, versioning, and reproducibility. Such an approach ensures that drought assessment accurately casts an emerging or ongoing drought relative to the current climate.

For drought assessments used in long-term planning, such as those designed for seasonal to multiyear expectations of drought conditions and impacts (prediction and early warning), for analysis of recent drought events in the context of a region's or location's long-term drought history (post-event assessment), and for long-term planning and drought impact mitigation (projection), the framework should emphasize the explicit use of nonstationary approaches that ingest the full available observational record and model-based predictions/projections to allow statistical parameters to evolve with time and/or physically meaningful covariates (e.g., temperature, circulation indices, water demand, land use and land cover).

Recommendation 8-2: NOAA/NIDIS, in collaboration with other agencies such as USDA, should develop a common drought assessment framework that integrates approaches for both short-term operational and long-term planning applications. In this framework, short-term operational assessments should be based on contemporary baselines, with clear rules for baseline refreshing, documentation, versioning, and reproducibility; and long-term planning assessments should be based on nonstationary models that use the full available observational record (including the paleoclimatic record) together with model-based predictions and

projections, and that allow distribution parameters to evolve over time and/or with physically meaningful covariates.

The focus of this report is on drought assessment that is designed to inform understanding, decisions, and actions to address current drought conditions and reduce long-term risk of drought and drought impacts. To meet information needs of all users and stakeholders, efforts to advance drought assessment to incorporate nonstationary considerations should include representatives of key groups with interest in drought assessment.

Recommendation 8-1: To support the development of a common drought assessment framework, NOAA/NIDIS should facilitate the establishment of a consortium that includes representatives from the research community, operational agencies and practitioners, and standards and regulatory stakeholders.

Recommendation 8-3: NOAA/NIDIS should facilitate development, with a consortium of key drought sector representatives, of a set of application-specific guidelines, specifying baseline lengths, update frequency, documentation standards, and reporting requirements for short-term and long-term drought analysis, with complementary guidelines tailored to specific applications or sectors.

The short-term operational drought assessment capability in the United States, with leadership and contributions from NOAA/NIDIS, the National Drought Mitigation Center (NDMC), and many others across the drought community, is already well established and can be steadily improved to ensure that consideration of nonstationarity enables reliable and reproducible drought monitoring, early warning, and emergency drought relief practices. The explicit incorporation of nonstationarity into drought assessment for long-term planning can take better advantage of ever-improving climate prediction and projection capabilities to anticipate future drought-related challenges across the nation (all 50 states and U.S. territories), avoid maladaptation, and develop strategies to ensure resilience.

UNDERSTANDING AND ASSESSING THE DRIVERS OF NONSTATIONARY DROUGHT

There is a growing need to invest in gaining *a deeper understanding of drought drivers under nonstationarity.* Traditionally, the risk of drought has been associated with the risk of anomalously low precipitation. As temperatures continue to increase, however, more research focus is needed on the increasing atmospheric demand for moisture and how this demand works through subsurface geology, soils, vegetation, and snow to intensify, and in an increasing number of cases, to initiate drought. The same processes, ultimately driven by atmospheric warming, are already leading to long-term drying trends, and this trend toward greater "aridification" can also change the nature of precipitation-driven droughts, usually by making them more frequent, severe, and longer.

Much remains to be learned about the nature of precipitation variability and change, and how to simulate this variability and change with state-of-the-art climate and Earth system models used for climate prediction and projection. As flash droughts become more common, there is an urgent need to gain a better predictive understanding and early warning capability of these rapidly intensifying drought events, including constraints on how temperature extremes interact with precipitation variability. All parts of the United States are at risk of worsening drought impacts, but unprecedented twenty-first century heat, drought, and wildfire across the Western United States warrant special concern and research attention. To what degree is this region experiencing long-term aridification, how are trends in temperature and precipitation driven now and into the future, what are the implications for human and natural systems, and what mitigation and adaptation strategies are feasible? Use-inspired research is key to success and must be expanded to ensure drought resilience in the face of nonstationarity.

Recommendation 4-1: NOAA, NSF, NASA, and other science partners involved in the national drought assessment enterprise should prioritize scientific research into drought dynamics and aridification, including how climate variability and change influence the frequency, severity, duration, onset, intensification, and other aspects of drought needed to support relevant decision-making. The research should also prioritize improving approaches used to assess drought and aridification risks seasons to decades into the future.

DROUGHT ASSESSMENT DATA, INDICATORS, AND INDICES

Data sources, continuity, and stewardship are becoming even more important as nonstationarity acts to make drought assessment more complex and drought resilience more difficult to achieve. Drought data serve diverse stakeholders with fundamentally different temporal horizons, information needs, and tolerances for uncertainty. Therefore, understanding these distinct requirements is essential for designing observation systems and data products that effectively support both operational response and long-term planning. For example, short-term operational drought management, exemplified by systems such as the U.S. Drought Monitor, requires not only accuracy but also timeliness, interpretability, and consistency with established decision frameworks. Effective short-term operational monitoring also recognizes that physical indicators need to be integrated with impact data that document observed consequences for water supply, agriculture, ecosystems, and human livelihoods.

Long-term drought planning, on the other hand, operates on fundamentally different temporal scales and information requirements than operational monitoring. Water resource planning models, infrastructure investment decisions, insurance programs, natural resource and public lands management, and regional adaptation strategies require stable baseline climatology, explicit quantification of uncertainty, and mechanistic understanding of drought processes rather than purely empirical relationships. The challenge of nonstationarity is particularly acute in this context. Under a changing climate, historical records may systematically misrepresent future conditions, because the statistical properties of past droughts no longer reliably bound the range of conditions that infrastructure and water systems will face. Adjusting historical data to reflect current climate states, while preserving information about variability structure, is one approach to this problem; water resource planning models in California, for instance, have adopted methods that modify historical hydrology to account for contemporary temperature and evaporative demand while maintaining realistic spatial and temporal patterns. Paleoclimatic data are increasingly being used (e.g., by the United States Bureau of Reclamation and in scenario planning) to provide observation bounds on what is possible, and also as a challenge to understand both what drives exceptionally long or severe multidecadal megadroughts and the possible implications of these drivers for the future.

Successful drought assessment under nonstationarity requires both long-term observational records and contemporary high-resolution datasets. In particular:

Recommendation 5-1: Federal agencies (such as USGS, NOAA/NWS, USDA, USCRN) operating in situ hydrological networks (streamflow, COOP, SCAN, SNOTEL, USCRN, and state-operated hydrological and mesonet networks) should prioritize continuity of long-term datasets with strategic placement across diverse soil types, crop covers, topographic settings, climatic zones, and ecosystem types to capture the heterogeneity of drought response and strengthen standardized data archiving, quality control protocols, and open-access frameworks to facilitate seamless integration with satellite and model-based products.

Recommendation 5-2: To ensure continuity and support proactive planning, NASA and USGS, in coordination with NOAA, should develop explicit mission succession strategies with multidecadal funding commitments to preserve critical Earth observation records, thereby avoiding gaps in records essential for drought detection and assessment. This includes incorporating explicit prelaunch cross-calibration protocols with predecessor systems, overlapping periods enabling robust inter-sensor comparison, and prioritizing long-term homogeneity essential for detecting climate signals under nonstationarity.

Drought indicators, indices, and reference periods all need special attention in the pursuit of improved and more useful drought assessments under nonstationarity. Useful and usable drought assessments are built, in part, on transparent metadata. Likewise, they foreground a rich variety of inputs, perspectives, and representation. To this end, efforts should continue within the drought assessment community to explore transparent and reproducible approaches to drought assessment that recognize that expert judgment, local expertise, Indigenous and Traditional Ecological Knowledge, and other ways of knowing provide critical perspectives not fully captured by purely quantitative approaches. Importantly, reference periods should be treated as adaptable parameters depending on assessment and decision-making contexts; given nonstationarity, it is no longer feasible to assume that fixed climatologies remain valid over time.

Recommendation 6-1: NOAA, USDA, USGS, affiliated regional climate centers, and national drought assessment partners such as the National Drought Mitigation Center (NDMC), should develop flexible methods to examine drought information with different reference periods in consultation with drought data providers, practitioners, and end users. This could include producing multiple datasets concurrently using different reference periods (e.g., the last 30 years, the most recent climate normal period, and the full period of record) or enabling dynamic generation of drought indices using user-defined reference periods. In doing so, methods should balance flexibility for system-specific applications with the need for consistent, transparent, reproducible, and comparable assessments of drought conditions across space and time.

For both short- and long-term drought assessments under nonstationarity, transparent documentation of analytical methods, reference periods, and uncertainty is essential for ensuring that drought metrics are interpretable, comparable, and appropriately applied as climate conditions and land use/land cover evolve.

Recommendation 6-2: NOAA, USDA, USGS, and affiliated regional climate centers, in coordination with academic and practitioner communities, should develop and adopt shared standards for documenting and publishing metadata associated with drought metrics, including methods, reference periods, and uncertainty.

Recommendation 6-3: NOAA, USDA, and USGS, in collaboration with state and federal agencies (including the USDA Climate Hubs and NCEI's Regional Climate Centers), should convene key communities affected by drought to identify reference periods that align with risk profiles of specific systems, to better inform decision-making for each system.

Particular recognition is due to the U.S. Drought Monitor, their products, and those who contribute to and produce them at regular intervals, in many cases on a voluntary basis. At the same time, there is a sense that all those involved in the U.S. drought assessment enterprise, especially including those using the USDM for decision-making purposes, might be able to improve and build upon the tool as drought assessment information continues to expand. Expanded drought decision-support information could include, for example, separate short- and long-term drought assessment maps and products, decision-specific drought products and maps, or sector- or drought-type-specific maps.

DROUGHT IMPACTS AND IMPACT DATA

Drought impacts and impact data are becoming ever more valuable for drought assessment under nonstationarity, as well as for drought mitigation and adaptation in the short- and long-term at national, state, and local levels. This is especially true as drought assessment methods, artificial intelligence (AI), and other innovations continue to improve. At the same time, the reporting of impact data and information needs to become more consistent across geographies, drought types, sectors, and time, all optimized for decision-making.

Sector or system exposure and adaptive capacity are important components of drought risk and impact, and changes in either exposure or adaptive capacity can themselves be viewed as potential nonstationarities that in turn might affect the likelihood and/or severity of a drought impact. It is thus critical to track these components of drought risk and impact.

Conclusion 7-3: Assessment of drought impacts requires information on drought conditions as well as the status and adaptive capacity of affected systems to inform operational drought response and long-term planning, but mechanisms for collecting and using such data do not exist consistently across the United States. State government agencies (e.g., natural resource, agriculture, and environmental protection agencies) in collaboration with local governments may be best positioned to undertake collection of data and planning that are relevant to drought exposure (e.g., water use, stream gauge, and low flow measurements) and adaptive capacity across systems (e.g., through water supply and hazard mitigation plans) and use of that information to reduce drought impact risk (e.g., tabletop exercises of existing drought plans).

Recommendation 7-2: NIDIS should facilitate the development or improvement of systems for systematic collection, reporting, and integration of drought impacts consistently across sectors, regions, and interests, for multiple uses, including

drought assessment, adaptation, and other decision-making. In this work, NIDIS should collaborate with the U.S. Department of Agriculture (agriculture and forest), Department of Interior (coastal, ecological, water resources), Department of Homeland Security (drought response/resilience, national security), Bureau of Land Management (fire, rangeland), Health and Human Services (public health), Environmental Protection Agency (water resources, air and water quality), and Tribal communities, as well as the broader drought community.

Recommendation 7-1: NIDIS should work with decision-makers, scientists, and the broader drought community to develop a set of best practices by which drought impacts data can be consistently and effectively used for all aspects of drought assessment, especially for state drought plans and other policy and action plans.

ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING APPLICATIONS IN DROUGHT ASSESSMENT

Artificial intelligence and machine learning (AI/ML) are rapidly becoming ubiquitous in many areas of the human endeavor, and drought assessment is no exception. Moreover, the rate of AI/ML innovation is extraordinary and likely to enable great strides in the improvement and utility of drought assessment. While AI/ML may fit into numerous components of the drought assessment pipeline, there are four historical and emerging arenas with particular opportunity: assessment automation, state variable prediction, forecasting, and data synthesis. Special care is advised, particularly during the ongoing period of rapid AI/ML innovation and as the use of AI/ML is adopted more widely, to ensure methodological transparency, reproducibility, and an avoidance of bias. In particular, AI/ML can perpetuate inequalities and unfairly affect people if not used carefully. Good governance plus sustainable and ethical use of AI/ML is important for ensuring overall net benefit to society.

VISION FOR DROUGHT ASSESSMENT UNDER NONSTATIONARITY

This report recommends an improved framework for assessing drought under nonstationarity in the United States. The framework presented in this report is designed to be driven by decision-makers in society and the decisions that they need to make regarding drought, on both short-term operational and long-term planning timescales. The committee recommends that NIDIS and their partners articulate the specific decision drivers and details of how the framework will be designed and implemented. Examples of decision drivers are given in Figure S-1, with the overarching goal that an improved framework for drought assessment under uncertainty will lead to greater resilience to drought in the United States, both short-term and long-term. This framework provides approaches to incorporating nonstationarity into drought assessment; it is intended to enhance existing and future drought assessment approaches, rather than replace them.

This report weaves together an understanding of how the drivers and nature of drought are changing in the United States, and how drought assessment needs to change to meet the challenge of nonstationarity, especially in the form of a changing climate. This challenge will require a range of research, including on how the climate varied in the past, how the climate system works, and how climate will change in the future, and also on how scientific information—drought assessments included—can best inform decision-making under uncertainty. Special attention must also focus on observing systems, *in situ*, paleoclimatic, and space-borne, that are essential to the drought assessment enterprise; continuity of these vital systems must be assured. Existing drought indicators and indices, many of which are invaluable and already widely used, depend on observing systems, and the creation of new innovative indicators and indices will no doubt require new observing capabilities. The use of local knowledge and drought impact data can be expanded to make drought assessments more useful and effective.

Key to improved drought assessment will be the successful participation of all the partners essential to effective decision-making, as well as a high level of transparency in terms of how all elements of drought assessment are implemented. This includes making assessment methodologies as transparent and reproducible as possible and also ensuring effective governance and change management as assessment protocols improve. Improvement requires benchmarks and stress-testing that are also structured and transparent to all users of drought assessments. Understanding assessment uncertainty is critical to making effective decisions, whether they relate to predictions or projections of future climate, connecting drought to impacts, or any other aspect of the assessment endeavor.

As stressed throughout this report, NIDIS and the broader U.S. drought community have established an excellent foundation on which to build an improved operational drought assessment framework that takes nonstationarity into account. The nature of drought is changing in the United States, and so too must this country's ability to thrive in the face of increasingly complex and severe drought risks.

Appendix B contains a complete list of the study committee's conclusions and recommendations.

1
Introduction

NEED AND OPPORTUNITY FOR IMPROVED U.S. DROUGHT ASSESSMENT

Drought has affected humankind since before the beginning of civilization, yet changes in climate that became increasingly apparent beginning in the 1980s have exerted a growing influence on drought conditions virtually everywhere in the United States. While drought has long been recognized as a hazard with far-reaching consequences across every sector of the economy and every facet of human activity, its nature has undergone transformation in recent decades.

The current drought in the U.S. Southwest[1], the first multidecadal "megadrought" in the nation's history and the most severe of many such droughts over the past 1,200 years (Williams et al., 2022a). The nation has adapted to recent droughts and become more resilient to drought in multiple ways. Despite that progress, droughts and drought impacts are becoming more severe, as evidenced most clearly by a growing water crisis in the Southwest[2], groundwater running dry in parts of western Kansas, and declining more broadly across the High Plains[3, 4], and unprecedented hot drought and wildfire (Abatzoglou et al., 2016) affecting an ever-increasing swath of the nation.

Among billion-dollar weather and climate disasters in the United States, drought is the third most costly in terms of economic loss behind hurricanes (tropical cyclones) and severe weather (e.g., tornadoes). Between 1980 and 2025 in the United States, the economic cost of each of the largest droughts has averaged over $11 billion per event, with consequent wildfire events adding to this toll, averaging nearly $9 billion each.[5] In terms of human lives lost, drought and extreme heat combined are responsible for over 100 deaths per year, ranked behind only the human toll associated with hurricanes. Human deaths related to extreme heat events are on the

[1] As used in this report, the Southwest includes California, Nevada, Utah, Colorado, Arizona, and New Mexico; the West encompasses the area from the Rocky Mountains to the West Coast; the Midwest includes states in the Ohio Valley and along the Great Lakes; and the Southeast includes the states extending from Texas to Virginia, and especially Georgia and Florida.

[2] https://www.usbr.gov/newsroom/news-release/5326, accessed May 23, 2026

[3] https://kgs.ku.edu/news/article/groundwater-levels-fall-across-western-south-central-kansas, accessed May 23, 2026

[4] https://www.fastcompany.com/91018954/were-running-out-of-water-how-kansas-farmers-are-adapting-as-a-crucial-aquifer-goes-dry, accessed May 23, 2026

[5] https://www.climatecentral.org/climate-services/billion-dollar-disasters/summary-stats, accessed May 23, 2026

rise as well, as record heat and drought both become more common and often combine to make impacts worse.

Regional expressions of this transformation vary considerably across the country. In the West, a marked increasing trend in temperatures is drying soils faster and stressing ecosystems through enhanced evapotranspiration, coupled with low precipitation (King et al., 2024). Higher temperatures have altered regional hydrology, shifting a greater fraction of winter precipitation from snow to rain and reducing mountain snowpack that historically served as a natural reservoir, sustaining streamflow during the melt season (Barnett et al., 2005; Hale et al., 2023; Siirila-Woodburn et al., 2021). In the Midwest, conditions have generally trended wetter overall, yet the region has simultaneously experienced an increase in the frequency and intensity of flash droughts—rapid-onset events capable of inflicting severe agricultural and ecological damage. Notable examples include the 2012 drought that struck during the agricultural growing season (Basara et al., 2019) and the 2017 drought centered in the Northern Great Plains (Hoell et al., 2020). The Northeast, not traditionally associated with significant drought risk, has experienced historic drought conditions in 2000, 2016, 2020, and 2022 not seen since the 1960s (NIDIS, n.d.).

These ongoing and projected changes in the nature of drought are governed by the balance of multiple physical drivers, including atmospheric circulation patterns and their effects on temperature and precipitation, anthropogenically forced increases in mean temperatures, land cover modifications, and vegetation responses to rising CO_2 and temperatures. The cumulative effect of these shifts in the climate system poses fundamental challenges for drought assessment, which encompasses prediction, early warning, monitoring, post-event analysis, and projection.

Central to this challenge is the framework underlying drought assessment itself. Drought is, by definition, an anomaly—a departure from an expected baseline—and this definition embeds a series of analytical choices, foremost among them the selection of a reference period against which hydrologic departures are evaluated. A critical problem emerges when that reference baseline is no longer representative of prevailing climate conditions, giving rise to drought nonstationarity. Nonstationarity complicates the use of established diagnostic measures, including the indicators, metrics, and indices routinely employed in drought assessment, by rendering standardized drought measures and their associated severity thresholds physically and hydrologically incomparable across different baseline intervals.

While the challenges introduced by a nonstationary climate are considerable, they also present an opportunity to develop more robust and scientifically defensible frameworks for drought assessment. A rigorous and operationally practical approach to incorporating nonstationarity into drought assessment has the potential to improve drought preparation and response, thereby reducing societal and ecological impacts, informing long-term drought decision support, and promoting future resilience and discouraging maladaptation.

BUILDING ON A STRONG FOUNDATION

The drought of the early 1890s significantly impacted agriculture and caused the displacement of nearly 300,000 people; it led to greater investment in public works for agriculture, water supply, and transportation. The record Dust Bowl drought of the 1930s prompted the nation to take further action to reduce drought vulnerability, including the construction of additional reservoirs, improving domestic water systems, changing farm policies, and introducing new insurance and aid programs. These programs lessened the impacts of the next major drought, which happened in the 1950s (Riebsame et al., 1991).

Drought monitoring in the late nineteenth and early twentieth centuries relied upon meteorological indices that incorporated some measure of precipitation over a given period of time and hydrological indices based largely on streamflow. Throughout the twentieth century, indices that incorporated probability theory, antecedent precipitation, and evapotranspiration were developed. Palmer (1965) was the first to integrate these concepts into an index that quantified the total environmental moisture status by incorporating antecedent precipitation, moisture supply, and moisture demand into a hydrologic accounting system (Heim, 2002). The Palmer Drought Severity Index (PDSI) quickly became the de facto standard for drought monitoring in the United States.

The U.S. droughts of the 1960s in the Northeast and 1976–1977 in the West focused drought response on more flexible water systems operation and reduced water demand. In April 1977, a federal Interagency Drought Coordination Committee was formed that designated county-level drought disaster areas and coordinated federal drought relief programs. Drought research and policy workshops held in the 1970s and 1980s were followed by the development of comprehensive state drought response plans. Donald Wilhite advocated for a shift from reactive drought responses (crisis management after a drought occurs) to proactive responses (i.e., risk management, and including planning, monitoring, and preparation before drought hits) to build resilience (Riebsame et al., 1991).

Following the 1987–1989 drought, Riebsame et al. (1991) recommended the following actions: (1) conduct postaudits following droughts to guide strategic planning of future management options; (2) create a well-coordinated "drought watch" program that links federal, state, and local resources agencies on a continuous basis and provides a clearinghouse function for data and information that must be translated and disseminated to decision-makers; (3) improve the use of drought indices; (4) develop and apply climate impact models; (5) improve continency plans; (6) improve monitoring and collection of drought impact data in neglected sectors; and (7) improve dissemination of drought impact information, especially to the business and industrial sectors.

In the following decade, several states developed plans to respond to drought, and the National Drought Mitigation Center (NDMC) was launched in 1995 by Dr. Wilhite in partnership with the U.S. Department of Agriculture (USDA) and National Oceanic and Atmospheric Administration (NOAA) (Matteson, 2020; Gayman, 2022). The NDMC was designed to serve as a center to help decision-makers reduce vulnerability to drought, emphasizing monitoring, vulnerability assessment, planning, and drought mitigation.[6]

In response to the drought in 1995–1996, a federal interagency multistate drought task force was formed to evaluate and assess drought-relief programs available from federal, state, and local agencies from Southwest and Great Plains states. Simultaneously, in 1997 the Western Governors' Association (WGA) created the Western Drought Coordination Council to coordinate a comprehensive, integrated drought mitigation, preparedness, and response effort in the Western United States (Wilhite, 1997, 2000). In 1998, an act of Congress (Public Law 105-199[7]) established the National Drought Policy Commission whose purpose was to conduct a comprehensive study of federal, state, local, and Tribal drought preparedness and make recommendations for a national drought policy. The commission issued a report in 2000

[6] https://drought.unl.edu/Publications/FactSheets.aspx, accessed May 23, 2026

[7] National Drought Policy Act of 1998, H.R.-3035 (1998).

(National Drought Policy Commission, 2000) that contained several recommendations that ultimately led to the creation of the National Integrated Drought Information System (NIDIS).

Concurrent with these changes in drought response was a further evolution in drought monitoring tools. Advances in technology and computing power led to a proliferation of new drought indices that incorporated remotely sensed data and additional in situ data streams, and that were based on sophisticated land surface models. In the late 1990s, the convergence-of-evidence concept was developed to integrate or blend the numerous drought indices and indicators together into a single drought assessment. The U.S. Drought Monitor (USDM) (Svoboda et al., 2002) was developed in 1999 by NDMC, the USDA, and NOAA as one of the first composite drought products (Heim, 2002). The USDM quickly displaced the PDSI as the de facto U.S. drought monitoring standard. The composite drought product concept was adopted continent-wide with the North American Drought Monitor (NADM) in 2002 (Lawrimore et al., 2002). To support ongoing discussions of monitoring and assessment issues, the USDM and NADM authoring organizations hold quasi-annual forums, which representatives of the drought monitoring community attend, including state climatologists, Regional Climate Centers, Regional Climate Hubs, Climate Adaptation Science Centers, CAP-RISAs, other federal agencies, universities, state agencies, Tribal agencies, WGA, nongovernmental organizations, public and private entities, industries, and international partners.

National Integrated Drought Information System

The National Integrated Drought Information System is a National Oceanic and Atmospheric Administration program that coordinates drought monitoring, forecasting, planning, and information at federal, Tribal, state, and local levels across the country. It was created by an act of Congress (Public Law 109–430[8]) in 2006 through the efforts of the Western Governors Association (WGA) working with NOAA.

NIDIS, NOAA, and the U.S. Department of Agriculture held the Drought Assessment in a Changing Climate Technical Working Meeting in Boulder, Colorado, on February 28–March 1, 2023, to gather scientists and practitioners from federal, Tribal, state, and local agencies and academic institutions to address these concerns. The resulting report, *Drought Assessment in a Changing Climate: Priority Actions and Research Needs* (Parker et al., 2023), summarized the ideas shared by the participants and proposed several dozen priority actions and research questions that could advance drought assessment practices to account for the changing climate. Among the priority actions for NIDIS, under the "Benchmarking our Understanding and Assessment of Drought in a Changing Climate" section (p. 22), was a call for a National Academies study to extend this work:

> A National Academies (or similar) study is needed to benchmark our current understanding of drought in a changing climate. This study could approach the broader topic of drought and climate change. Key components of that study could focus on defining the drought-to-aridification continuum with the goal of developing a conceptual framework that can clearly differentiate between drought, multi-decadal drought, and aridification.

[8] National Integrated Drought Information System Public Law 109–430, H.R. 5136 (2006).

This priority action was echoed in a subsequent perspective paper (Lisonbee et al., 2025) as a series of high-priority research questions, including questions surrounding the physical drivers of drought and how they are changing, and how to improve drought indicators to account for nonstationarity, acknowledging that drought manifests differently in different ecosystems and regions.

COMMITTEE CHARGE AND STATEMENT OF TASK

At the request of the National Oceanic and Atmospheric Administration, the National Academies of Sciences, Engineering, and Medicine convened an ad hoc committee to consider approaches for future drought characterization, assessment, and response. The National Academies convened a committee of 12 members with expertise in meteorology, climate science, natural hazards, hydrology, economics, statistics, and risk analysis and communication. The committee's full statement of task is given in Box 1-1.

BOX 1-1
Study Statement of Task

The National Academies of Sciences, Engineering, and Medicine will convene an ad hoc committee to consider approaches for future drought characterization, assessment, and response.

More specifically, the study will:

- Discuss the drought-to-aridification continuum and differentiate among drought, multidecadal drought, and aridification. How do factors such as periods of record, drought type, regionality, and seasonality affect these classifications? How do current periods of record affect drought outlooks and predictions?
- Evaluate data sources currently used for drought assessment. What data will be needed to address non-stationarity? What methodologies can be used to improve future drought assessment, taking into account non-stationarity?
- Discuss metrics and indicators used in drought assessment and identify opportunities to inform decision making, including increasing integration of non-stationarity and incorporating uncertainty and/or confidence.
- Review existing and emerging approaches, both nationally and globally, for incorporating non-stationarity in drought assessment. Are some approaches more appropriate for specific regions and/or time periods?

The committee will recommend a framework for incorporating non-stationarity considerations into drought assessment, for use across a range of geographic regions and of spatial and temporal scales.

Considering the context for and applications of drought assessment in the United States, the committee recognized a number of additional layers and perspectives that it needed to consider when addressing its charge, in particular given the requirement in the statement of task that the committee's recommendations are useful for decision-making and response. These include defining the specific audiences for the report, a need to consider drought assessment applications and requirements for short-term and long-term decision-making, and framing the committee's work in risk and decision contexts.

AUDIENCES FOR THE REPORT

The primary audience for this report is producers and users of drought information in the United States. This audience includes **data providers** (such as the NOAA National Centers for Environmental Information [NCEI] and NOAA/NIDIS) who collect and package weather and climate information into useful and useable data products. It also includes federal and state **decision-makers** who rely on these data products to make drought designations that often have large financial and management implications for their constituents. At the federal level, these decision-makers include the U.S. Bureau of Reclamation (USBR) and the U.S. Department of Agriculture's Farm Service Agency (USDA-FSA) and Risk Management Agency (USDA-RMA). At the state level, these decision-makers include state climate offices and agencies managing agriculture and/or natural resources. These same state agencies are often tasked with **resource distribution to mitigate drought impacts**; they are also listed here for this reason. A related audience is the **state and federal policymakers** (including state legislators) who set priorities and establish policy for drought mitigation programs in the first place.

A second audience is the **general research community**. This report summarizes the current state of drought assessment in the United States and recommends a path forward for future drought assessment. It also identifies knowledge gaps and invites scientists—both biophysical and social—to fill those gaps. Federal research funding agencies may take note of the identified priorities. This research and modeling community audience includes federal agency personnel at the NOAA regional climate centers whose applied research is informed by the needs of communities—both geographical and communities of interest—who are experiencing drought. It also includes Cooperative Extension Services personnel and others within universities tasked with communicating science to the general public.

A third audience for this report is **those who experience drought and its impacts**. This includes Tribal entities who in addition to experiencing the impacts of drought also have extensive knowledge in managing and adapting to drought. Private and public purveyors of insurance will also find this report to be of value, as shifting patterns of drought and other extreme weather events increase their financial exposure to climate risk. Finally, the committee intends this report to be accessible to members of the general public who have a keen interest in understanding current methods of assessing drought and how they are changing, as drought affects us all.

Information Gathering

Over the course of the study, the committee hosted three publicly accessible information-gathering sessions where invited speakers briefed the committee on topics relevant to the statement of task.

The first public information-gathering session occurred on July 15, 2025, and focused on intermediary data providers for drought information, those who use, develop, and provide key drought data used by decision-makers for actions and responses to current and future droughts. Presenters included a USDM author and several state climatologists, NOAA Regional Climate Centers, and Climate Adaptation Partnerships.

A second information-gathering session was held on August 26, 2025, focusing on drought and nonstationarity. This session included presentations focused on defining drought nonstationarity, existing methods for adjusting for nonstationarity, data needs/limitations for detecting/modeling nonstationary drought patterns, existing tools to inform future research, and operational decision-making frameworks. Presenters included current and former federal science agency representatives from the United States Geological Survey (USGS) and NASA, as well as multiple academic researchers.

A third information-gathering session was held on October 14, 2025, to gather perspectives from drought data users and decision-makers. Drought decision-makers and users of drought information from a range of economic sectors and regions shared information regarding what drought information they use, how they use it, what timescales are used, and how it impacts their decisions. Presenters included federal drought-related programs, including former representatives from the USDA and United States Bureau of Reclamation (USBR), and state and local data users, including the California Department of Water Resources, the Missouri Department of Natural Resources, and the Southern Nevada Water Authority.

A TWO-PRONGED STRATEGY FOR CHARACTERIZING AND ASSESSING DROUGHT AND FOR SUPPORTING DROUGHT DECISION-MAKING

Drought assessment takes many forms and supports a broad set of decision-making, both of which are expanded in Chapter 2. The variety of decisions and applications that are informed by drought assessment can be generally grouped into one of two categories: (1) operational drought assessment and (2) long-term drought decision support. Operational drought assessment includes activities that inform decisions made in the context of preparing for an impending drought, responding to an ongoing drought, and evaluating a recent drought. Long-term drought decision support includes assessment activities that inform decisions made in the context of planning for future (i.e., not impending) droughts and reviewing decisions and impacts of past droughts. These two categories broadly align with the short-term/long-term temporal dimension of drought decisions discussed in Cravens et al. (2021). Although this two-pronged approach bifurcates drought decisions along only one of many dimensions on which drought decisions are made, the committee has determined this approach facilitates a comprehensive discussion of drought assessment and nonstationarity.

Conclusion 1-1: An enhanced framework for drought assessment under nonstationarity should consider and address the differing needs and components of drought assessment for both operational/emergency management and long-term planning applications.

RISK AND DECISION FRAMING IN DROUGHT ASSESSMENT

The study committee relied on a risk- and decision-centered approach to guide its evaluation of data sources, metrics, and indicators used for improving current approaches to operational drought assessment, as well as for the development of recommendations aimed at incorporating nonstationary considerations into longer-term drought assessment and decision support. This risk and decision framing emphasizes approaches to drought assessment that not only characterize anomalies in climate or hydrology but also align those characterizations with the risk faced by specific systems of interest and existing decision contexts surrounding those systems.

The committee recognizes the rich body of work that exists in the risk analysis and decision science literatures that may be relevant for drought assessment, including theories and frameworks to conceptualize risk and decision-making in the presence of extreme events and disasters. This literature employs terms, definitions, and concepts that are useful for characterizing practical and risk-informed drought assessment; some of these terms, definitions, and concepts will be used throughout this report. However, this study will not rely on a particular existing risk or decision framework to derive its conclusions and recommendations. While specific frameworks, such as the one presented in the Special Report of the Intergovernmental Panel on Climate Change (IPCC), *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* (IPCC, 2012), were considered for this study, the committee ultimately determined that the study statement of task can be addressed thoroughly without relying on a particular risk or decision framework. The committee also believes that a more general approach to risk and decision framing will allow the conclusions and recommendations of this study to be applied more flexibly across the different geographic locations and extents and temporal scales over which drought assessments are made.

Risk Framing

Risk management frameworks are prevalent in the climate change and disaster literatures. Notable examples include the aforementioned IPCC framework (IPCC, 2012), the progression of vulnerability framework (Wisner, 2016), and the social amplification of risk framework (Kasperson et al., 1988). The degree to which these frameworks have been applied toward relevant and effective practice in disaster risk reduction has also been studied (Wisner and Alcántara-Ayala, 2023).

There is an increasing interest in, and acknowledgment of, the compounding and cascading nature of hazards, which have been explored in the drought assessment context in terms of drought-related compounding or cascading hazards such as heatwaves, wildfires, and floods (AghaKouchak, 2023), as well as their impacts on social, economic, and environmental systems (UNCCD, 2023). This study takes a more general approach that prioritizes existing and emerging approaches for incorporating nonstationarity that allow for *risk-informed* drought assessment, that is, drought assessment that is driven by decision-makers' understanding and consideration of risk within specific systems of interest. Indeed, given that decision-making concerns, priorities, and strategies change through time, this study explicitly calls for continual engagement and co-development between those assessing drought and the wide range of decision-makers who use drought assessments.

In this general framing, drought risk emerges from the interaction among several characteristics of the occurrence of drought and the system of interest. One main component is the drought *hazard*, or the physical expression of dryness, including its severity, frequency, speed of onset/intensification, and duration, shaped by nonstationary climate and hydrologic processes. The study committee defines drought as a hazard in greater detail in Chapter 2, and its relation to nonstationarity and climate change in Chapters 3 and 4.

Drought risk is also a function of *exposure*, which refers to the people, assets, and ecosystems in harm's way, and the *adaptive capacities* of the system of interest, which refer to the system's ability to react to the adverse effects of hazards and the ability to survive hazards. Exposure and adaptive capacity are related to and often interpreted as being components of *vulnerability*, which refers to the propensity of people, ecosystems, or assets in the system of interest to be adversely affected by the hazard. In addition to being system-specific, vulnerability can change over time concurrently with the hazard, complicating the various tasks of drought assessment. Hazard, exposure, adaptive capacity, and vulnerability together inform the committee's examination of drought metrics and indicators, leading to the two-pronged approach—introduced above and described in full in Chapter 8—that distinguishes the use of drought assessment in short-term operational monitoring and emergency response decisions from its use in long-term planning and intentional progress toward adaptation, and ultimately speaks to what are the appropriate reference periods for drought assessment.

A final component related to drought risk is drought *impacts*, or the negative effect that a hazard or disaster has on a particular system, place, or people. Impacts are modulated by the realized speed of onset, severity, and duration of the hazard, as well as the system's exposure and adaptive capacity. As described in Chapter 7, data on drought impacts themselves can serve as inputs to drought assessment (i.e., impact-based drought assessment [AghaKouchak, 2023]).

While the rest of this study will refer to hazard, exposure, adaptive capacity, vulnerability, and impacts, it will not rely on a framework that assumes that these components are mutually exclusive or are related to each other in specific ways. The study committee also acknowledges the widespread use of other concepts that help characterize risk in academic and practitioner circles, such as sensitivity, coping capacity, and resilience (Füssel, 2007; Graveline and Germain, 2022). Ultimately, the committee's goal was to allow for a risk-centered study approach such that drought assessment not simply characterizes anomalies in climate or hydrology but also provides decision-makers and those who experience drought and its impacts a better understanding of the contemporary risks they face.

Decision Framing

The study committee's adoption of a decision-centered approach entails a focus on inputs to decisions tied to actions that, in turn, influence the type and magnitude of socioeconomic and environmental impacts. In the context of drought assessment, important decisions include those made over shorter time frames, such as emergency response and water resource operations, as well as those that relate to longer-term planning and preparedness. This decision framing is tied closely to risk framing in that risk mitigation systems—including government programs, insurance systems, and infrastructure—involve decision-making that buffers risk or unintentionally sustains vulnerability by discouraging adaptation. These systems also include water users and stakeholders who undertake risk mitigation and adaptation based on drought information that is made available by the public and private sectors. Thus, improved drought assessment is not only valuable for government agencies but also for water users who rely on them to make better decisions when responding to and preparing for drought.

Identifying opportunities to integrate and incorporate nonstationarity in drought assessment, therefore, required the committee to first identify key socioeconomic or environmental impacts that society cares about, such as agricultural production, residential water supply, industrial water use, ecological flows, and cultural water uses, and then "work backwards" to identify existing decision contexts in the public and private sectors that influence those outcomes. After identifying these key decision contexts, the committee sought to characterize how drought assessments are used in those decision contexts and how nonstationarity is (or could be) incorporated or accounted for in those assessments. While the committee considered a large number of decisions linked to a variety of geographic areas, socioeconomic sectors, and temporal scales, it did not conduct a systematic or exhaustive review of these decision contexts.

Decision framing is justified, in part, by the statement of task for this consensus study, which requires the committee to "identify opportunities to inform decision making." Moreover, two of the priority actions described in the NOAA Technical Memorandum (Parker et al., 2023) for drought assessment in a changing climate include (1) assessing drought policies and programs through the lens of nonstationarity and (2) strengthening planning, management and adaptation. More broadly, the decision science literature highlights the importance of baseline uncertainty of decision-makers, and what is at stake as an outcome of their decisions, in determining the market and nonmarket values of improved information, such as what would be afforded by addressing nonstationarity, for information in general (Hirshleifer and Riley, 1979; Howard, 2007) and for Earth science information in particular (Bernknopf et al., 2018; Macauley, 2006).

Decision framing influenced the study committee's consensus study activities in several ways. For example, the committee's conclusions and recommendations are sensitive to the fact that decisions informed by drought assessments are usually not made in a vacuum but are often made within political and social contexts with differing objectives, resources, and constraints. Decision framing also recognizes that drought assessment is in part a risk communication exercise and has as one goal the sharing of practical information and response guidance among key partners and stakeholders that is continuous and builds public knowledge, assessment effectiveness, and trust over time. The committee itself is composed of experts who focus on the experience of drought assessment users, and the committee planned and hosted information-gathering sessions focused on drought data users and decision-makers and intermediary drought data providers who use, develop, and provide key drought data used by decision-makers, as described earlier. Particular attention was paid to considerations and implications of drought nonstationarity on the preparation of drought assessment and their use in decisions. Use of decision framing also informed the two-pronged approach of considering separately the implications of nonstationarity for drought assessment in operational drought response and relief, as well as in long-term planning and preparedness.

Finally, both operational drought response and long-term planning often require collaboration and cooperation across multiple decision-makers and may involve multiple funders and beneficiaries. Effective decision-making that leads to action requires agreement on a shared set of facts, and improved drought assessment can serve as a reliable anchor point for negotiation and facilitate the type of joint investments and agreements that will be pivotal in reducing or mitigating drought impacts, especially in the long term. This is a core value proposition of improved drought assessment and forecasting.

It should be noted that there are alternatives to adopting a decision frame as a guide for making recommendations for improving drought assessment. For example, given enough time, the committee could have considered *all* possible approaches for incorporating nonstationarity in drought assessment, regardless of whether these approaches are expected to influence decision-making. A consequence of the committee's focus on decision frameworks is that the recommendations in this consensus study will emphasize those that generate market and nonmarket values from drought assessment that are important as means to achieve human ends or satisfy human preferences—while intrinsic values, such as the notion of knowledge being valuable for its own sake, will be deemphasized. For example, this study would not prioritize a recommendation that would lead to "improved understanding" of a particular component of drought dynamics if that improved understanding is unlikely to influence decision-making.

STRUCTURE, TRANSPARENCY, AND REPRODUCIBILITY IN DROUGHT ASSESSMENT

In addition to incorporating nonstationary considerations, the committee will refer to several other generally desirable attributes for a drought assessment process. A component of the drought assessment process is understood to be *transparent* if there is sufficient documentation of the component such that every choice that could plausibly affect the result is visible to a reader. Transparency requires clarity around the quantitative and qualitative information that was used in drought assessment, the way the information was processed, the analytical methods used, and any assumptions being made. Importantly, an assessment can be transparent even if experts interpreting the same information arrive at different conclusions about drought; in these cases, transparency requires documentation of these points in which “judgment rather than rule” is applied.

The quantitative tasks of drought assessment are considered to be *reproducible* if another analyst who is given the same data and transparent documentation of the methods can rerun the assessment workflow and obtain the same results within a predefined tolerance. Reproducibility may require more than just transparent documentation, such as versioned data, executable computer code, and documented computational environments. While full reproducibility may be difficult to achieve in a drought assessment process that uses qualitative data or involves tasks in which different experts interpreting the same information may reasonably arrive at different conclusions, such assessments can still employ a *structured* approach that follows an organized scheme rather than one that emerges ad hoc. Ways in which a drought assessment can follow a structured approach include pre-defining the set of questions to be answered and the data and methods that will address them, outlining a consistent sequence of steps in the task’s workflow, and standardizing the format of outputs, including standardized vocabularies and metadata.

REPORT ROADMAP

This report is the committee’s response to its Statement of Task, with individual chapters addressing core components of that charge, with considerable connections across nine chapters:

Chapter 1 establishes the need for improved drought assessment, describes the statement of task, outlines the audiences for this study, and introduces the risk- and decision-centered approach that guided the study.

Chapter 2 provides a foundation for the report by defining drought and discussing the various drought types and characteristics, how these characteristics are affected by regionality and seasonality, and drought assessment components.

Chapter 3 addresses the physical mechanisms that initiate and sustain drought across the contiguous United States. The chapter discusses the overarching factors that control drought in general, followed by a more detailed look at the geographical and seasonal dependencies that make each region unique in its drought characteristic, and how anthropogenic climate change alters the balance of factors that contribute to drought.

Chapter 4 lays out the challenge that climate nonstationarity poses for drought assessment. The chapter discusses the components of nonstationarity, aridification, and megadrought, and examines how they interact with drought classification and monitoring, before turning to the implications of nonstationarity for decision-making and maladaptation.

Chapter 5 describes the various datasets that are used to characterize droughts, as well as the importance of data continuity, metadata, and innovation.

Chapter 6 evaluates how drought indicators and indices are constructed and used under climate nonstationarity, with emphasis on key analytical choices (data, timescales, statistical standardization, and reference periods). It examines how those choices alter drought classification and uncertainty, considers system-specific interpretation and offers recommendations for transparent documentation and risk-aligned decision support.

Chapter 7 describes how drought impacts, defined as an indicator of the potentially harmful outcomes of drought, are an essential element of drought assessment and are affected by nonstationarity.

Chapter 8 arrives at recommendations for a decision-centered approach to incorporating nonstationary considerations into drought assessment that aligns analytical choices with the decisions the analysis is meant to inform, anchored by the two-pronged approach for characterizing and assessing drought. This chapter also makes a call for strengthening impact-based drought analysis and summarizes likely challenges in implementing the recommended framework.

Chapter 9 illustrates the recommended two-pronged framework for drought assessment in a nonstationary world using tangible examples for both the short-term operational and long-term planning decision contexts.

Readers primarily interested in the framing and application of the committee's work may choose to read Chapters 2 and 7 on drought assessment and drought impacts, respectively, before moving to Chapters 4 (describing the heart of the problem) and 9 (application of the committee's recommended two-pronged approach). Readers desiring a more comprehensive technical understanding of the committee's conclusions and recommendations will also find useful the remaining chapters, which provide the additional detail necessary to motivate the study (Chapter 3 on drought drivers) and explain how nonstationarity necessarily alters the data sources (Chapter 5), analytical choices (Chapter 6), and overall framework of drought assessment (Chapter 8).

Given this chapter structure, Table 1-1 lists the chapter in which each statement of task component is addressed within the study. Table 1-2 lists core terms used in this report and where in the report each is introduced or defined.

TABLE 1-1 Location of Core Text Addressing Statement of Task Components

Statement of Task Component	Where Addressed
Bullet 1	
Discuss the drought-to-aridification continuum and differentiate among drought, multidecadal drought, and aridification.	*Chapter 2* discusses primary drought types; geographic, temporal, and other drought dimensions; and a definition of drought. *Chapter* 4 discusses aridification, multidecadal drought, and climate nonstationarity.
How do factors such as periods of record, drought type, regionality, and seasonality affect these classifications?	*Chapters 2 and 3* discuss geographic and seasonal dimensions of drought classifications (Chapter 2) and drivers of drought (Chapter 3). *Chapter 6* discusses periods of record (see below).
How do current periods of record affect drought outlooks and predictions?	*Chapter 5* discusses record length for available drought data sources.

Statement of Task Component	Where Addressed
	Chapter 6 provides considerations for period of record selection for drought indicators for specific applications, and implications of those choices for drought monitoring.
Bullet 2	
Evaluate data sources currently used for drought assessment. What data will be needed to address non-stationarity?	*Chapter 5* provides a detailed review of data sources for drought assessment and how record length and spatial detail affect ability to assess trends and nonstationarity in individual datasets. *Chapter 7* reviews drought impact data and their uses in drought assessment.
What methodologies can be used to improve future drought assessment, taking into account non-stationarity?	*Chapter 4* provides a review of drought assessment approaches in the context of nonstationarity.
Bullet 3	
Discuss metrics and indicators used in drought assessment and identify opportunities to inform decision-making, including increasing integration of non-stationarity and incorporating uncertainty and/or confidence.	*Chapter 6* provides an extensive discussion of drought metrics and indicators for use in drought assessment, to inform decisions focused in both the near- and long-term, with consideration of the incorporation of uncertainty and confidence in those metrics. *Chapter 7* drought impact data discussion includes consideration of impact data to inform decisions.
Bullet 4	
Review existing and emerging approaches, both nationally and globally, for incorporating non-stationarity in drought assessment. Are some approaches more appropriate for specific regions and/or time periods?	*Chapter 4* provides a review of drought assessment approaches in the context of nonstationarity.
Closing Sentence	
Recommend a framework for incorporating non-stationarity considerations into drought assessment, for use across a range of geographic regions and of spatial and temporal scales.	*Chapter 8* describes the proposed framework for incorporating nonstationary considerations into drought assessment. *Chapter 9* illustrates this framework for drought assessment under nonstationarity using specific examples for three different geographies in the United States.

TABLE 1-2 Core Report Terms

Term	Where Introduced or Defined
Convergence of evidence	The "convergence-of-evidence" approach to drought assessment—introduced in the "Building a Strong Foundation" section (above) and in Box 2-1—is defined and discussed in detail in the "Convergence-of-Evidence" section in Chapter 6.
Drought	The definition of drought used in this report is provided and discussed in the "Defining Drought" section in Chapter 2. Box 2-1 provides a list and description of the primary types of drought discussed in this report.
Drought assessment	Drought assessment, including its key inputs and components, are introduced in the "Drought Assessment" section in Chapter 2. Figure 2-7 lists primary drought assessment components, along with descriptions, examples, and needs of each.
Drought impacts	Drought impacts are introduced as part of the "Risk Framing" section in Chapter 1. Chapter 7 provides a thorough discussion of drought impacts and drought impact data in drought assessment.
Drought indicators and indices	Drought indicators and drought indices are introduced in the "Drought Assessment" section in Chapter 2, and are covered in depth in Chapter 6.
Drought nonstationarity	Chapter 4 provides a comprehensive overview of nonstationarity, including a definition and framing for drought nonstationarity in the "Overview of Drought Nonstationarity" section of that chapter.
Period of record Reference period	In Chapter 5, the section "Data Records and the Decline of Stationarity" introduces and discusses these terms and their role in drought assessment, in particular in the context of nonstationarity. Additional detail is provided in the "Implementation" section of Chapter 8.

2
Defining Drought Monitoring and Assessment

Chapter 2 provides a foundation for the report by defining drought and discussing the various drought types and characteristics, how these characteristics are affected by regionality and seasonality, and drought assessment components. It introduces basic terms and concepts that will be used throughout the report.

This chapter includes four case studies of drought to illustrate the breadth of drought challenges across the United States. Two focus on significant recent drought events: Box 2-2 discusses the current megadrought that is occurring in the Southwest, and Box 2-3 discusses recent flash droughts that occurred in the Great Plains and Midwest. The other two cases consider drought dynamics in the Southeast and in Alaska: Box 2-4 illustrates how increasing evaporative demand can result in drought even though regional precipitation is generally increasing. Box 2-5 discusses the importance of drought propagation and development factors, especially climate, in the development of ecological drought in Alaska.

DEFINING DROUGHT

Drought has affected humankind since before the beginning of civilization (Sheffield and Wood, 2012; Finlayson, 2014; Pausata et al., 2023). It can affect every sector of the economy and, indeed, every facet of human activity. But it is difficult to define, and its definition can depend on the economic sector that is exposed, the timescale considered, and the drought indicator being examined (Cook et al., 2018). Unlike natural hazards such as floods, earthquakes, or tornadoes, which have a specific beginning and end and can occur in their entirety on sub-daily timescales, droughts often develop gradually with their effects accumulating slowly over time (Wilhite, 2000). Even rapidly developing droughts ("flash droughts") take weeks to emerge (Otkin et al., 2018; Christian et al., 2024).

Drought is generally defined as the *absence* of water that results in an imbalance between water supply (precipitation in natural systems) and water demand (atmospheric evaporative demand in natural systems); however, drought largely differs from water scarcity in its duration and with respect to the average condition of a region. Many attempts to define drought have focused on the water supply side of the equation (Cook et al., 2018; AMS, 2025; NIDIS, 2025a; WMO, 2022). For example, the 2006 public law that established the National Integrated Drought Information System (NIDIS) (NIDIS, 2006) defined drought broadly as:

"A deficiency in precipitation—

(A) that leads to a deficiency in surface or subsurface water supplies (including rivers, streams, wetlands, ground water, soil moisture, reservoir supplies, lake levels, and snowpack); and

(B) that causes or may cause—

(i) substantial economic or social impacts; or
(ii) substantial physical damage or injury to individuals, property, or the environment."

The water demand side of the drought equation is equally important. Palmer (1965) factored water demand into the computation of his drought index. Redmond (2002) argued that drought could occur when water supply is decreased while water demand remains constant, or when supply is relatively constant but demand increases. Otkin et al. (2018) argue that the water supply side (i.e., a deficit in precipitation) is the basic requirement for drought to develop, but above-normal evaporative demand caused by excessively high temperatures, low humidity, strong winds, and high insolation (sunshine) can exacerbate existing drought conditions or, by increasing soil moisture deficits, can contribute to the development of agricultural and ecological drought conditions. Walker, Vergopolan, et al. (2024) conducted a worldwide survey of flash droughts and identified several flash drought types, with the key unifying characteristic across the types being rapid intensification of soil moisture or hydrological drought. For them, the rapid drying could be caused by decreased moisture supply or by excessive moisture demand.

Water demand can also be influenced by human decisions and actions, resulting in water deficits via increases in human water demand that outweigh water supply. Examples of human (anthropogenic) dimensions of water demand include overpumping of groundwater for crop irrigation or residential or commercial water supply due to population growth, urbanization, and industrial and agricultural development. These dimensions of water demand are distinct from elevated evaporative demand caused by variability in natural systems, but they are nonetheless important contributors to drought (AghaKouchak et al., 2021). In addition, anthropogenic activities (i.e., the emission of greenhouse gases from the burning of fossil fuels) are contributing to rising temperatures that are increasing atmospheric evaporative demand (Overpeck and Udall, 2020; AghaKouchak et al., 2021).

For use in this report, the study committee offers a broader definition of drought:

> Drought is a period of anomalous water deficit arising from reduced precipitation, elevated temperatures, and/or increased atmospheric water demand, potentially exacerbated by human activities. Droughts often disrupt the typical functioning or well-being of people, ecosystems, or societies.

The committee's drought definition differs from the 2006 public law definition in that it addresses both sides of the drought equation, water supply (i.e., a precipitation deficit) and water demand (i.e., increased atmospheric evaporative demand and potential human drivers of demand), whereas the 2006 public law definition addresses only the water supply side. Drought impacts are of central concern to society and within this report. Both definitions note that droughts may cause impacts (disruptions); the committee's framing recognizes that droughts can have clear impacts but that impacts do not need to be present for a drought to occur.

Conclusion 2-1: Drought definitions should encompass both reduced water supply and increased water demand.

Key to the definition of drought is that drought is a temporary phenomenon—it has a beginning and an end. While the characteristics of drought can vary widely, such as its duration, severity, onset speed, spatial footprint, and domain of impacts, all droughts will share the feature that they are temporary and defined as an anomaly relative to a local climate. Droughts can last for a few weeks to several years. If they are unusually severe and their duration stretches to two or more decades, then they are termed herein megadroughts (see Chapter 4: severe and exceptionally long droughts relative to the instrumental period; Woodhouse and Overpeck, 1998; B. Cook et al., 2016). The temporary nature of droughts distinguishes them from aridification. Aridification is a process that results in a more permanent change in the climate state itself and is discussed in Chapter 4. It should be noted that wet periods can occur during a drought—there can be wet months during a multiyear drought and wet years during a multidecade drought, and localized flooding events are possible during a drought—but the dominant hydrometeorological pattern during a drought is anomalous and persistent dryness due to reduced precipitation and/or increased evaporative demand. The types and characteristics of drought are discussed in the following sections.

Types of Drought

Multiple types of droughts are linked through the "drought cascade" (see Figure 2-1; Changnon, 1987; Entekhabi, 2023). Drought typically begins with meteorological drought, associated with dry weather conditions (low precipitation and high evaporative demand); if these conditions continue, drought affects more of the geophysical environment, propagating through the various drought types: agricultural, hydrological, socioeconomic, ecological (see Box 2-1 for more details on each type of drought). Recently, AghaKouchak et al. (2021) extended these categories to include anthropogenic drought, which is drought that is caused or made worse by human actions and distinguishes anthropogenic drought from socioeconomic drought, which affects human systems but is not necessarily caused or made worse by human actions.

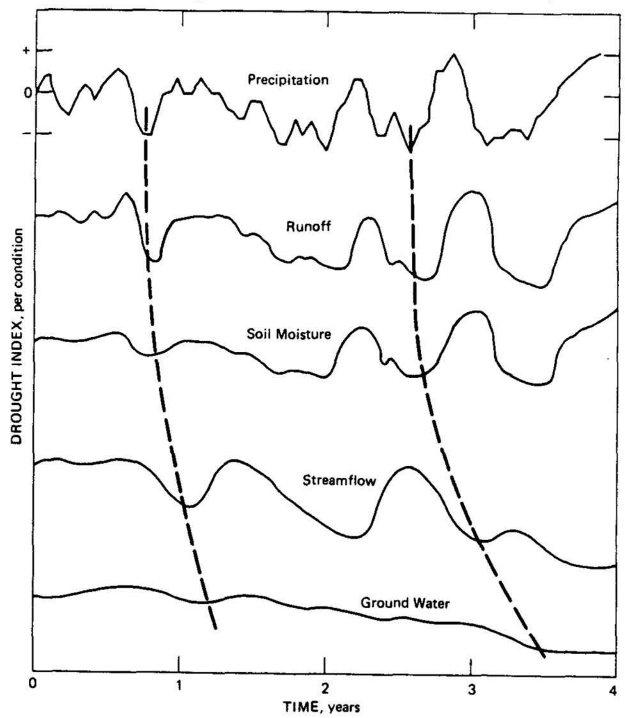


FIGURE 2-1 A schematic showing the translation of precipitation deficiencies during a hypothetical 4-year period through other components of the hydrologic cycle over time. NOTE: The horizontal curves represent hydrological aspects of the different drought types: meteorological drought (precipitation, runoff), agricultural drought (soil moisture), and

hydrological drought (streamflow, groundwater). The vertical dashed curves represent how a moisture deficiency propagates over time through the hydrologic system or different drought types.
SOURCE: Changnon, 1987.

BOX 2-1
Types of Drought

Drought definitions and types have largely been grouped into five categories: meteorological, agricultural, hydrological, ecological, and socioeconomic (Crausbay et al., 2017; Cook et al., 2018) (see Figures 2-1, 2-2), with the various drought types developing as drought propagates through human and natural systems.

Meteorological drought. Droughts typically begin as a meteorological phenomenon (a precipitation deficit, often accompanied by anomalously high evaporative demand). *Snow drought* (reduced snowfall resulting in a reduced snowpack due to either low precipitation or high temperatures that cause the precipitation to fall as rain rather than snow) is a subset of meteorological drought.

Agricultural drought develops once the meteorological drought depletes soil moisture with a resulting impact on vegetation, including reduction of crop yield. Wilhite and Glantz (1985) note that an operational definition of agricultural drought should account for the variable susceptibility of crops at different stages of crop development.

Hydrological drought occurs when surface or subsurface water resources (runoff; streamflow; mountain snowpack; and storage in aquifers, lakes, and surface reservoirs) are reduced, and it generally takes longer to manifest than agricultural drought.

Ecological drought focuses on water deficits that impact ecosystems, driving them beyond thresholds of adaptation and affecting ecosystem services to the point of triggering impacts in natural and/or human systems (Crausbay et al., 2017).

Socioeconomic drought can be viewed as the impact of meteorological, agricultural, or hydrological drought on the supply and demand of some social or economic good (Wilhite and Glantz, 1985; AMS, 1997; Heim, 2002), or on human institutions and behavior that influence both societal vulnerability and physical drought dynamics (Cook et al., 2018) (for example, irrigation of croplands, groundwater withdrawals, and water conservation policies).

Flash droughts are a hybrid of meteorological and agricultural droughts: they are a recently recognized type of extreme event distinguished by sudden onset and rapid intensification of drought conditions (Pendergrass et al., 2020), which quickly dry out soils and impact vegetation, especially crops.

Groundwater drought is a subset of hydrological drought that occurs when there is a decrease in groundwater (Mishra and Singh, 2010).

Megadrought is an unusually severe and persistent drought relative to droughts of the instrumental period that, in North America, last for two or more decades (Woodhouse and Overpeck, 1998; B. Cook et al., 2016).

Anthropogenic drought refers to drought which is caused or exacerbated by human activities such as overgrazing or over pumping of groundwater (AghaKouchak et al., 2021; Nie et al., 2024). Burning of fossil fuels is adding greenhouse gases to the atmosphere, which is increasing temperatures and atmospheric evaporative demand, thus affecting the water demand side of the drought equation. So, in this sense, anthropogenic drought is affecting all other categories of drought.

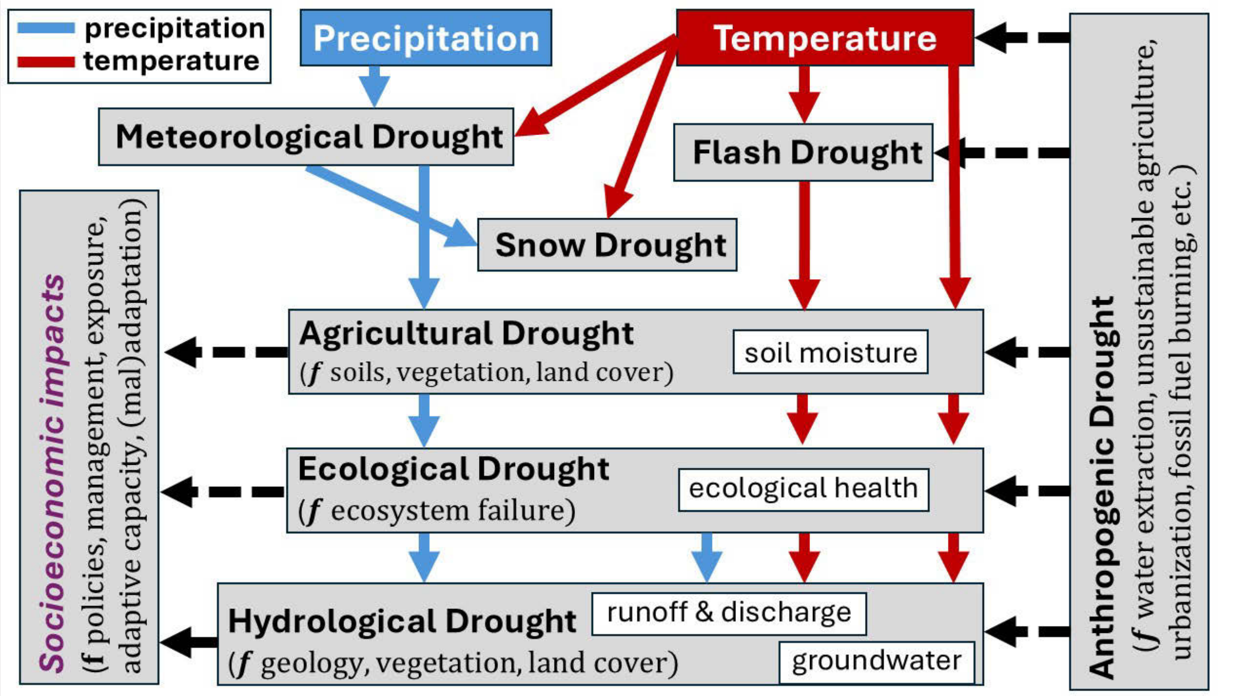


FIGURE 2-2 Classical definitions of drought and the associated processes.
SOURCE: Adapted from Cook et al., 2018 and Van Loon, 2015, CC-BY 4.0.

Droughts have been characterized by the timescale of their initiation, intensification, and duration. Beyond the classic drought types (see Box 2-1), two additional types that have received attention recently in the literature are flash drought and snow drought. Flash drought has become a widely used label for drought that initiates, or an existing drought that intensifies, more rapidly than what would be expected in the local climate, often in a matter of weeks (Otkin et al., 2018; Pendergrass et al., 2020). Flash droughts result from severe short-term precipitation anomalies that are often exacerbated by elevated evaporative demand (Ford and Labosier, 2017; Christian et al., 2024). They develop rapidly and can be short-lived.

Snow drought describes a reduction of precipitation falling as snow that results in a reduced snowpack (referred to here as snow*fall* drought), or when an existing snowpack is rapidly and significantly reduced (snow*pack* drought). Snowfall drought occurs when (1) there is a deficit in overall precipitation or (2) precipitation is normal or above normal but most of the precipitation falls as rain due to unusually warm (above freezing) temperatures (Harpold et al., 2017). Snowpack drought develops when an existing snowpack is reduced due to unusually warm and variable temperatures characterized by a decrease in the number of days below freezing (Gottlieb and Mankin, 2025). Snow drought impacts ecosystems, food and water security, and industries such as winter recreation and reservoir management (hydropower and flood control) (Huning and AghaKouchak, 2020), but it is most consequential in mountainous areas where the spring and summer melting of a thick winter snowpack provides an important water source during the dry warm season in arid and semiarid climates (Mote et al., 2005, 2018; Dierauer et al., 2019; Gottlieb and Mankin, 2022)–thus presenting a risk to summer water supply.

The nature of drought (its characteristics, type, and propagation) differs across the United States due to differences in the background climate (Fuentes et al., 2022; Heim et al., 2023), differences in human interactions and systems around water (Emi Fergus et al., 2022; Gaines et al., 2022), and factors including soil type and stratigraphy, topography, vegetation cover and physiology, and geology affecting groundwater/surface water connections within river catchments (Sheffield and Wood, 2012, p. 33, 35; Rim, 2013; Cartwright et al., 2020; Fuentes et al., 2022; Liu et al., 2023).

BOX 2-2
Case Study: The Ongoing U.S. Megadrought

Snowpack at the start of February 2026 was at or near a record low[1] across much of the Southwest United States, including parts of the Upper Basin headwaters of the Colorado River, making it clear that the longest drought in U.S. history would continue into its 27th year. Considered a “megadrought” because of its multidecadal length, this drought has expanded and contracted across much of the U.S. West since 1999 and has remained most persistent in the Colorado River Basin and Southwest. It has dramatically reduced the flows of the two largest rivers of the region in terms of streamflow volume, the Colorado River and Rio Grande; greatly reduced soil moisture; and led to widespread forest mortality and an increase in large severe wildfires. At times, this megadrought has extended deep into Mexico, as well as into Canada, and has been felt in California eastward into the Midwest.

Extensive tree-ring and other paleoclimatic research has revealed that the Southwest naturally experiences megadroughts, with many multidecadal megadroughts having occurred over the last 2,000 years, some lasting many decades and even centuries, and sometimes extending across the entire country (Cook et al., 2016; Todd et al., 2025). What sets the ongoing megadrought apart, however, is how much hotter it is than previous droughts, which increases the evaporative demand on top of reduced precipitation, making this megadrought more severe than previous megadroughts. The source of the extra heat, and thus higher moisture demand from the atmosphere, is anthropogenic climate change (see Figure 2-3).

The unprecedented flow reductions of the Colorado River since 1999 (now approaching 30 percent below pre-drought flow levels) have likely been driven by both warming and reductions in winter/spring precipitation (Vano et al., 2014; Udall and Overpeck, 2017). The substantial decline in observed snowfall (i.e., snow drought) could be a result of anthropogenic climate change, or it could be due to natural multidecadal variability in the climate system (see Chapter 3, Drivers of Drought). Either way, it appears that even lower flows in the Colorado, as well as more severe and widespread drying of soils and vegetation, will result from the warming-driven aridification that is almost certainly going to continue for as long as concentrations of greenhouse gases keep increasing in the atmosphere (NASEM, 2025).

Regardless of whether the current Southwestern megadrought persists, it is clear that megadroughts can blur the distinction between droughts and their baseline: they are anomalies relative to centennial-length records, but for those living through them, they are also the climate itself, exemplifying the convolution of drought and nonstationarity. (See Chapter 4 for a deeper discussion of this challenge.)

[1] https://www.drought.gov/drought-status-updates/snow-drought-current-conditions-and-impacts-west-2026-02-05, accessed 5/23/2026

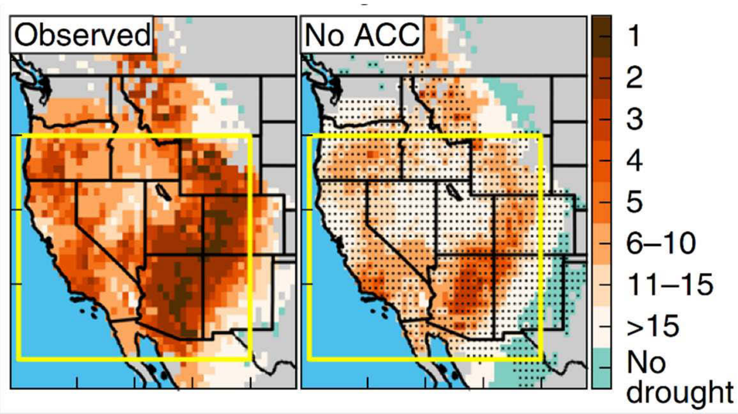


FIGURE 2-3 Impact of anthropogenic climate change on the current U.S. megadrought.
NOTE: Map on the left shows grid-cell specific rankings of 22-year negative soil moisture anomalies (drought rank) over 2000–2021 compared to the driest 22-year period in each previous drought event back to 800 CE. The map on the right is the same as the map on the left, but after removal of multiclimate model mean anthropogenic climate change (ACC) trends (stippling, 75 percent of the CMIP6 climate models agree on a net ACC drying effect in 2000–2021; turquoise, above average 2000–2021 soil moisture; grey, excluded due to lack of drought-sensitive tree-ring records back to 800 CE).
SOURCE: Williams et al., 2022a. Used with permission from Springer Nature.

Droughts are characterized in multiple dimensions that include duration, intensity, and spatial coverage (Wilhite and Glantz, 1985; Wilhite, 2000; Wilhite and Buchanan-Smith, 2005; Sheffield and Wood, 2012). Additional dimensions offered by Zargar et al. (2011) include magnitude, severity, and frequency (return period).

Temporal Dimensions

Droughts have been described as a "creeping phenomenon" whose effects from lack of precipitation accumulate slowly over time (Wilhite, 2000), with a New Mexico rancher once saying he felt like the drought was slowly choking him (Heim et al., 2023). However, when a severe short-term precipitation deficit is accompanied by excessive atmospheric evaporative demand (AED), droughts can develop quickly (Otkin et al., 2018; Pendergrass et al., 2020; Christian et al., 2024).

The temporal dimensions of drought span a wide spectrum. Drought duration describes how long the drought has persisted and can range from only a few weeks to several years (multiyear droughts) or even decades (megadroughts). In operational drought monitoring (e.g., U.S. Drought Monitor [USDM] operations), droughts that last from a few weeks to 6 months are termed short-term droughts, while those lasting longer than 6 months are termed long-term droughts (Heim et al., 2023). There can be alternating wet periods and dry periods within a drought, resulting in concurrent alleviation of certain types of drought (e.g., agricultural drought) and worsening of other drought types (e.g., hydrologic drought), depending on timescale that cause variations in moisture with soil depth. Thus, hydrometeorological variability within a drought event complicates monitoring and assessment, especially when different timescales indicate opposite moisture conditions. Examples include:

- short-term (e.g., 1- to 3-month) wet conditions and long-term (6- to 24-month) dry conditions;
- short-term (1- to 3-month) dry conditions and long-term (6- to 24-month) wet conditions; and
- wet conditions in the short term (e.g., 1 to 2 months), very dry at intermediate timescales (e.g., 6 to 12 months), and neutral or wet conditions at longer timescales (e.g., 24 months), or similar combinations.

As noted earlier, droughts develop slowly, which makes it difficult to know if a drought has developed when the dry conditions are occurring, until the appearance of tangible drought impacts, at which point it becomes possible to trace the drought's beginning to when the abnormally dry weather started. For example, in his monthly drought index, Palmer (1965) did this through a backstepping procedure. For each month, Palmer's model computes the probability that a dry spell has started. A probability of 100 percent indicates that drought is occurring, but the start of the drought would be set for the first month the probability was greater than zero. Palmer uses a similar process to determine when a drought has ended. The dry conditions propagate through the hydrologic system (see Figure 2-1), with the different drought types developing—and the various economic sectors affected—at different times in the process. All of this complicates the assessment of drought duration and beginning and ending times (Van Loon et al., 2024). When moisture conditions are integrated across multiple timescales, as is done in some drought indices, a more definitive assessment of the drought's beginning and ending times can be determined, especially for short-term and long-term droughts. See Chapter 6 for a discussion of this challenge as it relates to drought indices and USDM drought indicators.

Megadroughts provide another example of complications created by hydrometeorological variability. Megadroughts are droughts that are defined by extreme duration and severity, often beyond that observed globally in the twentieth century (Woodhouse and Overpeck, 1998; Williams et al., 2020; Stahle, 2020). They have been observed on every continent outside of Antarctica over the past 2,000 years, and they often cause catastrophic impacts to ecology, agriculture, water resources, and societal stability (Cook et al., 2022; Hankin et al., 2024). Dry areas within a region associated with a megadrought may move around, sometimes going away altogether for a few months or even years and then returning, and flash droughts may develop within a megadrought as extreme conditions occur; throughout this time, the drought's impact on rivers and ecosystems continues.

The timing of the onset of the precipitation shortage is a factor in the initiation of a drought and in its magnitude (Wilhite and Buchanan-Smith, 2005). This is an important consideration for meteorological droughts: in regions with a pronounced seasonality in precipitation, a precipitation shortage during the dry season will have less impact than a precipitation shortage during the wet season (Heim et al., 2023). It is also important for agricultural droughts: a severe shortage of rainfall during critical stages of crop growth can damage crops and reduce yield even if the seasonal or annual precipitation total is normal or above (Bruins, 2000; Wilhite, 2000). For flash droughts, in those regions with pronounced seasonal swings in temperature, above-normal AED during the warm half-year will have a greater impact on drought evolution than during the cold half-year (Heim et al., 2023), so flash droughts tend to be summer or spring growing season events (Otkin et al., 2018).

By depleting soil and atmospheric moisture, droughts contribute to low moisture in foliage and surface fuels, making them more flammable; this increases the potential for widespread fire (Littell et al., 2016). Droughts during the cool wet season will reduce foliage growth and subsequent fuel load; droughts during the summer, when combined with fire weather—high temperatures, low humidity, and strong winds—are associated with increased wildfire activity (Richardson et al., 2022).

A review of the published literature and user perceptions gauged from user-engagement workshops (Leeper et al., 2022; Heim et al., 2023) indicates that location and landscape inform typical drought duration in different climate zones, with typically shorter durations in tropical, humid temperate, and southerly continental climates, such as the Eastern United States generally east of the Mississippi River, and typically longer durations in polar tundra climates, dry climates, temperate climates with dry warm seasons, and northerly continental climates, such as the Western (Rocky Mountains to West Coast) and Central (Rocky Mountains to Mississippi River) United States. During 2000–2019, in the United States, flash droughts occurred most often in the Great Plains to the Southeast (Pendergrass et al., 2020; Leeper et al., 2022).

BOX 2-3
Case Study: The Expanding Impact of U.S. Flash Drought (2012 and 2017 Examples)

Steadily warming temperatures and associated increases in atmospheric moisture demand, along with increasing precipitation deficits, are giving rise to a global increase in the frequency, speed of onset, severity, and duration of flash droughts (Seneviratne et al., 2021; Yuan et al., 2023; Zeng et al., 2023). Flash droughts are characterized by fast onset and rapid intensification, for example, a "two category change in the U.S. Drought Monitor (USDM) taking place in 2 weeks, sustained for at least another 2 weeks" (Pendergrass et al., 2020). There is high confidence that warming will continue and thus drive worsening flash droughts in the United States and elsewhere around the globe, as long as greenhouse gas concentrations continue to increase in the atmosphere (NASEM, 2025; Zeng et al., 2023). There is less confidence in how precipitation patterns will change and thus play a role in driving flash droughts in the future, but it is clear that precipitation deficits are also critical ingredients for flash droughts (Pendergrass et al., 2020).

Despite an observed increase in average annual precipitation in the U.S. Great Plains and parts of the U.S. Midwest (USGCRP, 2023), more frequent flash droughts are already being observed in these regions. One widely studied flash drought occurred in 2012 when dry and extremely warm weather persisted for several weeks to months, intensifying drought to D3 (Extreme) and D4 (Exceptional) drought (see Figure 2-4) within 2–3 months of initial drought onset across the Central United States (Basara et al., 2019; Pendergrass et al., 2020). This flash drought had considerable impacts on agriculture (federal crop indemnity payments alone exceeded $17 billion; USDA, 2013), ecology (Solomon et al., 2022), and river-borne transportation (Pendergrass et al., 2020).

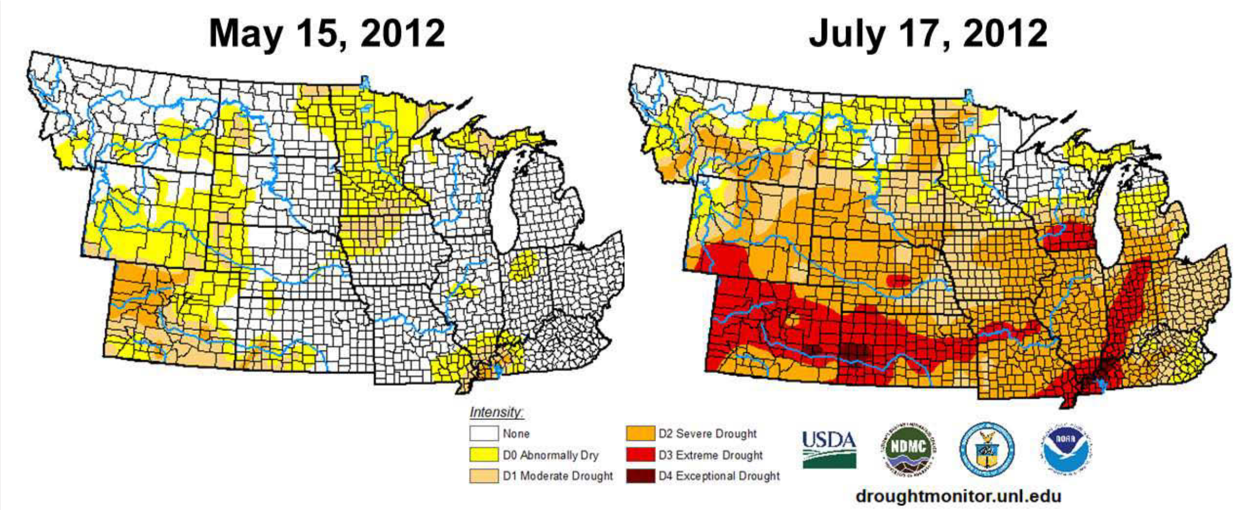


FIGURE 2-4 Illustration of drought onset and intensification seen with the 2012 U.S. flash drought.
NOTE: Drought categories across the Central United States for May 15, 2012 (i.e., prior to flash drought onset) and July 17, 2012 (i.e., after flash drought development) as indicated by the U.S. Drought Monitor.
SOURCE: USDM map archive (https://droughtmonitor.unl.edu/Maps/MapArchive.aspx). The U.S. Drought Monitor is jointly produced by the National Drought Mitigation Center at the University of Nebraska–Lincoln, the United States Department of Agriculture, the National Oceanic and Atmospheric Administration, and the National Aeronautics and Space Administration. Map courtesy of NDMC.

Another notable flash drought occurred in the summer of 2017 in the Northern Great Plains of the United States (see Figure 2-5); this flash drought extended into Canada, gained considerable public attention, and was driven in part by exceptional precipitation deficit. Impacts were not as geographically extensive in the United States as in the 2012 drought but nevertheless were costly in terms of agricultural production losses (exceeding $2.6 billion in the United States), widespread wildfires, poor air quality, damaged ecosystems, and degraded mental health (Hoell et al., 2020).

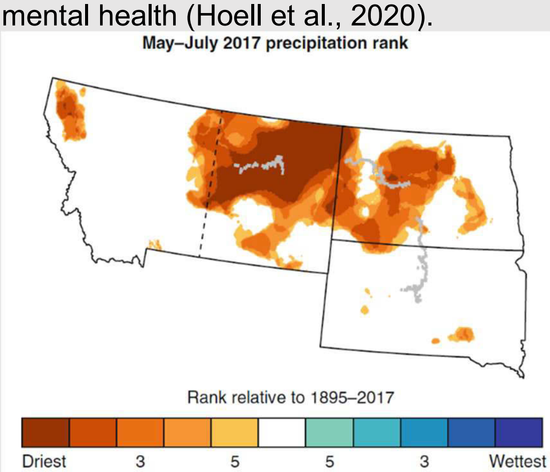


FIGURE 2-5 Extent of 2017 flash drought rainfall deficit.
NOTE: Rank of accumulated May–July precipitation relative to the 1895–2017 climatology.
SOURCE: Pendergrass et al., 2020, used with permission from Springer Nature, adapted from Hoell et al., 2019, CCO 1.0.

Geographic and Regional Dimensions

The spatial coverage of a drought can range from small localities to large regions and even significant portions of a nation or continent. Droughts generally begin locally, with the area affected expanding gradually as local droughts merge to become regional in scale; the regions affected can shift from season to season (Wilhite, 2000; Wilhite and Buchanan-Smith, 2005; Zargar et al., 2011), and the area covered can expand and contract as precipitation patterns change with time. The areal coverage can be assessed for all intensity categories of the drought or for specific intensity categories, such as in the time-series analysis provided by the USDM.[2] Van Loon (2015) notes that there are differences in scale and duration between drought types. For example, meteorological droughts are dependent on large-scale atmospheric drivers that usually cover a large area and can change quickly. Hydrological drought is dependent on local catchment characteristics and how they change the drought signal when it propagates through the terrestrial hydrological cycle; hydrological droughts are thus more patchy and can last longer.

BOX 2-4
Case Study: Persistent Drought Risk in an Increasingly Wet Climate.
The Southeast U.S. Drought of 2011–2012

A major drought in the Southeast United States in 2011–2012 generated a significant interstate legal water conflict involving the United States Supreme Court (United States Supreme Court, 592 U. S. ____ (2018)). At issue were the flows of three major rivers that collectively formed the Apalachicola-Chattahoochee-Flint (ACF) River Basin that flow from northern Georgia down through the Florida Panhandle and into the Gulf of Mexico (Corn, 2008; Lathrop, 2009). When the severe 2011–2012 drought reduced the flows in the ACF rivers, Florida challenged Georgia's water use as excessive, a case that Florida was unable to prove, and thus win (U.S. Supreme Court, 2020).

The Southeast drought of 2011–2012 (see Figure 2-6) was one of the most notable of many droughts that have recurred over time in the region, even in the midst of an observed trend of increasing average winter rainfall coincident with a trend of increasing temperatures (USGCRP, 2023); this highlights that even where there may be a longer-term trend of increasing precipitation, it is still possible to get multiyear periods of unusually low precipitation contributing to drought. The regular drought recurrence in the region is due to a well-understood connection with the predictable climate of the equatorial Pacific Ocean and its oscillation between El Niño and La Niña states (see Chapter 3). When the Pacific is in its La Niña state there is an increased chance of drought in the Southeast United States. And with climate change, there is an increasing chance that each future drought will be hotter, and thus more severe than the last.

The tight connection of a Southeast drought and the La Niña climate state in the Pacific means that Southeast droughts will continue to be a regular occurrence in the future, with increasing odds of being ever hotter and more severe as well. The good news is that La Niña

[2] https://droughtmonitor.unl.edu/DmData/TimeSeries.aspx, accessed May 23, 2026

events generally last just a couple years and Southeast droughts generally do not persist for long. All together, this adds to the knowledge that can form the basis of long-term planning and resilience to drought in the region.

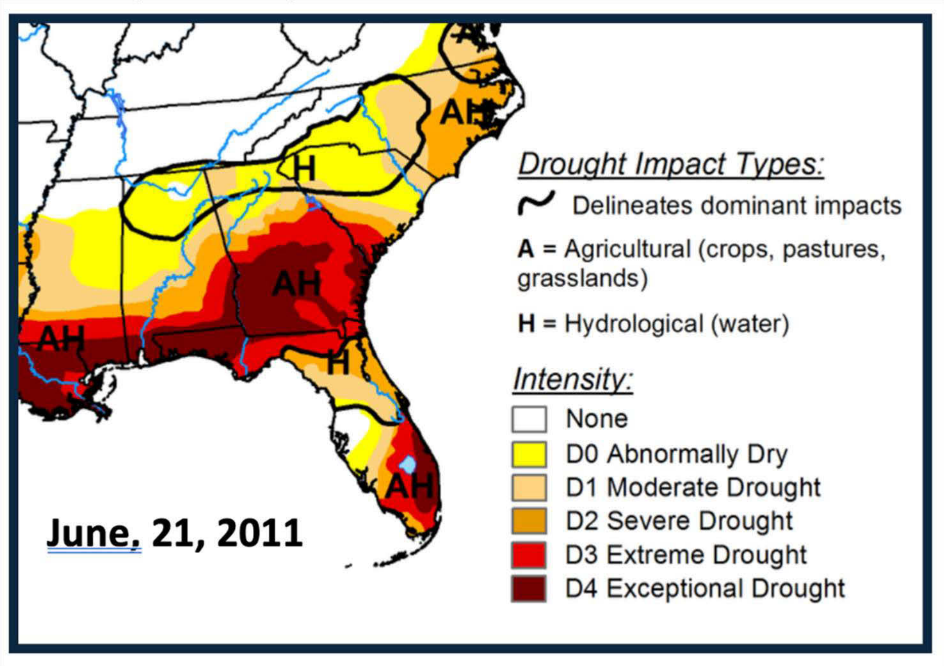


FIGURE 2-6 U.S. Drought Monitor assessment of Southeast drought on June 21, 2011.
NOTE: The Southeast drought of 2011–2012 was set up by Abnormally Dry (D0) and Moderate Drought (D1) conditions in the winter of 2010–2011 and intensified to more serious drought levels like those shown here.
SOURCE: After https://droughtmonitor.unl.edu/Maps/MapArchive.aspx. The U.S. Drought Monitor is jointly produced by the National Drought Mitigation Center at the University of Nebraska–Lincoln, the United States Department of Agriculture, the National Oceanic and Atmospheric Administration, and the National Aeronautics and Space Administration. Map courtesy of NDMC.

Intensity and Magnitude Dimensions

The intensity of a drought is the degree of the moisture deficiency (caused by a precipitation shortfall and/or anomalously high evaporative demand) and/or the magnitude of the impacts associated with the shortfall (Wilhite, 2000; Wilhite and Buchanan-Smith, 2005). The significance of a moisture deficiency depends on the local climate, so it is generally related to some climatic normal (Wilhite, 2000; Wilhite and Buchanan-Smith, 2005).

The term *severity* has been used to describe how bad a drought is. Its definition varies by researcher and practitioner. For this report, the severity of a drought depends on the combined duration and intensity/magnitude of the drought (Sheffield and Wood, 2012) and antecedent conditions (i.e., lingering memory from preceding droughts; Van Loon et al., 2024), as well as its spatial extent and the demands made by human activities and by the vegetation on a region's water supplies (i.e., the drought's impacts; (Wilhite and Glantz, 1985).

Zargar et al. (2011) define the drought frequency (return period) as the average time between drought events that have a magnitude that is equal to or greater than a threshold. The USDM converts the measured departure of an indicator to a percentile based on the historical record; the percentile is related to specific return periods that define intensity categories (see Box 2-6 for the USDM categories and Table 6-1 for the percentile ranges).

BOX 2-5
Case Study: Drought in Alaska

Drought in Alaska is very different from other parts of the United States. The Alaska Panhandle is one of the wettest parts of North America, yet an extreme drought developed that caused significant impacts. October 2016 to December 2019 was an unusually warm and dry period for southeast Alaska, with high summer evaporation. Water restrictions were imposed, lake levels reached record lows, reservoir levels were too low for hydropower generation, salmon fisheries suffered, and a hemlock sawfly outbreak ultimately defoliated 530,000 acres of forest. The drought's impact on fisheries was not limited to the southeast; unprecedented warm river and ocean surface waters in 2019 caused massive salmon die-offs in other parts of the state (Hoell et al., 2022).

Southeast Alaska has a temperate rain forest, but the climate to the north and west ranges from continental (Köppen “D” climate), with boreal forests, to Arctic tundra (Bathke et al., 2019; Halofsky et al., 2019; Leeper et al., 2022). Long winter nights put the state into a deep freeze for months, and permafrost cuts off access to groundwater for much of the state and limits agriculture to small-scale farms. Agriculture in Alaska is limited to the short but intense summer growing season, and the long summer days increase evapotranspiration. Drought can develop if the surface soil layer (“active layer” above the permafrost) dries out, so precipitation during June–August is crucial to agriculture (Shulski and Wendler, 2007; Heim et al., 2023). With limited farming, subsistence agriculture (e.g., wild berries and roots), fishing (especially salmon), and hunting are important sources of food. Thus, drought impacts on ecosystems and habitats cause ecological drought to be the most important type of drought in Alaska, followed by hydrological and socioeconomic drought (Walsh et al., 2015; Heim et al., 2023). The generational dependence on ecosystems for livelihoods makes Traditional Ecological Knowledge crucial for Alaskans (Bennett et al., 2014; Walsh et al., 2015; Jantarasami et al., 2018; Avery et al., 2025), especially since little research has been done on drought impacts in cold climates; drought indices were developed mainly for low- and mid-latitude locations and are ill-suited for climates outside the contiguous United States or unavailable due to a lack of adequate data (Walsh et al., 2015; Bathke et al., 2019; Walston et al., 2023; Druckenmiller et al., 2025, p. 107).

For areas outside the panhandle, reduced snowpack (snow drought) and absence of late summer precipitation are important factors giving rise to drought in Alaska (Sheffield and Wood, 2012, p. 35–36; Halofsky et al., 2019). Rising temperatures are thawing the permafrost (Halofsky et al., 2019; Gu and Gao, 2025). Besides destabilizing the foundation for infrastructure, the thawing of permafrost affects the structure and physiology of live fuels, which increases the potential intensity of wildfires (Miller et al., 2023), and increases stream acidity and levels of toxic metals, which degrade water quality, compromise aquatic habitat, erode biodiversity, and impact rural drinking water supplies and subsistence fisheries (Druckenmiller et al., 2025).

Wildfires are an important drought-related impact in Alaska. The summer of 2004 was unusually hot and dry, with record lightning activity; these factors led to a record fire season with over 6.5 million acres burned (Shulski et al., 2005). Both the area burned by wildfire and the length of the fire season have been growing in recent decades; smoke from wildfires can spread widely and cause significant health issues for people. Most wildfires occur in the boreal forest in central Alaska between the Brooks and Alaska mountain ranges, although fires are increasing in tundra areas (Thoman and McFarland, 2024).

Precipitation is the dominant control on drought in southern areas, while environments in the interior and northern parts of the state are moisture-limited with temperature playing a larger role (Walston et al., 2023). Rising temperatures are increasing evapotranspiration, lengthening the growing season, decreasing snowfall, thawing permafrost, and intensifying the hydrologic cycle. Even if precipitation increases, future water availability is expected to be reduced in much of the state because of the increased evaporation, thus affecting drought occurrence (Halofsky et al., 2019; Walston et al., 2023; Druckenmiller et al., 2025).

DROUGHT ASSESSMENT

Due to the multiple factors that influence water supply and demand, drought monitoring requires the use and analysis of multiple data sources, which serve as indicators and are often transformed into indices. A *drought indicator* is a raw variable or parameter that describes a hydrometeorological state such as precipitation, temperature, soil moisture, streamflow, or groundwater level. A *drought index* is a computed numerical representation of drought severity derived from one or multiple indicators and is most often presented in standardized units. The standardization requires the determination of a *reference period,* which is the time period used to define the mean and other statistics (historical benchmark or "normals") for the drought index. A *drought impact* is the direct or indirect negative effect that a drought has on a particular system, place, or people, resulting from the combination of a geophysical condition and human or nonhuman system vulnerability; drought impacts can be described in quantitative or qualitative terms (see Chapters 7).

Operational drought assessment generally relies on a convergence-of-evidence approach (Svoboda et al., 2002), in which multiple indicators, indices, models, and impact reports are evaluated together (by human experts) to inform assessments about drought severity.

Drought Assessment Products

Traditional drought assessment generally comprises five key components: prediction, early warning, monitoring, post-event analysis, and projection (see Figure 2-7). All five components require accurate and actionable information and clear and effective risk communication.

Drought Assessment Components

Drought Assessment	Purpose	Examples	Needs
Prediction	Forecast and communicate potential changes in drought status, conditions, and impacts	CPC Monthly Drought Outlooks	skillful forecasts; effective communication
Early Warning	Communicate potential or imminent changes in drought status, conditions, and impacts	CPC Monthly Drought Outlooks	skillful forecasts; effective communication; leading indicators
Monitoring	Measure and communicate current, real-time, ongoing drought conditions and impacts	U.S. Drought Monitor	high fidelity indicators and impact reports; effective and timely communication
Post Event Analysis	Analyze and communicate features and impacts of a drought event after it has ended. Inform improvements in response and management strategies	2017 U.S. Northern Plains Drought Assessment	cross-sector collaboration, impact collection, effective communication, plan and policy assessment
Projection	Analyze and communicate future risk, decades to centuries	Flow percentiles, Action Trigger Levels	skillful climate models; uncertainty quantification; effective risk communication

FIGURE 2-7 Matrix of the core components of drought assessment, including their primary purpose(s), existing examples, and needs of each.

Both *drought prediction* and *early warning* are activities to provide usable and actionable forecasting and forewarning of potential or imminent changes in drought status, conditions, and impacts. The current state of drought prediction in the United States operates on timescales ranging from weeks to decades, while early warning activities typically occur on timescales of days to seasons. Effective drought prediction and early warning require skillful forecasts from weather forecast and climate forecast models, and effective risk communication to stakeholders and decision-makers to ensure the prediction and/or warning can inform emergency response, short-term planning, and mitigation actions. Prediction and early warning are useful for short-term emergency management to help with preparation of drought impacts, such as convening decision-makers, increasing communication, and pre-allocating resources for response.

Drought monitoring encompasses activities that measure, observe, and communicate the current and ongoing drought conditions and impacts experienced. Drought monitoring activities are often repeated on daily to monthly timescales to ensure a good understanding of the current state of drought and its impacts to a region or system. Effective drought monitoring requires high-fidelity drought indicators and impact reports, and effective and timely communication, to ensure the monitoring can inform emergency response and short-term planning. Drought stakeholders, including Tribes, agricultural producers, natural resource managers, and water managers, play important roles in providing local knowledge and perspectives to monitoring. Drought monitoring is useful for short-term emergency management to help understand the current status of drought and respond accordingly with resource allocation, adjusted communication and outreach strategies, and declarations of drought statuses that may trigger relief and other actions.

Drought post-event analysis comprises activities that analyze and communicate the features and impacts of a specific drought event, often after the event has ended. Post-event analysis is critical to inform improvements in drought emergency response and management, drought planning and policy, and long-term adaptation. Post-event analysis often occurs months to years after a drought event has ended, although analysis can also occur during a drought event. These analysis activities require cross-sector collaboration between local, state, and federal entities; high-quality drought impact report collection and summary; and relevant plan and policy evaluation. Drought post-event analysis provides stakeholders an opportunity to review and evaluate their response and plans of action, and make necessary improvements before the next drought event. Post-event analyses are useful for short-term emergency management to help with allocation and prioritization of resources and assistance, and post-event analyses also provide important information for long-term planning, including lessons learned during response to past drought events and historical documentary accounts of past drought events that can be used to benchmark present or future drought events (e.g., McGregor, 2015; Glotter and Elliott, 2017; Brázdil et al., 2018).

Drought projection activities comprise longer-term (i.e., multiyear to centuries) simulations of future drought characteristics and impacts for the purpose of analyzing and communicating future drought risk. Projections differ from prediction in the timescale (decades-centuries vs. weeks-seasons). Projections are typically generated from models that are run with specific scenarios, whereas predictions are generated from models that are run with realistic or observed conditions. Predictions provide a probabilistic or deterministic forecast for what can be expected to happen in the near future, while projections provide general guidance about how drought may evolve in the future given changing human behavior, but do not provide actionable information about whether a drought will occur in a given season. Drought projection activities require skillful models, including global and regional climate models, water supply models, groundwater models, and so on; comprehensive uncertainty quantification; and effective risk communication. Drought projection activities are mainly used to inform long-term planning and adaptation, or to inspire mitigation to avoid or limit future impacts.

BOX 2-6
The U.S. Drought Monitor

The U.S. Drought Monitor (USDM; Svoboda et al., 2002) is a composite product that incorporates drought and climate indices and indicators, output from numerical models, and drought impact reports provided by regional and local field experts from around the country. The indices, indicators, and model data are first converted to a standard percentile-based form using the history (reference period) of the input dataset (Svoboda et al., 2002; USDA, 2020). The percentile-based data are then merged manually by a cadre of USDM authors into the map product using a convergence-of-evidence methodology. The USDM expresses drought intensity in percentile-based “Dx” categories, each corresponding to a specific range of return-period rarity (see Table 2-1 for the USDM categories and Table 6-1 for the corresponding percentile ranges). The USDM has become the de facto standard for U.S. drought monitoring. Numerous states make drought response decisions, and federal agencies allocate drought relief funds, based on the drought severity as depicted on the USDM (USDA, 2020). Currently, the USDM is used as a source to inform understanding of both drought severity (for drought relief) and drought rarity.

TABLE 2-1 USDM Drought Monitor Categories

Category	Description
	Normal or wet conditions
D0	Abnormally Dry
D1	Moderate Drought
D2	Severe Drought
D3	Extreme Drought
D4	Exceptional Drought

SOURCE:USDM, n.d., https://droughtmonitor.unl.edu/About/AbouttheData/DroughtClassification.aspx, accessed December 7, 2025. The U.S. Drought Monitor is jointly produced by the National Drought Mitigation Center at the University of Nebraska–Lincoln, the United States Department of Agriculture, the National Oceanic and Atmospheric Administration and the National Aeronautics and Space Administration.

Examples of Drought Assessment Applications

Drought assessment informs a wide variety of decisions made by government agencies, communities, firms, and individuals, often functioning either as a trigger mechanism for taking action or as one component of a broader convergence-of-evidence approach to decision-making. Below are some examples of uses of drought assessment for a variety of decision-maker types; while illustrative, these examples do not represent an exhaustive list of drought assessment applications.

Drought assessments are explicitly embedded in federal disaster and emergency programs targeted at the agricultural sector. Several major U.S. Department of Agriculture programs rely on the U.S. Drought Monitor as a trigger or eligibility benchmark. USDA Secretarial Disaster Designations are automatically "fast-tracked" when counties meet specified USDM intensity thresholds (7 CFR Part 759), which in turn makes producers eligible for Farm Service Agency Emergency Loan assistance (USDA, 2024a). USDM classifications have also been used to determine eligibility for drought disaster assistance programs, including the Livestock Forage Disaster Program, the Emergency Livestock Relief Program, and Commodity Credit Corporation surplus stock sales (CRS, 2023; Kuwayama et al., 2019; USDA, 2003, 2025b,c). The 2018 Farm Bill (Public Law No. 115-334[3]) amended the Conservation Reserve Program (CRP) to allow emergency haying and grazing on selected CRP acres when a county is experiencing drought classified as severe by the USDM. Beyond USDA programs, the Internal Revenue Service relies on USDM classifications to determine the time frame for waiving gains from livestock replacement purchases due to drought (TREAS, 2016). In addition, the U.S. Department of the Interior's Bureau of Land Management (BLM) has policy and guidance for consideration of drought conditions for planning and decision-making. At the broadest level, BLM must use the USDM to determine "if drought and water availability need to be addressed," while specific

[3] Agriculture Improvement Act of 2018 - Public Law 115–334, H.R. 2 (2018).

drought indicators such as precipitation, temperature, streamflow, groundwater and reservoir levels, soil moisture, snowpack, and remote sensing data are used to evaluate drought severity at the relevant landscape scale[4] (BLM, 2024).

The Federal Crop Insurance Program primarily relies on historical yield and revenue data, and increasingly on weather information, to trigger indemnity payments. This linkage between drought-related information and crop insurance is significant because drought and high temperatures are leading causes of indemnified losses, accounting for 41 percent of total indemnity payments since 2000 (USDA, 2025d). Some Risk Management Agency insurance policies make indemnity payments to producers based on current losses related to below-average yields or below-average revenue. For example, yield insurance plans are based on a producer's actual production history over the last 4 to 10 years (USDA, 2025a). To the extent that drought nonstationarity influences yields and revenue, it may have implications for the time frames over which average yields or revenue ought to be calculated.

An example of a weather-indexed product is the Pasture, Rangeland, Forage Pilot Insurance Program, which employs a grid-based Rainfall Index derived from National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center data. Under program standards, expected grid indices employ average precipitation from 1948 to 2 years prior to the insured crop year (or from 1990 for Hawaii), and indemnities are triggered when realized precipitation falls sufficiently below these historical expectations (USDA, 2024b).

Beyond formal program triggers, it is well documented that farmers and ranchers access climate and drought information to guide operational decisions, including planting, grazing, input purchases, and adaptive management strategies. Survey research and case studies document active use of drought outlooks and related climate information in agricultural decision-making (Cabrini et al., 2023; Donaldson et al., 2024; Mase and Prokopy, 2014; Muller et al., 2024).

At the state level, many drought management plans explicitly incorporate the USDM and other drought indices into alert and phased response systems that advise governors to issue drought proclamations and activate drought emergency operation centers. For example, the Missouri Drought Mitigation and Response Plan links drought response system phases to specific values of the USDM, the Standardized Precipitation Index (SPI), the Palmer Drought Severity Index (PDSI), the Crop Moisture Index (CMI), and 28-day streamflow (Missouri DNR, 2023).

Drought assessments also inform municipal water management decisions. For example, the South Florida Water Management District cites rainfall deficits compared to historical averages when issuing landscape irrigation restrictions for residents and businesses in its service area (SFWMD, 2026). In Texas, the Green Valley Special Utility District imposes staged water use restrictions, including limits on landscape irrigation, vehicle washing, and pool filling, based on drought response triggers tied to levels in the Edwards Aquifer (GVSUD, 2023).

Some groundwater management agencies likewise use drought assessments to determine potential pumping curtailments. The Hill Country Underground Water Conservation District in Texas employs its own local drought index, which is based on water levels in two aquifers, flow data from a stream gauge, 10-month cumulative rainfall amounts, and the PDSI value for the Edwards Plateau to establish a critical drought stage that leads reductions in water use for

[4] Bureau of Land Management. *National Drought and Water Availability.* Instruction Memorandum No. 2024-034. Washington, DC: U.S. Department of the Interior, Bureau of Land Management, August 7, 2024. https://www.blm.gov/policy/im2024-034, accessed May 23, 2026

permitted wells (HCUWCD, 2026). The Hays Trinity Groundwater Conservation District, also in Texas, has drought stages defined by PDSI values and river flow rates, which trigger pumping curtailment goals and restrictions on the construction of new wells (HTGCD, 2023).

Indicators of ecological drought, such as streamflow and water temperature, are used by state fish and wildlife agencies across the West to make decisions for recreational fishing, including fishing closures, time-of-day restrictions, stocking changes, and harvest-limit adjustments (see, for example, Montana Administrative Rule 12.5.507). Some state agencies also consider drought conditions when setting annual big game hunting quotas (see, for example, Nevada Board of Wildlife Commissioners Commission Regulation 24-12[5]).

Drought information is also used in wildfire preparedness and response. In a survey of wildland fire managers, between 23 and 39 percent of respondents reported using information from the National Drought Mitigation Center (NDMC) or NIDIS before and during the fire season (Frisvold et al., 2024). The National Interagency Fire Center, consisting of nine federal and state agencies, includes information from the USDM, the U.S. Seasonal Drought Outlook, and daily mean temperature and precipitation anomalies in their monthly National Significant Wildland Fire Potential Outlooks.

Finally, drought assessments inform long-term infrastructure planning and resilience investments. The State of California's Long-Term Drought Plan for the State Water Project outlines strategies to enhance flexibility, efficiency, and capacity in response to persistent drought risk, illustrating how drought information supports not only short-term triggers but also structural adaptation and capital planning decisions (CA DWR, 2024). The U.S. Bureau of Reclamation's (USBR) WaterSMART Drought Response Program, which provides financial assistance to water users to conduct drought contingency planning and implement long-term drought resiliency projects, explicitly indicates that, while an understanding of future droughts can be informed by the observed past, the incorporation of paleoclimate and projected future climate will contribute to more robust and effective plans (Department of Interior, 2025). Drought assessment can also inform adaptive investments in institutions and human capital. For example, water management institutions that wish to establish more flexible option contracting for water transfer during droughts require consistent and broadly acceptable metrics to declare and forecast drought conditions in the context of changing climate conditions.

[5] https://www.ndow.org/news/nevada-board-of-wildlife-commission-approves-2024-2025-big-game-hunting-tag-quotas/, accessed May 23, 2026

3
Drivers of Drought in a Changing Climate

This chapter addresses the physical and biological mechanisms that initiate and sustain drought in the United States. The goal of the chapter is to first delineate the overarching factors that control drought in general, including the geographical and seasonal dependencies that make each region unique in its drought characteristics. And next to explain how the factors that control drought are changing due to human influences on the climate system and the land surface.

PHYSICAL FACTORS THAT DRIVE DROUGHT

A variety of factors control the natural occurrence of drought, including weather patterns and land-atmosphere and ocean-atmosphere interactions, and land use decisions.

The initiator of drought is typically an increased prevalence of atmospheric circulation (weather) patterns that reduce the likelihood of precipitation (either rain or snow), and often bring high temperatures, low humidities and strong wind speeds to a given region. Collectively, these weather patterns lead to reduced water availability due to decreases in water sources (precipitation) and/or increases in water loss (via evaporation and transpiration). Short-lived circulation patterns that can initiate and/or perpetuate drought can arise spontaneously due to the chaotic dynamical nature of the atmosphere and are typically short-lived (on the order of days to weeks), with predictability limited to 1–2 weeks.

Atmospheric circulation patterns conducive to triggering drought conditions may also occur as a remote response to specific ocean conditions. Because these oceanic conditions typically persist longer than the typical duration of intrinsic atmospheric variability, they can drive longer-term trends in weather patterns. For example, sea surface temperature fluctuations in the tropical and north Pacific associated with the interannual El Niño–Southern Oscillation (ENSO) phenomenon and its multidecadal counterpart, the Pacific Decadal Oscillation (PDO), can perturb the large-scale atmospheric circulation over North America. In particular, the negative phases of ENSO and the PDO have been dubbed “the perfect ocean for drought” due to their ability to shift the storm track north of its usual position, causing widespread drying over the Southwestern United States (Hoerling and Kumar, 2003).

The large geographical scale of atmospheric circulation patterns associated with meanders in the jet stream, whether generated within the atmosphere itself or as a response to oceanic conditions, imprints on the spatial extent of drought over continental areas. For example, over the continental United States, anomalously dry/hot conditions in the west typically contrast with anomalously wet/cold conditions in the east in association with ridging and troughing, respectively, and vice versa. Thus, drought is often widespread, extending over large portions of the continent at any given time.

Once drought takes hold due to meteorological drivers, the relatively dry soils can in turn affect atmospheric properties, including temperature, humidity, and precipitation, by modifying the surface energy balance (see Figure 3-1). In the moisture-limited conditions that define drought, low soil moisture leads to greater partitioning of incoming radiation into sensible heat, which generally warms the near-surface air, and reduced partitioning into evaporating or transpiring water from the surface. Air that is warmed from below will become more buoyant, which in turn will aid in deepening the planetary boundary layer, thereby entraining drier air from above and reducing cloud cover (see Figure 3-1). In the drier Western United States, this tends to lead to reduced probabilities of rainfall (and the associated cloudiness), and thus there is a positive (amplifying) feedback between the surface and atmosphere that can lead to further persistence and growth of drought (Tuttle and Salvucci, 2016). In the more humid Eastern United States, the relationship can be reversed (e.g., high soil moisture reduces the probability of rain, or a negative (damping) feedback; Tuttle and Salvucci, 2016), although it is possible that a positive feedback could occur when conditions are anomalously dry. The existence of very dry soils, both at the surface and at depth, can also directly affect the persistence of hydrological drought, wherein new precipitation largely goes to refreshing soil water rather than increasing streamflow (Brooks et al., 2021).

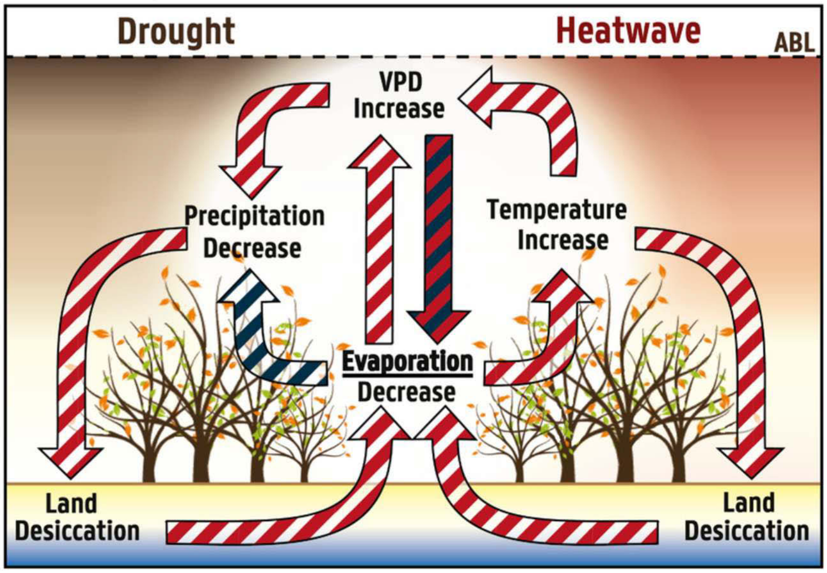


FIGURE 3-1 A schematic demonstrating land-atmosphere feedbacks that can amplify drought. NOTE: The red arrows indicate a positive/amplifying feedback, whereas the blue arrows demonstrate a negative/damping feedback. VPD stands for vapor pressure deficit, defined as the difference between the saturated vapor pressure (a metric of the amount of water vapor the air can hold before it condenses into liquid) and the actual vapor pressure (a metric of the actual humidity). ABL stands for atmospheric boundary layer. The boundary layer is the layer of the atmosphere closest to the ground, within which the atmosphere is generally viewed as well-mixed. The feedbacks shown can also alter the height of the boundary layer, which affects the probability of cloudiness (see main text).
SOURCE: Miralles et al., 2018. CC BY NC 4.0

SPATIAL AND SEASONAL DIVERSITY IN DROUGHT

Because drought is generally defined as occurring when conditions are unusually dry, the definition of drought, and the factors to consider when defining drought, vary across the United States. One reason for the geographic variability in drought is the strong differences in the seasonality of precipitation across the country. For example, California receives nearly all of its water-year precipitation during the cool season, and little to no rainfall during summertime, while the Southeast receives approximately equal amounts of rain in each season. As a result, a weather pattern that prevents rain from occurring in California in the summer would be typical, whereas a weather pattern limiting rain in the Midwest or Southeast in the summer could quickly push the region into drought.

Relatedly, the potential for natural and human-created water storage systems will affect the downstream impacts of precipitation anomalies. In the West, where there are high mountains and strong seasonality in precipitation, cool-season precipitation that falls as snow is stored and ideally slowly released as winter turns to spring and summer, resulting in downstream water availability even when new precipitation is not falling. This process, however, is directly influenced by temperature: if winter precipitation falls as rain rather than snow, it will not be stored, and if spring heats up quickly, the snow will melt quickly and reduce water availability in the later spring and summer. As a result, precipitation totals alone will not provide a sufficient picture of water availability. Further, the United States has created substantial hydrological infrastructure (e.g., a reservoir system) in the West that allows water to be transported, stored, and released on a schedule, and this infrastructure can insulate some industries and users, such as farmers working with irrigated fields and household water users, from short-term and seasonal variability in precipitation. However, this infrastructure will not reduce impacts on less managed sectors, such as ranchers and natural ecosystems, and could fail altogether if there were long-term shifts in water availability. Conversely, precipitation in the East is more uniform spatially and seasonally, so there has been less investment in infrastructure to smooth out water availability; as a result, short-term changes in precipitation tend to have large impacts. Finally, changes in precipitation impacts extend beyond simple reductions in amount and can include shifts in seasonality or in the length of dry spells that lead to a misalignment between water availability and water needs.

DRIVERS OF DROUGHT TRENDS

Long-term trends in drought can be caused by both natural climate fluctuations and by anthropogenic factors associated with the burning of fossil fuels and the accompanying emissions of greenhouse gases and aerosols. Land cover modifications associated with, for example, changing agricultural practices, urbanization, groundwater depletion, deforestation, and wildfire may also contribute. Separating natural from human-caused contributions to long-term trends in drought can be challenging, especially if observational records of drought are limited in duration. In order to understand the natural- and human-caused components of drought trends now and in the future, it is productive to consider the changing nature of the aforementioned physical drivers of drought: atmospheric circulation and attendant impacts on temperature and precipitation, and rising temperatures due to anthropogenic causes. While the former contains a considerable proportion from natural climate variability and thus introduces a range of unpredictable outcomes, the latter is a result of human activities (IPCC, 2021) and will increasingly dominate as greenhouse gases continue to rise unabated. In particular, it is useful to view the evolving balance of driving mechanisms in terms of dynamical (circulation-related) factors versus thermodynamic (warming-related) factors.

Dynamical (Circulation-Related) Factors

Weather patterns that cause low precipitation and sunny, windy, and warm conditions are the most direct initiator of drought over the United States. While anthropogenic climate change may affect the frequency and severity of such drought-inducing circulation patterns, the signal is relatively weak compared to the naturally occurring fluctuations in these circulation types. Thus, a reasonable first assumption is that dynamically induced drought is mainly attributable to natural climate variability as opposed to anthropogenic climate change.

That said, some notable exceptions to this paradigm are emerging, potentially allowing for improved knowledge about the direction of dynamically induced drought in the coming decades. In particular, as discussed earlier, the atmospheric circulation over the United States responds to changes in tropical Pacific sea surface temperatures (SSTs). These SSTs have shown a recent decades-long trend toward a La Niña–like state, defined by anomalously cool conditions in the eastern Pacific compared to the western Pacific. This trend in SSTs has caused a shift toward drier conditions in the U.S. Southwest by altering the path of the jet stream and storm track into a more northerly position (Lehner et al., 2018; Seager et al., 2023; Alessi and Rugenstein, 2024), thereby contributing to the ongoing drought (and, conversely, increasing the incidence of atmospheric rivers in the Pacific Northwest; Li and Ding, 2024). A reversal of the SST trend pattern (i.e., El Niño) would favor an increase in precipitation over the Southwest United States, while a continuation of the current trends in the tropical Pacific would perpetuate the drought (Seager et al., 2023; Alessi and Rugenstein, 2024; Heede et al., 2025). It is not yet clear the extent to which the recent SST trends are a result of natural multidecadal variability, in which case they will likely reverse in the future, or are indicative of a human-caused climate change signal that will persist into the future. The specific pattern of aerosol emissions from fossil fuel burning and wildfire may also be contributing to the current SST trends and their associated circulation-induced impacts on Southwest U.S. precipitation (Kuo et al., 2025; Park and Soden, 2025; Klavans et al., 2025; Todd et al., 2025) Thus, further studies are needed to establish the relative importance of natural multidecadal variability as compared to anthropogenic climate change in causing the recent drought-inducing SST trends in the tropical Pacific (Klavans et al., 2025; Chang et al., 2025).

In addition to influences from inherent atmospheric circulation variability and regional patterns of tropical SST change, the climate over the Southwestern United States is also sensitive to changes in the Hadley Circulation, a global-scale circulation with descending motion in the subtropics and rising motion near the equator. The descending branch of the Hadley Circulation is associated with a surface high-pressure system that favors clear skies, low humidity, low precipitation, and high temperatures, all of which promote a semiarid climate. Over the past few decades, the descending branch of the Hadley Circulation in the Northern Hemisphere has expanded slightly poleward (approximately 1.5 degrees of latitude over the past 30 years) as a result of both natural variability and in response to increasing greenhouse gas emissions (Staten et al., 2020; IPCC, 2021). Earth System Models consistently project further widening of the Hadley Circulation in response to increasing greenhouse gases in the future, with the largest Northern Hemisphere changes occurring in the autumn season (Grise and Davis, 2020). As the associated subtropical anticyclone also expands in tandem, dry areas will extend further into mid-latitude regions such as the Southwestern United States and contribute to more frequent droughts as well as aridification.

Thermodynamic (Warming-Related) Factors

In contrast to changes in atmospheric circulation, there are clear and predictable signals in temperature related to increasing atmospheric concentrations of greenhouse gases that will influence future drought. The annual-average temperature in the contiguous United States has warmed by 2.5 degrees Fahrenheit (1.4 degrees Celsius) since 1970 (USGCRP, 2023, ch. 2) and will likely continue to warm at an equal or greater rate for the coming decades. Three direct implications of this warming are relevant for drought.

First, a warmer atmosphere can "hold" more moisture before that moisture condenses into rain at a rate of approximately 7 percent per degree Celsius warming, following the Clausius-Clapeyron relationship. Evaporation and transpiration (collectively evapotranspiration, or ET) respond in part to the vapor pressure deficit (VPD), defined as the difference between the saturation and actual vapor pressure. The saturation vapor pressure is an exponential function of temperature; as a result, all else being equal, higher temperatures will lead to more water being evaporated or transpired from the land surface, reducing surface water availability and extending the season for which ET exceeds precipitation. In reality, all else is not equal, and the contributions of other factors are discussed at the end of the chapter.

Second, increased temperatures will cause a shift from snow to rain in cases where historical temperatures are near the rain-snow threshold. While this will not cause decreases in precipitation in sum, it will affect the natural storage mechanism of snowpack. As a result, more water will be available in the winter, but less in the spring and summer due to loss of snowpack; further, snowmelt following drought years may preferentially replenish soil moisture, rather than increase streamflow (Lapides et al., 2022).

Third, due to the greater water vapor holding capacity of a warmer atmosphere, it is expected that a greater fraction of precipitation will be concentrated in extreme events, with longer periods of dry days in between. This phenomenon is generally predicted by climate models as well (Chang et al., 2025; Prein et al., 2017; Swain et al., 2025). The concentration of precipitation into fewer, more extreme events will tend to reduce the effectiveness of precipitation in replenishing local soil moisture, because the incoming water will run off once the soils become saturated.

Land Use and Land Cover Changes

Land use and land cover changes can modify different components of the hydrological cycle and affect the availability of water for humans and the biosphere through multiple pathways. Land use changes can happen quickly, such as through conversion of natural land cover to urban, or slowly, such as reforestation of previously cleared forests. Due to the diversity of possible land cover changes, this overview does not aim to discuss them comprehensively, but instead to highlight examples where there can be major influences on the hydrological cycle, primarily through changing the partitioning of water between different land and atmospheric reservoirs.

One major pathway for the state of the land surface to modify water availability is through altering the partitioning of precipitation between different reservoirs. The installation of impermeable surfaces such as asphalt will lead incoming precipitation to runoff rather than restore soil moisture and groundwater (Loiola et al., 2019; Sharp, 2010). Intensification of cropping, wherein more biomass is produced per unit area, leads to increased transpiration, or passive water lost that occurs when plants open their stomata in order to fix carbon. This moves water from the surface to the atmosphere and has led to increases in near-surface humidity and decreases in near-surface temperature on years with sufficient surface water available (Mueller et al., 2016; Jiang et al., 2018). Forest clearing for cropland expansion increases soil erosion rates and lowers infiltration capacity; for example, cropland expansion over three centuries resulted in a 2.5 percent increase in annual runoff volumes for North America (Haddeland et al., 2007). Conversely, forest regrowth in parts of the Eastern United States following agricultural abandonment can increase evapotranspiration and reduce runoff and streamflow; in a southern Appalachian watershed, old-field succession increased evapotranspiration by 4.5 percent and reduced water yield by 5.4 percent after the first decade of regrowth (Elliott, 2017).

Groundwater pumping is another major pathway for modifying water availability. As of 2015, about 29 percent of freshwater in the United States comes from groundwater (Dieter et al., 2018), which is water that is naturally stored in the pores of rocks underground. In theory, groundwater can provide a buffer in cases where surface water (provided by precipitation) is limited; in practice, the rate of groundwater use often exceeds the rate that groundwater can be naturally restored, depending on the type of aquifer. Across the United States, the total volume of groundwater decreased by nearly 1,000 cubic km from 1900 to 2008 (Konikow, 2015), which is equivalent to about 2.5 years of total freshwater use in the United States, or about twice the volume of water contained in Lake Erie. Groundwater use, however, is not uniform across the United States, and the majority (about two-thirds) of the total depletion has occurred in the High Plains Aquifer in the Central United States, the Mississippi Embayment aquifer system, and the Central Valley of California (Konikow, 2015). Before groundwater is depleted, it can serve as a resource to moderate the impacts of weather-induced drought. However, as it becomes more limited or overdrawn, it can no longer serve as a backstop against poor climatic conditions, thereby exacerbating drought. Further, depending on the subsurface geology, groundwater depletion can ultimately lead to the collapse of the pores that can store subsurface water, leading to subsidence of the land surface and preventing future recharge. This collapse, which typically leads to visible land subsidence at the surface, primarily occurs in fine-grained soils (clays and silts) (Galloway and Burbey, 2011). About half of the water used for irrigation to support agriculture comes from groundwater pumping (Dieter et al., 2018). After the water for irrigation is added to the surface, it either evaporates or transpires, percolates into the subsurface, or turns to runoff. Note that runoff from agricultural or urban surfaces will often be contaminated by chemicals. As a result, it cannot be directly used as a freshwater source, and can have negative impacts on the river, lake, and ocean ecosystems absorbing the runoff.

ARE WE HEADING TO A DRIER OR WETTER FUTURE ... OR BOTH?

The future of drought in the United States depends on the balance of the driving factors discussed above, some of which are largely changing in one direction due to climate change (e.g., thermodynamic or warming-related impacts), and some of which are mainly unpredictable due to natural variability (e.g., dynamic or atmospheric circulation-related effects). In addition, human modifications of the land surface are, on average, leading to reduced water availability through groundwater pumping at a rate that exceeds recharge. When considering the future of drought in the United States, it is helpful to explicitly consider how the balance between water gain through precipitation and water loss to either the atmosphere (through evapotranspiration) or the subsurface (through percolation) is expected to change.

The clearest signals for future drought are those that are linked to warming temperatures. As discussed above, warming temperatures lead to an increase in moisture demand from the atmosphere. To the first order, this will cause an increase in evapotranspiration, and a decrease in surface water availability as moisture moves from the land to the atmosphere. However, there are a few additional factors to consider.

First, in regions and during times of year that are dry, which are primarily in the Western United States, ET[1] tends to reduce with decreasing soil moisture, so reductions in surface water availability can be self-limiting (Seneviratne et al., 2010), although declines in ET during hot, dry years can also lead to reductions in atmospheric humidity (McKinnon et al., 2021) and associated increases in fire weather. Indeed, climatic factors, along with a reduction in Indigenous land use and fire stewardship practices, are contributing to an increase in the intensity and frequency of wildfires across much of the country, and most notably in Western U.S. forests (Holden, 2018; Williams et al., 2019). Wildfire itself can lead to increases in streamflow (Williams et al., 2022b), likely because there is a reduction in evapotranspiration due to loss of vegetation, and burned soils have reduced infiltration capacities

Second, vegetation can respond to high CO_2 conditions through either closing their stomata, which would allow for comparable carbon uptake through photosynthesis (since there is a larger "pool" of carbon in the atmosphere) while reducing water loss through transpiration, or producing more vegetation and increase the growing season, which can increase water use. The balance between these two factors will depend on water availability as well as plant type, but the two effects will tend to counteract each other (e.g., Zhang, Jin et al., 2022), leaving a dominant effect of increased ET due to greater atmospheric temperatures. In net, most climate models project overall decreases in soil moisture across the United States and increases in drought risk even in regions of precipitation increases (Cook et al., 2020).

Changes in precipitation can offset or exacerbate the expected drying associated with warming temperatures. In contrast to the clear signal in temperature, changes in precipitation in a warming world exhibit somewhat greater uncertainty due to the large contribution of unpredictable internal variability (Deser, 2020). On average, climate models project increases in annual-mean precipitation over most of the United States and decreases over parts of the Southwest (Marvel et al., 2023), although there is enormous spread across different simulations (e.g., Schmidt et al., 2021; Deser, 2020) due to both internal variability and differences in physics across models. Changes in annual-mean precipitation, however, are rarely the most relevant metric for drought, and clearer signals are present in other components of precipitation. For example, climate models consistently project declines in the spring season precipitation in the Southwest (Ting et al., 2018), and precipitation in the Northwest—while expected to increase on average—is projected to increase in the winter and decrease in the summer (USGCRP, 2023). Further, climate models are relatively consistent with their projection of greater precipitation extremes across the United States amidst substantial internal variability (Williams et al., 2024; Chang et al., 2025; Adhikari et al., 2025; Li et al., 2021), consistent with the expected shift toward both bigger extreme events and longer dry periods (Swain et al., 2025).

[1] Here, the reference is to actual ET, for example, the rate of water moving from the land to the atmosphere. This is contrast to potential ET, discussed in other chapters, which is the amount of ET we would expect from the atmospheric state if the surface were fully saturated with water. ET will typically decrease with drier soils, but potential evapotranspiration, or PET, will not.

Two additional signals for the future hydroclimate are closely linked to temperature and therefore can be expected with greater confidence. First, winter precipitation is more likely to fall as rain than snow, leading to reductions in snowpack and potentially snow drought, or conditions of below-normal snowpack. Snow drought can occur even if precipitation is normal if higher temperatures lead the precipitation to fall as rain instead of snow. It negatively affects seasonal water storage, winter tourism industries, and some ecosystems. For example, wolverine occurrence in the contiguous United States is closely tied to spring snow cover, while yellow-cedar decline has been linked to loss of insulating snowpack that leaves shallow roots vulnerable to freezing injury (Aubry, 2007; Schaberg, 2011). Second, warming temperatures are leading to an increase in flash drought, which is drought that onsets and intensifies quickly and often has additional negative impacts because stakeholders lack sufficient time to respond (Otkin et al., 2018; Christian et al., 2024). Flash drought is caused by a combination of critically low precipitation and a high evaporative demand by the atmosphere (Christian et al., 2021), the latter of which is directly linked to warming temperatures, as discussed above. While the relative contribution of each factor varies spatially, high atmospheric demand plays some role everywhere (Christian et al., 2021). As such, conditional on the limiting factors discussed above, flash droughts are expected to increase under warming.

In sum, while the exact timing of hydrological changes associated with global warming is uncertain due to the superimposed effects of unpredictable variations in atmospheric circulation (see earlier discussion), Earth System Models project a robust decrease in terrestrial water storage over the entire Western United States by the end of the twenty-first century, mainly driven by higher evapotranspiration and reduced snow resulting from higher temperatures, with the Upper Colorado River Basin as an emerging aridification hotspot (Ryu et al., 2025) (see Box 2-2). Thus, because of global warming due to anthropogenic greenhouse gas emissions, it is expected that dry days will be hotter, drought onset times can be faster, and snowpack will reduce. While thermodynamic effects are the dominant drivers of these impacts, circulation-induced precipitation variability may introduce some uncertainty in the timing and severity of the projected trends in drought onset, duration and frequency.

Conclusion 3-1: Drought assessment methodologies should incorporate both water supply and evaporative demand, as well as precipitation phase (snow versus rain).

Conclusion 3-2: Further research is needed to constrain regional projections of precipitation in the United States.

Conclusion 3-3: Drought assessment should aim to incorporate near-real-time information, as well as shorter timescale metrics, in order to better identify emerging flash droughts.

Conclusion 3-4: There is high confidence that climate warming, by itself, is likely to continue worsening trends in drought severity, frequency, duration, and possible onset speed, except where and/or when offset by sufficient increases in precipitation.

Conclusion 3-5: Further understanding of the physical and biological drivers of drought and how they may change as the climate warms, including assessing Earth System Model prediction and projection skill, is an urgent research need that underpins effective drought assessment.

4
Nonstationarity, Aridification, and Drought

This chapter examines how long-term shifts in the climate system create challenges for drought classification, monitoring, and assessment in the United States. It provides definitions of drought nonstationarity, megadrought, and aridification, and explains why nonstationarity undermines drought assessment frameworks built on assumptions of a stable climate. The chapter then considers how the components of nonstationarity (aridification and megadrought) create challenges for accurate drought classification and monitoring and how decisions made assuming a stable climate can become maladaptive under nonstationarity. Finally, the chapter assesses the strengths and limitations of existing approaches to nonstationary drought assessment.

OVERVIEW OF DROUGHT NONSTATIONARITY

Drought, by definition, is a negative hydrologic (water availability) anomaly; it is not a state; instead, it is an anomalous event, with a beginning, middle, and end. While an anomaly can be benchmarked to a nonstationary reference like a climate trend, in conventional drought monitoring, anomalies are referenced to a fixed background climate, or "baseline." Such a convention introduces a number of analytical choices, chief among them being the need to determine a representative climate baseline against which to define positive and negative hydrologic anomalies. What is the assumed "normal"? Is it the most recent decade? The last three decades? The full period of observational record? The Common Era as reflected in the paleorecord? These are choices that must be made (often before identifying drought metrics, indices, and thresholds to apply) with implications for what one analytically calls "drought," its characteristics, and thus its impacts (Li, Smerdon, et al., 2024; Hoylman et al., 2022; Lisonbee et al., 2024; Um et al., 2017). A chosen baseline itself can determine not just the magnitude or duration of drought, but whether a drought even occurred at all.

Herein lies the problem at the heart of this report. Because drought is defined with respect to time, benchmarked to a reference state, what happens if that reference baseline is no longer representative of current climate conditions? This creates *drought nonstationarity*, which the study committee defines as the change in drought statistics, including its characteristics and classifications, observed when a fixed baseline is applied to a changing climate.

The conceptual problem is not new; researchers have long recognized that drought indices calibrated in one period and applied in another produce systematic differences. Some earlier research introduced "relative" drought indices to disentangle the calibration baseline choice from the period being evaluated (Dubrovsky et al., 2009), indicating an early operational acknowledgment that drought index behavior is as tied to the baseline choice as the underlying climate. What has remained difficult is not the recognition that nonstationarity matters, but the implementation of monitoring, assessment, and decision-support practices that handle it consistently and transparently. Furthermore, the climate has trended considerably over the last decades, raising the operational consequences of stationary assumptions in monitoring and assessment.

As is unfolding in parts of the United States, drought nonstationarity implies that standardized drought measures and the thresholds that define drought class severities are no longer physically or hydrologically comparable across baseline intervals (see Figure 4-1). Simply, if the background climate shifts, becoming persistently wetter or drier over the decades, then a drought defined against an outdated baseline may over- or understate how unusual the conditions actually are for the present day. Operational drought monitoring uses multidecadal baselines, which sample high-frequency climate modes well, but may only partially capture lower-frequency climate modes that alter drought risks, such as the Pacific Decadal Oscillation (PDO) or Atlantic Multidecadal Variability. Internal variability, land surface changes, and anthropogenic warming can therefore each cause drought nonstationarity at the timescales relevant to drought assessment and monitoring. The definition above is agnostic about the cause; whichever driver dominates, the implications for drought monitoring are generally the same: the baseline against which drought is defined may no longer represent the climate in which drought occurs. Because this report centers on drought assessment in a nonstationary regime, the proposed framework to manage drought nonstationarity should be resilient and effective irrespective of the nonstationary driver (see “Components of Nonstationarity” section below).

To illustrate the challenge posed by drought nonstationarity, consider how drought severity categories are constructed. Nonstationarity complicates the use of percentiles or standardized anomalies, which are often used to define drought thresholds and imply the temporal invariance of drought (i.e., the assumption that their values indicate the same drought conditions regardless of when they are applied). For example, the U.S. Drought Monitor (USDM) defines a D4 or “exceptional” drought in part by a drought indicator (such as the Standardized Precipitation Index, or SPI) falling below the 2nd percentile of its historical distribution (Svoboda et al., 2002; McKee et al., 1993). A statistical approach like this is powerful: by construction, an exceptional drought is equally rare whether it occurs in the wet hydroclimate of Vermont or the arid one of Arizona. At issue, however, is whether it is equally rare for a specific region in the year 1930 or the year 2025 and whether the actual hydrologic severity of that drought—meaning its magnitude in terms of lost millimeters of precipitation, soil moisture deficits, reservoir levels, and the like—is comparable across time periods, owing to long-term climate changes.

Consider a schematic application of the USDM drought classification system percentiles (see Chapter 6, Table 6-1) to water-year (October–September, WY) precipitation over an arbitrary region in the United States (Figure 4-1). Under a stationary climate, one where its average and variability do not change, the absolute magnitude of a precipitation amount corresponding to a particular percentile threshold will be the same, regardless of the decades used in the baseline. But under nonstationarity, those amounts change. Under one multidecadal baseline (1st baseline), a D2 or “severe” drought (5–10 percentile range) might correspond to a maximum WY precipitation value of 64 mm. Under a second, drier baseline, that same D2 classification might correspond to less than 49 mm—a value that under the original baseline would instead be classified as a D3 or “extreme” drought. The same real-world drought event can therefore be classified differently just based on which period is used. This study committee explores these ideas further with real-world examples in Chapter 6, in particular in Figures 6-1 and 6-2.

Conclusion 4-1: Nonstationarity challenges drought classification and assessment because drought is conventionally defined using static thresholds relative to a baseline climate; if different baselines are used, or if the climate evolves relative to a fixed baseline (as with aridification), the same physical conditions can be classified differently or missed entirely.

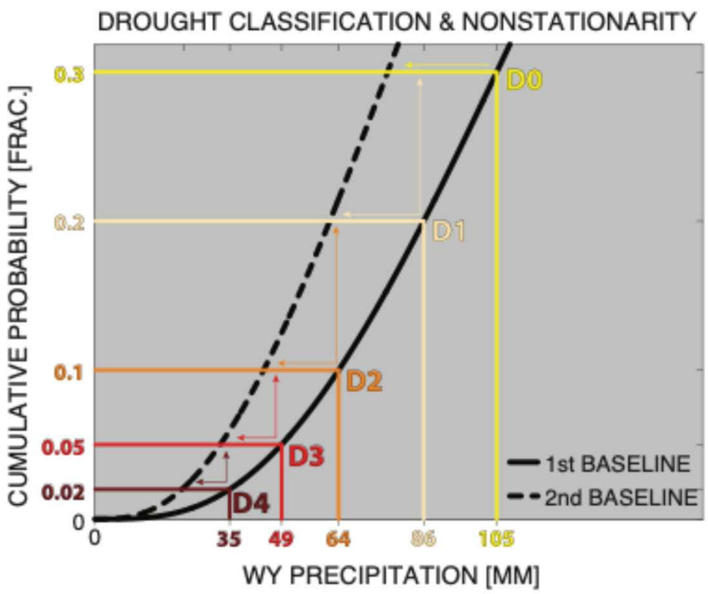


FIGURE 4-1 Drought nonstationarity and its consequences for drought monitoring and assessment.
NOTE: A schematic example of the effect of different hydroclimate averages (baselines) on drought classification for a single arbitrary location. The figure shows how the cumulative distribution function for water-year (October–September, WY) precipitation (in mm) changes between two reference baselines, one wetter (1st baseline) than the other (2nd baseline). What is clear is that the baseline can alter the hydrologic magnitudes (and thus drought impacts) that correspond to any threshold-based definition of drought classes. Here the change from the 1st to 2nd climate baseline is a drying, which as discussed in the text could arise from anthropogenic or natural forcing, or low-frequency variability. Irrespective of the source of changing climate baselines, however, the tendency in this example is twofold: first it makes the actual magnitude of drought thresholds drier (see left-pointing arrows), and it makes the likelihood of occurrence of old drought thresholds higher (see vertically pointing arrows) meaning more time spent in what used to be considered a DX drought class.
SOURCE: Adapted from Li, Smerdon et al., 2024. CC BY 4.0.

Across the United States, there are emergent features of drought nonstationarity in the USDM itself (see Figure 4-2). The USDM count of droughts over the 1,371 weeks between January 2000 and early April 2026 is presented in panel A of Figure 4-2. The West sees fewer droughts than regions east of the 100th meridian (median of 12 drought events in the 11 Western states of Arizona, California, Colorado, Idaho, Montana, New Mexico, Nevada, Oregon, Utah, Washington, and Wyoming, versus over 19 events in the non-Western United States). Yet the duration is much longer in the West, as presented in panel B of the figure, showing that the median Western drought is 51 weeks versus 14 weeks in the non-Western United States. As such, the number of weeks in drought, as captured in panel C, reflects this, with many locations in the Western United States experiencing drought residence times exceeding 20 percent, which is the percentile that defines a D1 drought. This more flashy quality of Eastern droughts is evident in panel C, which shows the grid point time to maximal drought severity for an average drought event. Non-Western U.S. regions reach maximal drought severity only 3 weeks after achieving a status above D0, while Western regions take over four times longer to achieve the eventual depth of their drought.

If the climate is stationary, the frequency with which a location is classified as "in drought" should approximate the percentile definitions. For instance, conditions meeting the D1 ("moderate" drought) threshold or worse, should correspond to the 20th percentile of the underlying indicators under climate stationarity. Under a drying trend, >D1 conditions might occur at frequencies higher than expected (e.g., Figure 4-1). This expectation can be tested by computing a "drought residence time" or the percentage of all weeks over the 2000–2026 period that a location was classified in at least D1 conditions (see panel D in Figure 4-2) (Mankin et al., 2021; Li et al., 2024). Note, this is simply a measure of how much time a place spent in an officially designated drought category. The map shows that most of the contiguous United States exceeded the stationary expectation, suggesting that the climate baselines underlying drought classification are not representative of the true hydroclimate state. While the diagnostic map presented in Figure 4-2D is not an attribution of the cause of nonstationarity, the residence-time pattern is consistent with the pattern of aridification and humidification associated with anthropogenic forcing. The map illustrates how drought classifications under fixed baselines can reflect longer-term shifts in climate, whether forced or unforced.

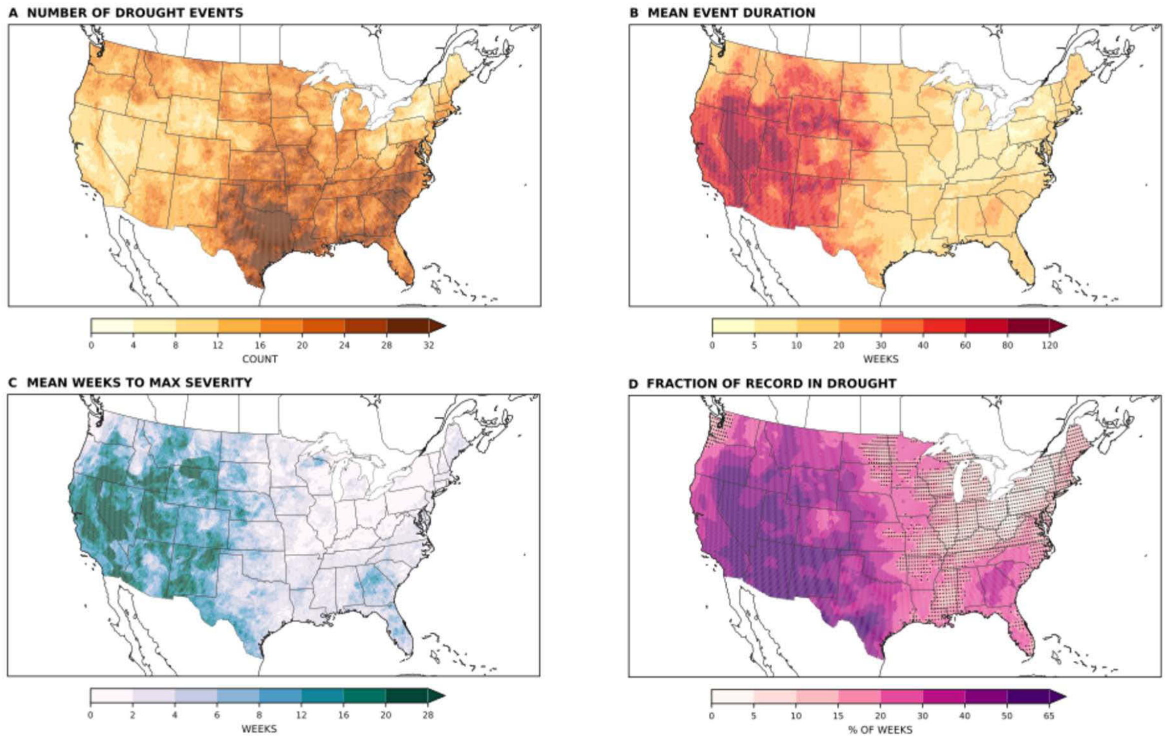


FIGURE 4-2 USDM climatology and evidence for drought nonstationarity.
NOTE: Grid cell drought event characteristics across the Contiguous United States (CONUS), January 2000 through early April 2026, derived from the weekly U.S. Drought Monitor, rasterized to 0.125-degree resolution. Events are defined as continuous periods of D1 (moderate drought) or worse, with gaps shorter than 2 weeks bridged as a single event. Panel A shows the total number of independent drought events per grid cell. The Western United States averages fewer events than the Eastern United States. Panel B shows the mean D1+ drought event duration in weeks; Western U.S. events persist roughly three times longer than non-Western U.S. events. Panel C shows the mean time from drought onset to maximum severity. Western U.S. areas take substantially longer to reach peak severity (median 12 vs. 3 weeks), consistent with slowly intensifying, persistent drought rather than flash events, as occurs in the more humid East, where events reach maximal severity much more quickly. Panel D shows the fraction of the USDM record spent in D1+ drought. Stippling marks grid cells where the drought fraction is below 20 percent, consistent with the baseline drought frequency expected by USDM design. Unstippled regions exceed this baseline, with the Western United States spending 44 percent of the record in drought on average versus 22 percent for the non-Western United States, consistent with the wider literature on aridification in the region.
SOURCE: Committee analysis; data from the USDM.

> *Conclusion 4-2: Across parts of the United States, the climatological reference period used in operational drought classification no longer matches the observed hydroclimate, with consequences for the character, frequency, and severity of drought.*

Components of Nonstationarity

A *stationary* process is one that does not exhibit changes in its mean, variance, or higher-order moments over time. A *nonstationary* process is one in which any of these statistical properties shifts. In the highly dynamic climate system, true stationarity at the local scale is elusive, as low-frequency variations in climate abound and the Earth system is never truly in an equilibrium state (Milly et al., 2008), even if over some intervals and for some measures stationarity was an acceptable assumption. For drought assessment, this matters because the baselines used to define "normal" implicitly assume some degree of stationarity (e.g., that the last 30 or 60 years of climate data can reliably represent the climate of the present or future). When that assumption breaks down, drought metrics calibrated to those baselines can become misleading (discussed in detail in Chapter 6).

It is important to note that nonstationarity in drought-relevant quantities is not limited to changes in the statistical average. Variability in quantities like precipitation, temperature, and soil moisture can also shift over time, as can the shape of their distributions, such as their most extreme tail values. A region could, for example, experience little mean change in annual precipitation, but a marked increase in consecutive dry days, which would alter drought characteristics absent long-term mean changes. This report's definition of nonstationarity therefore considers changes in any statistical property of hydroclimate that would limit the representativeness of a chosen baseline for drought assessment.

The committee identifies three broad categories of processes that can generate drought nonstationarity in the United States, each potentially operating on a number of timescales that can act through different mechanisms: (1) climate variability internal to the climate system; (2) land surface and human water and land management changes; and (3) externally forced climate change, both natural (e.g., due to changing volcanic forcing) and anthropogenic (i.e., due to emissions of greenhouse gas and aerosol pollution into the atmosphere). While the solutions to address the drought nonstationarity from each could be unique, all share the same consequence of undermining accurate drought assessment.

While these three categories of nonstationarity have very different origins and physical mechanisms, they can have common implications for drought monitoring and assessment: they all alter the representativeness of the local climate baseline against which drought and its characteristics are defined and assessed. A multidecadal drying in the 2nd percentile of 3-month precipitation in Oklahoma during the Dust Bowl, for example, might be similar to that resulting from a specific 30-year sea-surface temperature anomaly in the Pacific Ocean (30-year negative PDO). The origins differ, but the analytical problem for drought assessment is the same, which is a question of the most representative baseline. The framework proposed in this report must therefore be resilient to the source of nonstationarity. A monitoring system that accommodates one driver of baseline shift but not another would be inadequate for the range of factors determining U.S. drought presently and into the future.

Internal Climate Variability

Internal climate variability encompasses naturally occurring oscillations in the ocean-atmosphere system, which can collectively be culpable for persistent wet or dry conditions over a region over decades. In the United States, low-frequency variations in the Pacific, including El Niño Southern Oscillation (ENSO) and the more slowly varying PDO, alongside Atlantic multidecadal variability have been shown to exert persistent control over North American precipitation patterns, thereby making multidecadal climatological intervals wetter or drier (McCabe et al., 2004; Seager et al., 2005; Seager and Hoerling, 2014; Klavans et al., 2025). The ongoing twenty-first century American Southwest drought (Williams et al., 2020; Mankin et al., 2021), for example, has some of its origins with a shift to persistently cold conditions in the tropical Pacific, which has reduced the winter precipitation that is essential to the water-year there (Seager et al., 2023; Lehner et al., 2018). Because such sea-surface temperature variations can persist for decades, they can make successive 30-year climate baselines hydroclimatically distinct, even in absence of a longer-term human-forced trend, like that from global warming (Sung et al., 2024). Chapter 3 provides additional detail on the drivers of internal climate variability.

Land Surface and Water Management Changes

Land surface changes from deforestation, urbanization, agricultural expansion, or groundwater depletion could likewise persistently alter local land-atmosphere coupling, with consequences for the underlying hydroclimate state. More broadly, human activities, including increasing water demand as populations or economies grow, as well as decisions, policies, development, and adaptation (or lack thereof), are major drivers of drought and drought-related impacts (van Dijk et al., 2013; Xu et al., 2019). Urban development, landscape management, water supply and drainage infrastructure, energy systems, food production, and transportation significantly impact, but also rely on, sustained water availability and quality. Planning and design, adaptation and transformation, and myriad other human decisions and policies can therefore modify water availability and thus potentially shape the impacts of drought, even if not explicitly altering its frequency, intensity, and extent.

The Dust Bowl in the United States, for example, was borne in part of the agricultural practice of denuding the Great Plains of deep-rooted grasses that generated persistent land-atmosphere feedback. These feedbacks then depressed long-term precipitation by reducing terrestrial water recycling (Cook et al., 2009; Brubaker et al., 1993), and through energy-water interactions that determine soil moisture variability (Brubaker and Entekhabi, 1996). Empirical and modeling work has identified regional structure to soil moisture-precipitation coupling across the continental United States, with positive feedback dominant in the eastern United States and weaker or negative feedback in the arid Southwest (Findell and Eltahir, 1997, 2003; Tuttle and Salvucci, 2016). Similar dynamics have been extensively studied over the Sahel region of Africa, where hypothesized desertification feedbacks from overgrazing and land degradation (Charney, 1975; Hulme, 1974) were later shown to interact with ocean-forced precipitation changes to alter drought risks (Giannini et al., 2008). In the U.S. context, other work shows that land management such as logging (Hewlett and Helvey, 1970; Bowling et al., 2000) or forest risks, like wildfire (Williams et al., 2022b; Hasan et al., 2020; Wine et al., 2020), can alter river runoff profiles, generating additional runoff even in the face of drying land surface conditions. Groundwater pumping and its impacts on wider terrestrial water storage and irrigation impacts would also feed back to shape the severity, duration, and recovery timescales of water supply droughts (Scanlon et al., 2012; Apurv and Cai, 2020). The latter impact is distinct from land changes that modify precipitation itself, as water supply deficits and thus droughts could occur even without changes in the baseline climate.

Human management on the land can alter drought through at least two pathways: first, modifications to the land (e.g., irrigation, land cover changes, agriculture) can shift climate baselines through land-atmosphere feedbacks as noted above. A second pathway may not directly influence long-term P-ET (precipitation minus evapotranspiration) or an underlying climate baseline, but would impact land water states around groundwater, runoff, and soil moisture and thus the experience of droughts. These paths include groundwater withdrawals, surface diversions, and reservoir operations. It is noteworthy that both paths are increasingly considered central to drought as determinants as the literature looks to more explicitly identify the various paths through which humans influence drought (Van Loon et al., 2016; AghaKouchak et al., 2021). Human modifications to the land that alter long-term surface hydrology may initially be defined as drought, but as the change becomes permanent and the contemporary reference period catches up to the new hydrological state, it is often no longer considered to be drought. Disaster relief can be used for a time to mitigate the impact of the reduction in water supply until society adapts to the new conditions. Inadvertent events such as infrastructure failures (e.g., the break of a supply pipe or canal for irrigation) may temporarily impact water supply, but they are not considered causes of drought.

Climate Forcing Changes

Changes in climate forcing, whether aerosol-, solar-, or human-caused greenhouse gas–based, can generate persistent hydroclimate trajectories that impact drought (AghaKouchak et al., 2021; Chiang et al., 2021; Diffenbaugh et al., 2015). In the U.S. Southwest, human-caused warming has amplified the effects of precipitation variability, increasing the severity of the current multidecadal drought to rival those megadroughts that punctuate the paleoclimate record of the Common Era (Williams et al., 2020; Williams et al., 2022a). The impact is to alter the direction trend of hydroclimate from wetting to drying or vice-versa, making baselines from earlier decades unrepresentative of the conditions in which present droughts are occurring. Additional details on climate forcings are available in Chapter 3.

ARIDIFICATION AND NONSTATIONARITY

Aridification, or the regional trend toward a climatologically drier hydroclimate state that is not expected to reverse on decision timescales relevant to capital-intensive infrastructure, can induce drought nonstationarity by shifting the baseline against which drought is assessed. The distinction between aridity as a long-term state and drought as a short-term departure from that state is well-established across disciplines (AMS, 2012; Lian et al., 2021; Lisonbee et al., 2022; Maliva and Missimer, 2012; Sohoulande Djebou, 2017). But the temporal distinction among the two, drought and aridity, is precisely what nonstationarity erodes: when the long-term climate shifts, the baseline to which drought is referenced also shifts, and thus the two begin to interact. This is illustrated in Figure 4-1, which theorizes how the severity of drought classifications varies as a function of the level of aridity in the background climate, forcing static drought classes to track a moving target.

The Challenge of Estimating Aridity Changes

Aridity is at least as multivariate as drought (see Chapter 7); it can be defined atmospherically (e.g., via vapor pressure deficit, or VPD), hydrologically (e.g., via runoff) or ecologically (e.g., via vegetation stress) (Lian et al., 2021). It can be measured through a wide array of indices that privilege different variables, but many of which rely on potential evapotranspiration (or PET), which represents the theoretical constraints on surface water evaporation (see Table 4-1). Depending on the formulation, the constraints can include radiative energy (e.g., Priestley-Taylor) and/or aerodynamic ones such as winds or vapor pressure deficits (e.g., Penman, Penman-Monteith). Some of these measures include energy and moisture limitations on runoff (Budyko, 1961), the widely used United Nations Environment Programme (UNEP) aridity index of precipitation divided by potential evapotranspiration (Barrow, 1992), specific humidity-based approaches (Sahin, 2012), and vegetation-related metrics (Thornthwaite, 1948) among others. Each measure can produce different spatial patterns of aridity and its change in time, or aridification. This pluralism in aridification definitions is not pedantic or a simple cataloging problem; it has direct implications for detecting and characterizing aridification. Trends in atmospheric aridity from VPD, for example, can diverge from trends in hydrologic aridity (e.g., runoff efficiency) or ecological aridity (e.g., Normalized Difference Vegetation Index [NDVI] or Solar-induced Chlorophyll Fluorescence [SIF]), particularly under conditions where plant physiological responses to CO2 can decouple surface water availability from atmospheric demand through stomatal reductions (Roderick et al., 2015; Lian et al., 2021).

Many of the most widely used aridity metrics rely on PET, which complicates the assessment of nonstationarity. One part of this challenge is that the water balance is determined by P-ET, not P-PET, and so aridity indices can register large changes that do not correspond to the land water balance (e.g., Berg and Sheffield, 2018; Greve et al., 2014). The problem is that PET-based aridity measures assume that atmospheric demand for water is exogenous to the land surface, meaning that warming increases moisture demand in a way that straightforwardly dries the surface. But there is growing evidence that this assumption overstates long-term drying under warming. Plant physiological responses to elevated carbon dioxide, for example, particularly reduced stomatal conductance, may offset part of the atmospheric demand signal, implying that actual water availability may not decline as rapidly as PET-based indices suggest (Roderick et al., 2015; Lian et al., 2021). Additionally, aerodynamic PET formulations (such as Penman-Monteith) may improperly treat the atmosphere as independent of surface conditions, leading PET to overestimate aridity changes in coupled land-atmosphere systems (Zhou and Yu, 2025). This has direct implications for nonstationary drought assessment. Standard Precipitation Evapotranspiration Index (SPEI) and other PET-dependent drought indices (see Table 4-1) inherit whatever bias exists in the underlying PET calculation, potentially overstating aridification trends and the nonstationary signal they are intended to detect. As such, assessing drought conditioned on trends in aridification can quickly become a complex combinatorial domain for developing nonstationary drought monitoring and assessment practices. This also has direct implications for drought-related decision-making: if the nonstationary signal in PET-dependent indices is itself uncertain, then the question of whether a region is experiencing transient drought or secular aridification becomes harder to resolve, with asymmetric consequences for emergency management and adaptation. This report addresses those questions in the "Nonstationarity and Decision-Making" section below, and Chapter 6 provides a detailed discussion of drought indicators and indices.

TABLE 4-1 Diverse Approaches to Diagnosing Aridity and Its Underlying PET Estimates

Aridity Indices	Description	Source(s)
De Martonne Index (IDM)	IDM = P / (Tmean+10) P = mean annual precipitation (mm) T = mean annual temperature	Djebou (2017)[1], De Martonne (1926)[2]
Erinç Index (IM)	IM = P / Tmax P = mean annual precipitation (mm) Tmax = mean annual max temp (°C)	Djebou (2017), Erinç (1965)[3]
Budyko Index (AIB)	AIB = R / LP R = mean annual net radiation at the surface P = mean annual precipitation L = latent heat of evaporation 0 < AIB ≤ 1.1 = humid (surplus moisture regime; steppe to forest vegetation), 1.1 < AIB ≤ 2.3 = semi-humid (moderately insufficient moisture; savanna), 2.3 < AIB ≤ 3.4 = semi-arid (insufficient moisture; semi-desert), 3.4 < AIB ≤ 10 = arid (very insufficient moisture; desert), 10 < AIB = hyper-arid	Gao and Giorgi (2008)[1], Budyko (1961)[4], Djebou (2017)
Aridity Index or UNEP Aridity Index (AI)	AI = P/PET Berdugo et al. seem to just call AI (P/PET), as do Delgado-Baquerizo, et al. Likewise for the UNEP aridity index. According to Djebou, this is the most widely accepted aridity index.	Lian et al. (2021)[5], Berdugo et al. (2020)[6] Delgado-Baquerizo et al. (2013)[7], UNEP (1992), Djebou (2017)
Sahin Index (IQ)	IQ = P / Q P = mean annual precipitation (mm) Q = annual mean specific humidity (g/kg)	Djebou (2017), Sahin (2012)[8]
Emberger index	"obtained by tracking the mean annual precipitation as well as the mean temperature of both the coldest and hottest months"	Gavrilov et al. (2019)[9], Emberger (1932)[10]
FAO aridity index	"the ratio between the total annual precipitation and potential evapotranspiration"	Gavrilov et al. (2019), FAO (1977)[11]

Megadroughts

Megadroughts, unusually severe and persistent multidecadal drought relative to droughts of the instrumental period and typically identified in the paleoclimatic record, often via tree ring reconstructions and other proxies, add an additional complication (Cook et al., 2007; Woodhouse et al., 2010; Cook et al., 2022) (see also Box 2-2 on the ongoing megadrought). Scientists have learned a great deal about hydroclimate variability from investigating megadroughts; such work has revealed the historical low-frequency variability latent in hydroclimate and has helped clarify the drivers and consequences of past climate intervals, providing essential context for the present one (Woodhouse et al., 2010; Cook et al., 2022). But megadroughts blur the distinction between drought and its baseline: they are both a drought (relative to a centennial, or longer, timescale) and a climate baseline (for anyone experiencing them). The current quarter-century dry interval in the U.S. Southwest (shown in Figure 4-3) exemplifies this ambiguity: research has placed the current 20+ year interval as a megadrought rivaling the severity of those from the medieval period, and increasingly, indicating it is the climate to which the region must adapt (Williams et al., 2020, 2022a; Cook et al., 2022; Seager et al., 2023). The latter is clear from the sizable anthropogenic contribution Williams et al. (2022a) attribute, representing nearly 20 percent of the cumulative soil moisture deficit associated with the drought.

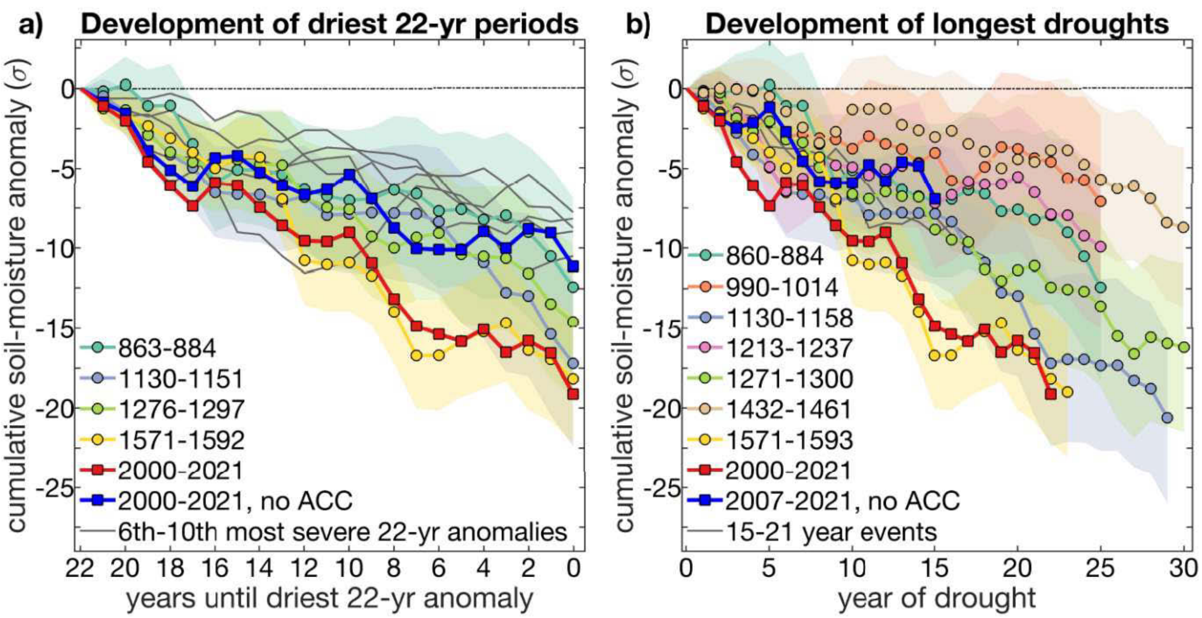


FIGURE 4-3 The development and attribution of the most severe and persistent droughts in Southwestern North America (SWNA) since 800 CE.
NOTE: Panel a shows the time series of the top five most severe 22-year droughts in Southwestern North America, in terms of cumulative standardized soil moisture deficits. The red line highlights the magnitude of the 2000–2021 period as observed, versus how that event magnitude would have differed without anthropogenic climate change (ACC) as estimated using a 50-year low pass filter on the CMIP6 historical and SSP2-4.5 scenarios. Panel b contextualizes the 2000–2021 SWNA event relative to the most persistent droughts in the paleorecord in the region, again delineating the contributions of anthropogenic climate change via the difference between the red and blue lines. The blue ACC line is shorter than the red observed line in panel b because the drought would not have started until 2007 in the absence of ACC contributions. Shading, 95 percent CI for the reconstructed droughts.
SOURCE: Williams et al., 2022a.

Visualizing the Drought-Aridification Convergence

One way to visualize how aridification and drought can converge is to track how the climatological aridity index (AI), defined as the ratio of potential evapotranspiration to precipitation, or PET to P, shifts over time relative to the aridity conditions that historically defined drought. While imperfect as a measure of the hydrologic state on the land, the aridity index is useful in that it grounds drought and aridification in the same physical framework: the long-term balance between atmospheric water demand (PET) and supply (P). Values near or above 1 indicate that demand approaches or exceeds supply, the energy-limited and water-limited regimes that the Budyko framework formalizes (Budyko, 1961). Comparing a region's recent climatological AI to its AI during historical severe-drought years, such as those defined in the USDM, offers a simple test of whether the background climate has begun to resemble the drought state itself (see Figure 4-4).

Implementing this test across the continental United States shows a clear epoch change toward drier climatological conditions between 1980 and 1999 and between 2010 and 2024 (see

Figure 4-4A). These drier climatological AI values make the region look more drought-like; in fact, in the Western United States, 93 percent of grid cells analyzed show climatological movement toward the drought state, closing about half the gap between AI values during the 1980–1999 period and the AI values during USDM-defined D2+ (or "severe") droughts. A convergence of 100 percent would mean that the recent average climate has fully arrived at the historical severe-drought aridity; a convergence of 0 percent would mean no movement toward the drought state. The climatological background, in other words, is increasingly aridifying toward what would, under an earlier baseline, have been classified as drought.

Conclusion 4-3: A stand-alone aridification product that tracks the local climatological water balance does not currently exist but is needed to help distinguish transient anomalies from secular climate trends in both the research and water planning communities.

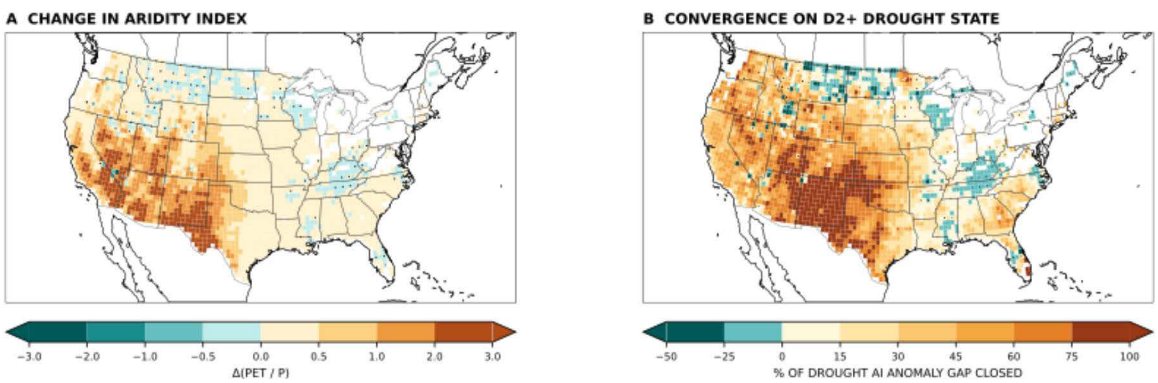


FIGURE 4-4 Aridification and drought convergence across the continental United States.
NOTE: Panel A shows the change in the annual aridity index (AI = PET/P) between 2010 and 2024 and between 1980 and 1999, where positive values indicate increasing aridity. Panel B shows the convergence of the climatological AI anomaly toward the USDM D2+ drought state, expressed as the percentage of the gap between early-period (1980–1999) and D2+ drought AI anomalies closed by the late period (2010–2024). The panel illustrates that climatological AI is converging on the AI during "severe" or worse drought events as classified by the USDM. Annual AI is computed as the ratio of annual PET to annual P totals at each 0.5° grid cell. D2+ years are defined as calendar years with 3 or more months of D2+ conditions at a given cell. Both panels show the ensemble mean across four independent dataset combinations (ERA5 and CPC precipitation; ERA5 and CRU TS Penman-Monteith PET), with stippling where fewer than three of four members agree on the sign of change. Across the Western United States, 93 percent of grid cells have moved toward the drought state, with a median convergence of 50 percent (ensemble range: 46–56 percent). The non-Western U.S. median is 14 percent.
SOURCE: Committee analysis; data from the USDM, CPC, ERA5, and CRU.

NONSTATIONARITY AND DECISION-MAKING

Any set of fixed operational rules, legal regime, policy, infrastructure, or practices that encodes a static climate assumption can become maladaptive as the climate drifts from that static-state assumption. Regional hydrologic infrastructure and water management regimes at various scales are designed to be optimal for a given baseline climate, from the size of reservoirs to legal agreements around rights allocations to expected runoff volumes and their seasonal timing. A drought management regime that is designed to rely on spring water deliveries from mountain snowpack, for example, may be able to buffer a single snow drought year, but may not be resilient to the year-on-year loss of water from seasonal snowpack owing to underlying nonstationarity from warming (Siirila-Woodburn et al., 2021). The vulnerability of any given decision regime to nonstationarity depends on how tightly coupled it is to a historical baseline and how quickly that baseline is shifting, relative to the system's innate flexibility and its capacity to adapt.

Drought classifications enter emergency management through statutory and programmatic triggers, such as emergency response plans, state-level disaster declarations, and federal compensation programs. As noted earlier, U.S. Department of Agriculture's (USDA) Livestock Forage Disaster Program, or LFP, authorized under 7 CFR Part 1416, for example, ties rancher compensation to USDM drought classifications directly, and has paid out over $12 billion in aid over the 2008–2022 period (USDA-FSA, 2018; Hrozencik et al., 2024). The same USDM thresholds underpin the USDA Secretarial disaster declarations, which trigger Farm Service Agency emergency loan access (7 CFR Part 759). Such decision structures are vulnerable to nonstationarity, as programmatic support can become decoupled from actual hydrologic conditions (Krueger et al., 2024). Hrozencik et al., (2024) show that a stationary assumption can lead to over- and underpayment of disaster assistance and can impose risk on future federal budgets. As climate drifts from a USDM baseline, percentile-based drought thresholds increasingly fail as a credible signal of who needs support and when, with consequences for trust in the federal programs built on top of them.

California's reservoir operations also illustrate how such coupling between climate and decisions can generate costs to drought management. Federal flood control rule curves require empty winter reservoir capacity to buffer from atmospheric river floods. Such rules are static, based on decades-old assumptions of seasonal flood risk magnitude and timing (Delaney et al., 2020; Forbis and Ly, 2024; Jasperse et al., 2020). Under drought nonstationarity, an explicit trade-off between flood and drought management emerges: aridification makes stored water more valuable, but rule compliance means managers release water even though it will make warm-season drought management more costly. Moreover, the fixed flood risk profile from atmospheric river events may itself be influenced by nonstationarity, as storms become more intense and the snowfall fraction associated with them changes. The development of forecast-informed reservoir operations (FIRO) has partially addressed this problem by replacing static rule curves with forecast-responsive reservoir operations. FIRO-based operations at Lake Mendocino, for example, helped yield an additional 20 percent in water storage during the severe 2020 drought year (Delaney et al., 2020). The gap between what the old rules produced and what FIRO enables is a measure of the maladaptation cost of operating under stationary assumptions. That gap widens as the climate drifts further from the historical conditions that the rules were calibrated to. Documented examples of maladaptation at the water-user level include federal crop insurance disincentivizing farmer adaptation to extreme heat (Annan and Schlenker, 2015) and access to groundwater from the Ogallala Aquifer leading to a shift toward more water-intensive crops, increasing drought sensitivity in irrigated counties (Hornbeck and Keskin, 2014).

Conclusion 4-4: Nonstationarity erodes the utility of drought classification for emergency management while simultaneously increasing the maladaptation costs of drought assessment regimes that encode static climate assumptions.

The Decision Implications of Distinguishing Drought from Aridification

More broadly, the inability to reliably distinguish transient drought from secular aridification creates asymmetric risks for emergency management and adaptation. Whether better information improves decisions depends on whether institutions are positioned to act on it; the risks discussed below illustrate what might happen if they are not. If monitoring systems overstate aridification, decision-makers may interpret what is still a transient, reversible drought as evidence of a permanent hydroclimate shift, triggering costly and potentially irreversible adaptation investments (e.g., fallowing agricultural land, reengineering hydrologic infrastructure, or renegotiating allocation compacts) that are premature given the actual trajectory of water availability. Conversely, if the true pace of aridification is faster than monitoring products suggest, as could occur where land-atmosphere feedbacks amplify drying or where internal variability temporarily masks a forced trend, systems may remain locked in emergency management mode, cycling through repeated drought declarations and short-term relief rather than undertaking the structural adaptation that the persistent shift demands. Notably, emergency relief is generally offered to those affected, whereas structural adaptation is generally asked of those making adaptations, raising equity questions that are discussed in Chapter 9.

In either case, the question confronting decision-makers is not only whether current conditions are anomalous, but how long the anomaly must persist before the appropriate institutional response shifts from emergency management (temporary conservation measures, disaster relief, short-term supply augmentation) to adaptation (permanent changes to infrastructure design standards, legal allocation frameworks, land use, and demand management). That threshold is system-specific and depends on the decision lifetime of the assets and institutions involved (Hallegatte, 2009; Smith et al., 2011): a seasonal crop decision may tolerate several years of ambiguity about whether conditions reflect drought or aridification, whereas a capital-intensive multidecadal reservoir investment or interstate compact renegotiation cannot. Long-lived infrastructure decisions with consequences spanning 50–200 years (Hallegatte, 2009) are particularly exposed, because the climate baseline in which they will operate may differ substantially from the one against which they were designed. Compounding this challenge is the maladaptation risk inherent in premature commitment: if a region adapts its water infrastructure to a drier baseline driven in part by multidecadal oceanic variability, and that ocean state subsequently reverses, the adaptation itself becomes a source of inefficiency or even harm.

The Colorado River Compact offers an instructive case. The 1922 compact allocated water based on overly optimistic streamflow estimates from a wet early-twentieth-century period; however, alternative observational estimates and subsequent tree-ring reconstructions later revealed that the long-term mean flow was substantially lower than the allocation assumed (Kuhn and Fleck, 2021; Woodhouse et al., 2006). The resulting over-allocation has generated persistent structural water deficits that now interact with warming-driven aridification to compound the basin's water crisis (Udall and Overpeck, 2017; Schmidt et al., 2023). The compact therefore locked in an institutional baseline calibrated to a transient wet anomaly rather than a true hydroclimate state, producing maladaptation whose costs have compounded over a century. This is precisely the kind of path dependency that nonstationary drought assessment should help decision-makers avoid.

The design challenge, then, is not simply to correct for PET biases in drought indices but to develop monitoring and assessment practices that help decision-makers distinguish the timescale and reversibility of the nonstationarity they face, thereby directing emergency management resources toward transient anomalies (drought) and adaptation investments toward persistent, forced trends.

The federal disaster assistance case illustrates a specific channel through which this problem operates. If monitoring tools are calibrated to an outdated baseline, a producer experiencing genuine hardship may fall outside the thresholds that trigger federal disaster assistance, not because conditions are less severe, but because the classification system has not kept pace with the climate. A drought assessment framework resilient to nonstationarity must serve operational and long-term planning needs, or at the least, be clear about which decision-types it is serving. As the National Integrated Drought Information System (NIDIS) technical memorandum on drought assessment concluded, the ability to distinguish temporary drought from long-term climate change is fundamental to directing resources toward the appropriate response: short-term conservation during episodic drought versus long-term adaptation to permanent change (Parker et al., 2023; Lisonbee et al., 2025). For planners, the distinction between forced and unforced nonstationarity becomes essential: a precipitation deficit driven by a Pacific Decadal Oscillation phase may reverse in coming decades, but one amplified by anthropogenic warming will not. Without making this differentiation visible, drought monitoring risks conflating emergency management with the broader challenge of hydroclimate adaptation (Mankin et al., 2021). The USDM residence time analysis in panel D in Figure 4-2 illustrates one element of this problem: when, over a multidecadal period, a location spends a large fraction of weeks in classified drought, the classification has, at minimum, ceased to identify emergencies in the percentile-anomaly sense it was designed to convey. Whether the underlying driver is forced and persistent, or unforced and recoverable, is a separate question that the residence-time pattern alone cannot answer. Resolving that question, and matching the institutional response to the timescale of the driver, is what the committee's proposed framework will inform.

Conclusion 4-5: The decision costs of drought nonstationarity are large and an assessment framework resilient to nonstationarity must serve both operational needs (i.e., reflecting true current conditions) and planning needs (i.e., the drivers and timescales of baseline changes), or be transparent about which aim it is serving.

Recommendation 4-1: NOAA, NSF, NASA, and other science partners involved in the national drought assessment enterprise should prioritize scientific research into drought dynamics and aridification, including how climate variability and change influence the frequency, severity, duration, onset, intensification, and other aspects of drought needed to support relevant decision-making. The research should also prioritize improving approaches used to assess drought and aridification risks seasons to decades into the future.

EXISTING AND EMERGING APPROACHES FOR DROUGHT NONSTATIONARITY

A growing body of research has sought to develop drought metrics to explicitly account for nonstationarity, and the findings and their limitations define the frontier for improving drought assessment. This section summarizes the current state of nonstationary drought analysis, considering factors like baseline selection, non-climatic drivers, and propagation of uncertainty.

Baseline Selection as a Design Choice

Selecting a baseline is as fundamental to drought monitoring as is selecting a drought index or variable. Both recognizing the baseline as an explicit decision-related design choice and being transparent about what it is should be the most basic practice for all drought classification, monitoring, and assessment going forward. While typical practice leverages fixed (often 30-year) baselines (Svoboda et al., 2002), a number of studies have shown that this choice impacts drought diagnosis (Hoylman et al., 2022; Li et al., 2024; Sung et al., 2024), with static baselines showing a consistent drying under aridification and rolling baselines underrepresenting long-term shifts.

The European Drought Observatory (EDO) systematically evaluated the impact of operational drought classification based on static versus nonstationary SPI baseline (Cammalleri et al., 2022). The tension the study engages is one very relevant to the present report, that of providing a stable benchmark versus providing a reliable estimate of event rarity. There is an imperative to accomplish both: to provide a consistent point of comparison between historical and present-day measurements so that an extreme drought represents the same physical water deficit on the one hand, and the need to provide an accurate probabilistic assessment of how likely or rare an event is relative to present-day conditions on the other hand. Nonstationarity creates tension between these two aims. Cammalleri et al. (2022) conclude that implementing a nonstationary SPI (nSPI) operationally would be too challenging and instead suggest adopting a rolling baseline that is updated every 5 years, a more rapid update schedule than the 10-year normals typically practiced by the World Meteorological Organization (WMO) and the EDO (Cammalleri et al., 2022). Such rapid updates of normals are not without precedent in the U.S. operational context: the National Oceanic and Atmospheric Administration’s (NOAA) Climate Prediction Center, for example, updates the base period for Niño 3.4 sea surface temperature anomalies every 5 years to isolate secular oceanic warming that would otherwise bias ENSO classification[1] (L’Heureaux et al., 2012). On drought specifically, that this problem is already detectable in Europe where precipitation nonstationarity is generally weaker than in the American West, and where the dominant driver of drought intensification (temperature-driven increases in evaporative demand) is excluded from the SPI framework entirely, suggests that the operational challenge for indices incorporating temperature, such as the SPEI and Palmer Drought Severity Index, or PDSI, is likely more severe. As Lisonbee et al. (2024) note, drought index estimates are sensitive to reference period choice across multiple index families, reinforcing the conclusion that baseline selection is a design parameter with direct consequences for drought diagnosis, not a neutral methodological default.

[1] https://www.climate.gov/news-features/understanding-climate/watching-el-ni%C3%B1o-and-la-ni%C3%B1a-noaa-adapts-global-warming, accessed May 23, 2026

Conclusion 4-6: Baseline selection is not a neutral methodological choice; instead, it is a design choice for drought-related decision-making and should be treated as such.

Conclusion 4-7: Because baseline choice materially affects drought classification and the decisions it informs, drought monitoring products and decision-support tools should communicate the baseline used, its limitations under nonstationarity, and the implications for interpretation.

Nonstationary Drought Indices

Nonstationary drought indices, such as nSPI or nSPEI, have emerged to address some of these concerns. Methodologically, drought indices often rely on a parametric statistical transformation of the distribution to ensure that they are standardized in space and time. Such nonstationary indices, at their core, allow for the underlying distribution to vary in time (e.g., Russo et al., 2013), often relying on approaches like Generalized Additive Models in Location, Scale and Shape (GAMLSS) to model parameters as functions of drought covariates, such as El Niño, or other factors (Li et al., 2015; Wang et al., 2015; Bazrafshan et al., 2022; Shao et al., 2022). Some studies have extended this to nonlinear covariate relationships, finding that the nonlinear dependence of distribution parameters on climate indices like ENSO, PDO, SAM (Southern Annular Mode), or DMI (Dipole Mode Index) can help to better represent drought dynamics than linear specifications.

Nonstationary drought indices like nSPI (or SnPI as Russo et al., 2013, termed it), have considerable advantages over stationary equivalents. They can better reproduce observed rainfall variability and capture drought termination timing more accurately. The EDO evaluation confirmed this finding operationally: even where two successive static baselines broadly agreed with each other (1981–2010 versus 1991–2020), neither reliably tracked the true magnitude of nonstationary index values across its full period of use, and the gap widened in regions with the strongest precipitation trends (Cammalleri et al., 2022).

LIMITATIONS OF EXISTING METHODS

Most frameworks still treat drought as a primarily meteorological phenomenon and give limited attention to human water management, land cover change, or evolving demand, which can strongly modulate observed nonstationarity in hydrological and agricultural drought (Xu et al., 2023; Tomasella et al., 2023; Bazrafshan et al., 2022). Such factors would shape the timescales over which nonstationarity is corrected or accounted for. They are also the domains where drought decisions operate, such as the California reservoir operations considered above. The maladaptation of static flood control rule curves does not arise from the failure to update the SPI drought index quickly enough; it is a function of outdated operational rules now tasked with managing flood risks and ensuring sufficient water supply simultaneously in a shifting climate, as the FIRO case discussed above makes clear. On some level, nonstationary drought indices, however sophisticated, must also be grounded in their decision context around water provision and management over short emergency management and long planning timescales alike. The limitations of nonstationary drought indices catalogued below should be read alongside the limitations of conventional stationary indices, which are discussed in Chapter 5. Stationary indices share similar limitations (data gaps, structural uncertainty), face others more acutely (retrospective framing, baseline-length trade-offs between sampling natural variability and reflecting current climate), and have been the implicit alternative against which nonstationary methods are being proposed. The discussion here focuses on the limits of nonstationary indices, not as a tacit endorsement of the stationary alternative but because they have been advanced as a response and warrant their own evaluation.

> *Conclusion 4-8: Existing nonstationary drought indices represent an important methodological advance but also face limitations, including too narrow a focus on meteorological variables and limited engagement with the broader impacts of drought.*

Beyond this central gap other limitations are worth noting in nonstationary drought indices. First, covariate selection is ad hoc, with limited physical justification for linking specific climate modes or anthropogenic drivers to particular parameters, raising concerns about overfitting and extrapolation outside the historical range of the data (Slater et al., 2021; Ragno et al., 2019). Second, many existing studies impose relatively simple parametric forms (e.g., simple linear or low-order polynomial trends) on distribution parameters, which may not capture nonlinear responses, regime shifts, or the complex multidecadal modes that are evident in long-term paleoclimate records and large ensembles (Sung et al., 2024), meaning they are insufficiently modeling the nonstationarity that the methods work to correct. Third, data gaps in long-term evapotranspiration, soil moisture, groundwater, and vegetation indicators, together with inconsistencies among reanalyses and models, introduce substantial structural uncertainty that is rarely propagated through to nonstationary drought risk estimates (Gebrechorkos et al., 2025). Fourth, all of these nonstationary characterizations are retrospective, looking at the climate as it has been, rather than including future information about how the climate is trending. There is the possibility of centering a baseline on the current year and having that baseline span historical and future years, though there would be numerous decisions to be made to implement such a baseline choice. Such methodological and hydrological data gaps constrain progress toward a generalized, process-consistent framework for nonstationary drought analysis to meet emergency management and planning needs.

More widely, a key limitation is a practical one: what aims should a drought classification and monitoring regime achieve? What do decision-makers most need? A drought monitoring regime should be simple to understand, transparent in its assumptions, reproducible, and decision-relevant, meaning it can separate short-term emergency management from long-term planning. The limitation is that a single classification framework, such as the USDM, cannot achieve these aims at once, implying that more than one classification and monitoring regime might be necessary—one for emergency management, one for hydrologic adaptation. As noted above, nonstationarity creates a tension where one can either characterize how current conditions compare to the full period of record or assess how current conditions compare to present expectation.

Addressing these issues will require closer integration of physically based process understanding with flexible statistical architectures, and more explicit treatment of baseline choice as a design parameter rather than a fixed assumption.

5
Drought Assessment Data Sources and Nonstationarity

Chapter 4 demonstrated how nonstationarity undermines drought assessment frameworks built on assumptions of a stable climate. It made the case for an assessment framework that serves both short-term operational needs and longer-term planning needs (or is transparent about which need it is meeting). Chapter 4 also made the case for treating baseline selection as a design choice rather than treating it as fixed. Chapter 5 builds on that foundation by discussing the various data sources that are used for drought assessment, with a particular focus on data needed to address drought nonstationarity for both short-term operational purposes and longer-term planning.

Data sources and their various periods of record are foundational to the study statement of task, including those stated in the first bullet—*How do current periods of record affect drought outlooks and predictions?*—and the second bullet—*Evaluate data sources currently used for drought assessment. What data will be needed to address nonstationarity?*. As discussed throughout the chapter:

- Current observations are particularly important as land use and land cover changes from conversions of forest to agriculture and many land cover types to urban uses. Data sources that are contemporary are most needed to characterize nonstationarity.
- Continuous long-term observations are also important for preserving statistical diversity and establishing baselines for comparison.

The discussion starts with the major issue of temporal baselines and periods of record, then turns to methods for extending and augmenting limited observational datasets. Chapter subtopics include considerations of spatial and temporal sampling, continuity of satellite Earth observation systems, the distinct data requirements for operational versus planning applications, and frameworks for evaluating the development of drought products. The chapter concludes by discussing multiproduct integration strategies, with particular examples of standardized soil moisture-derived indices that enable coherent synthesis across heterogeneous datasets. Ultimately, the chapter highlights how these data considerations directly serve the fundamental challenge, that is, drought assessment in a climate system that is no longer governed by historical precedent.

DATA SOURCES AND REQUIREMENTS FOR UNDERSTANDING DROUGHT UNDER NONSTATIONARITY

As demonstrated in Chapter 4, a central methodological imperative across all aspects of drought assessment under anthropogenic climate change is the adoption of dynamic reference periods that are regularly updated while maintaining parallel long-term baselines. This dual approach enables decision-makers to assess both contemporary drought severity relative to current climate regimes and historical context relative to long-term variability. From data infrastructure and monitoring systems to impact assessment and forecasting frameworks, this strategy provides the foundation for drought management in a climate system no longer governed by historical precedent. The intensification of anthropogenic climate change has fundamentally undermined the assumption of stationarity in hydrological systems, which previously justified reliance on historical data records for the prediction and management of drought (Milly et al., 2008). This shift carries profound implications: observed changes in the probability distributions of precipitation, evapotranspiration, temperature, storage, and runoff directly affect water resources management, agricultural planning, and ecosystem resilience (Ehret et al., 2014; Sarhadi et al., 2018). The representation of nonstationarity through increasingly variable and extreme climate regimes demands an evolved approach to drought assessment that recognizes spatial and temporal shifts in both hazard and impact profiles (Ehret et al., 2014; Williams et al., 2022a).

Accurate understanding and monitoring of drought under these evolving conditions require robust data infrastructures that are temporally consistent, spatially comprehensive, and methodologically traceable (Lisonbee et al., 2025). This challenge extends beyond simply accumulating large observational archives. Specifically, the reliability, quality, and temporal representativeness of these archives should be rigorously scrutinized, particularly as measurement platforms, methods, and standards evolve over time (Devasthale and Karlsson, 2023; Popp et al., 2020). In recent years, modern drought science and assessment demand the integration and harmonization of multiple data streams, including traditional in situ measurements, satellite remote sensing, model reanalysis, and where feasible, paleoclimate reconstructions (Nandi and Biswas, 2024; Seo and Lee, 2019).

Data Records and the Decline of Stationarity

The concept of period of record, referring to the temporal span over which data are available and deemed representative for analysis, lies at the heart of drought assessment methodology (Sun et al., 2018). Traditionally, drought assessment has relied on long-term historical records to establish baselines and characterize the rarity of conditions, often drawing on the longest available period (e.g., 60+ years). This convention emerged from an era when climate variability was primarily understood through natural forcing mechanisms, supporting the conceptual foundation that climate statistics estimated from historical records could represent future conditions (Cammalleri et al., 2022).

While 30-year climate normals established by the World Meteorological Organization (WMO) are widely used in climatology and have been applied in some drought contexts, longer records have generally been preferred where available, assumed to better capture extremes. However, under increasing nonstationarity, these long-term historical baselines may no longer provide a stable reference for assessing current-day drought conditions and risk. Specifically, fixed reference periods risk masking underlying nonstationary trends in drought-relevant variables, failing to capture the increasing spread of drought extremes now emerging under climate change, and systematically underestimating contemporary drought risk (Schwarz et al., 2025; Vélez-Nicolás et al., 2022). The challenge is particularly significant because the selection of baseline period fundamentally shapes drought detection, classification, and communication. A baseline drawn from earlier decades may classify current conditions as more anomalous than one drawn from recent decades, yet neither fully captures the trajectory of ongoing change.

On the other hand, this dilemma demands careful navigation between competing imperatives. Indeed, long observational records preserve statistical diversity, enable detection of rare extreme events, and provide context for assessing whether current conditions are truly unprecedented (Khan et al., 2022). Yet these long records blend different climatic regimes, potentially obscuring the emergence of new drought dynamics. Conversely, shorter records centered on recent decades are more relevant for contemporary decision-making and better reflect current climate states, but sacrifice statistical stability and may not capture the full range of natural variability (Gangopadhyay et al., 2022; Skiadaresis et al., 2021).

Addressing these competing imperatives requires the adoption of regularly updated dynamic reference periods maintained in parallel with longer-term baselines (Gangopadhyay et al., 2022). This dual approach enables assessment of both contemporary drought conditions relative to current climate regimes and long-term context relative to the full envelope of historical variability. The necessity of this framework is particularly evident in regions like Western North America, where temperature-driven evaporative demand now likely dominates some components of drought severity more than precipitation deficits alone (Williams et al., 2022a). In such contexts, relying solely on unmodified historical baselines provides misleading guidance for risk assessment, infrastructure design, and early warning systems. Regular updating of reference periods, paired with preserved access to longer records, thus represents a methodological imperative for drought assessment under anthropogenic climate change.

Conclusion 5-1: Effective drought assessment under nonstationarity requires both long-term observational records and contemporary high-resolution datasets. In situ observations like precipitation and streamflow may span over a century whereas more recent Earth observations are available only for a few decades. To better leverage multiple data sources for drought assessment under anthropogenic climate change, dynamic reference periods can be used that are regularly updated while maintaining parallel long-term baselines that preserve historical context.

Recommendation 5-1: Federal agencies (such as USGS, NOAA/NWS, USDA, USCRN) operating in situ hydrological networks (streamflow, COOP, SCAN, SNOTEL, USCRN, and state-operated hydrological and mesonet networks) should prioritize continuity of long-term datasets with strategic placement across diverse soil types, crop covers, topographic settings, climatic zones, and ecosystem types to capture the heterogeneity of drought response and strengthen standardized data archiving, quality control protocols, and open-access frameworks to facilitate seamless integration with satellite and model-based products.

Extending Datasets Beyond Instrumental Limits

The limited duration and spatial incompleteness of instrumental records fundamentally constrain some aspects of drought assessment, particularly for characterizing extreme events and low-frequency variability. Two complementary strategies that address these limitations are paleoclimate reconstruction and data assimilation frameworks.

First, paleoclimate proxies, principally tree rings but also including lake sediments, speleothems, and other natural archives, extend drought histories across centuries to millennia (Zaw et al., 2020). These reconstructions reveal that the instrumental period, typically spanning 100 to 150 years, captures only a limited sample of the drought variability possible within the climate system. Western North American tree-ring networks, for instance, document megadroughts of multidecadal duration and severity unmatched in modern observations, fundamentally challenging risk assessments based solely on twentieth-century experience (Meko et al., 2007; Routson et al., 2011; Cook et al., 2004; Todd et al., 2025; Gangopadhyay et al., 2022; Y. Zhang et al., 2022). The Colorado River Basin provides a stark example, in which streamflow reconstructions extending to the first millennium CE reveal second-century droughts that exceed both the current megadrought and well-documented medieval period droughts in duration and intensity (Gangopadhyay et al., 2022).

The scientific value of paleoclimate reconstructions depends critically on the strength and temporal stability of proxy-climate relationships, adequate spatial replication of proxy networks, and rigorous validation against independent data sources (Khan et al., 2022; Zaw et al., 2020). Successful reconstructions typically explain 40–60 percent of instrumental drought variance, with skill increasing for longer temporal averaging periods. However, challenges persist, including potential nonstationarity in the proxy-climate relationships themselves, divergence between proxies and instrumental records in recent decades, and confounding influences such as historical land management practices that can modulate tree growth responses independent of climate (Skiadaresis et al., 2021). A further limitation is that many drought proxies are calibrated against the instrumental record, so their reconstructed variability is not fully independent of the underlying gauge-based observations. Despite these complexities, paleoclimate data provide irreplaceable perspective on the range of drought variability that has occurred and may recur, cautioning against complacency based on limited modern experience.

Second, data assimilation and reanalysis systems represent a fundamentally different approach to extending datasets across space and during the twentieth and twenty-first centuries, one that leverages physical understanding rather than empirical correlation (Popp et al., 2020; Vicente-Serrano et al., 2010). Products such as ERA5-Land, GLDAS, and NLDAS (see Table 5-1) fuse heterogeneous observations with physically based land surface models to generate spatially complete, temporally consistent estimates of key variables including precipitation, temperature, soil moisture, evapotranspiration, and runoff (Muñoz-Sabater et al., 2021). This fusion propagates information from data-rich to data-sparse regions and periods, providing coherent fields that can be analyzed at user-defined spatial and temporal scales.

ERA5-Land exemplifies the capabilities of modern reanalysis, e.g., hourly soil moisture estimates across four depth layers at 9 km resolution from 1950 onward, which enables detailed analysis of flash drought onset, agricultural moisture stress, and hydrological deficits across regions where ground networks are sparse or nonexistent (Muñoz-Sabater et al., 2021; Vicente-Serrano et al., 2022). However, reanalysis products are not observations in the strict sense. They inherit biases from both the underlying models and the assimilated observations, and changes in observational networks over time can introduce spurious trends or discontinuities (Wu et al., 2020). The reanalysis will depend more on its underlying model in cases when or where there are limited observational products. Careful validation against independent observations, explicit characterization of uncertainty, and transparent documentation of changes in input data streams are essential for responsible use of reanalysis in drought assessment.

Temporal and Spatial Dimensions of Drought Observations

The temporal and spatial resolution of drought data fundamentally shapes which processes can be observed and how they can be analyzed. This principle has been recognized in drought assessment for many decades, from early work such as Palmer's Drought Severity Index

(PDSI) through more recent syntheses emphasizing the need to match indices and observations to process (Van Loon, 2015).

Flash droughts exemplify the temporal dimension of this challenge. These events are characterized by rapid soil moisture depletion and rapid increase in evaporative stress, typically unfolding over days to weeks rather than months to seasons (Liu et al., 2021). Detecting and monitoring flash droughts requires high-frequency observations with minimal latency, meaning the data are updated quickly enough for operational use, capabilities that satellite systems increasingly provide but that traditional monthly climate summaries cannot support. Conversely, multidecadal infrastructure planning and water allocation frameworks require stable, long-term records that resolve low-frequency variability and persistent anomalies (Dai et al., 2024). The scaling from daily to monthly to seasonal aggregates fundamentally changes which processes dominate and which indicators prove most informative.

This temporal scaling connects directly to the conceptual distinction between meteorological, agricultural, and hydrological drought. Meteorological drought, defined by precipitation deficits, typically manifests on shorter timescales and serves as the initiating condition for other drought types. Agricultural drought, defined by soil moisture deficits and plant water stress, emerges as meteorological deficits deplete root-zone moisture, typically over weeks to months. Hydrological drought, defined by streamflow and groundwater deficits, reflects integrated basin storage and release processes and therefore responds with delays relative to meteorological anomalies, often persisting long after precipitation returns to normal, as recovery of groundwater and reservoir storage may require sustained above-average precipitation (Dai et al., 2024). Multi-scalar drought indices computed over accumulation periods ranging from 1 to 24 months enable explicit analysis of this propagation, revealing how meteorological anomalies translate into agricultural and hydrological impacts and how these relationships may be changing under nonstationarity (Dai et al., 2024; Liu et al., 2021).

The spatial dimension presents equally fundamental considerations. In situ precipitation and streamflow networks provide high-quality, well-characterized measurements with long temporal records, making them indispensable for validation and calibration (S. Zhang et al., 2018). Historically, gauge placement has been driven primarily by human water management needs, resulting in systematic bias toward large, perennial, heavily regulated rivers draining densely populated watersheds, while headwater streams, non-perennial rivers, and ecologically sensitive areas remain chronically underrepresented (Krabbenhoft et al., 2022). However, rain and streamflow gauge densities have declined in many regions due to funding constraints and operational challenges, creating spatial gaps that are particularly problematic in complex terrain, arid lands, and remote areas where drought vulnerability is often highest (Morsy et al., 2021). Certain ecosystem types, particularly headwater streams and small ungauged catchments, are therefore chronically underrepresented in monitoring networks, limiting assessments of drought impacts on the aquatic species and riparian habitats that depend on these systems. These gaps coincide with regions where spatial variability in precipitation, soil properties, and vegetation creates strong heterogeneity in drought response, making sparse networks especially limiting.

In recent years, satellite remote sensing offers a complementary perspective, providing broad coverage with regular repeat observations (Gruber et al., 2019). The Global Precipitation Measurement mission delivers precipitation estimates at 0.1-degree resolution with latency of hours to months, enabling near-real-time monitoring of meteorological drought initiation at the low latency end of that range (S. Zhang et al., 2018). The Soil Moisture Active Passive (SMAP) mission provides surface soil moisture retrievals at 9 to 36 km resolution with 1- to 3-day latency directly observing agricultural drought conditions (Entekhabi et al., 2010), while its downscaled product can be up to 400-m resolution (Fang et al., under review, 2025). The Gravity Recovery and Climate Experiment (GRACE) measures total terrestrial water storage at approximately 300 km resolution with monthly updates, constraining groundwater depletion and long-term hydrological drought (Boergens et al., 2020). Each of these systems addresses specific spatial and temporal scales, and none alone provides complete drought characterization.

The integration of satellite observations with ground networks and reanalysis systems requires careful attention to scale matching, bias characterization, and uncertainty quantification. Triple collocation methods enable estimation of random error (residual/deviation) variances across independent datasets without requiring a good standard reference, supporting informed combination of products with different error (residual/deviation) characteristics (Gruber et al., 2019; Wu et al., 2020). Validation of large-footprint satellite observations against point measurements must account for spatial representativeness, with simulation studies indicating that ground sampling resolutions of 6 to 7 km or better are necessary to validate satellite soil moisture accuracy at required confidence levels over heterogeneous landscapes (Lv et al., 2020). These technical requirements underscore a broader principle: effective drought monitoring under nonstationarity demands multi-scale observation systems that span point measurements, regional networks, and global satellite coverage, with explicit frameworks for reconciling information across scales.

Table 5-1 summarizes the characteristics of major data sources for drought monitoring, providing context for subsequent discussion of their integration. The diversity of coverage, resolution, latency, and limitations reflected in this table motivates the multiproduct integration strategies developed in later sections.

TABLE 5-1 Characteristics of Representative Data Sources for Drought Monitoring and Analysis

Data Source	**Variable**	**Coverage, Resolution**	**Latency**	**Primary Applications**	**Key Limitations**
GPM IMERG	Precipitation	Global, 0.1°	4 hours to 3 months	Meteorological drought, flash drought detection	Terrain-related biases, challenges with snow-phase precipitation
CHIRPS	Precipitation	60N-S, 0.05°	Approx. 3 weeks	Meteorological drought	Land only, station data dependency, limited spatial coverage, wet season bias
CHIRTS-ERA5	Temperatures	60S-70N, 0.05°	Approx. 6 days	Meteorological drought, flash drought detection	Land only, station data dependency, limited spatial coverage

Data Source	Variable	Coverage, Resolution	Latency	Primary Applications	Key Limitations
SMAP L3 Enhanced (not downscaled)	Surface soil moisture (0-5 cm)	Global, 9–36 km	1 to 3 days	Agricultural drought, operational monitoring	Record begins 2015, radio-frequency interference in some regions
ESA-CCI Combined	Surface soil moisture (0-5 cm)	Global, 0.25°	Archived, not real time	Multidecadal trends, product intercomparison	Lower accuracy during sensor transition periods, coarser resolution
ERA5-Land	Soil moisture (four layers), evapotranspiration, temperature	Global land, 9 km	Approx. 5 days	Baseline climatology, gap-filling, multi-layer analysis	Wet bias in some regions, model-dependent uncertainties
GLEAM 4.2a	Surface and root-zone soil moisture, evapotranspiration	Global land, 0.1°	Approx. 7 days	Evapotranspiration stress, agricultural drought	Model-based rather than direct observation, input data dependencies
GRACE / GRACE-FO	Terrestrial water storage	Global, approx. 300 km	Approx. 1 week	Groundwater drought, basin-scale water balance	Coarse spatial resolution, monthly temporal resolution
NFDRS/RAWS Fuel Moisture	Fire fuel moisture (live and dead)	United States, approx. 1,700 stations	Daily to weekly	Wildfire-drought linkages, ecosystem stress	Limited to fire management zones, not spatially continuous
USGS Streamflow (and State Networks)	River discharge	United States, approx. 10,000 gauges; limited spatial coverage of headwater areas	Real-time	Streamflow drought, water management	Human influences (regulation, withdrawals), network gaps in some regions

Data Source	Variable	Coverage, Resolution	Latency	Primary Applications	Key Limitations
U.S. Drought Monitor	Integrated drought classification	United States, county scale	Weekly	Impact reporting, policy triggers	Expert judgment introduces subjectivity, classification lag, uncertainty communication

DATA NEEDS FOR DECISION-MAKING

Drought data serve diverse stakeholders with fundamentally different temporal horizons, information needs, and tolerances for uncertainty. Therefore, understanding these distinct requirements is essential for designing observation systems and data products that effectively support both operational response and long-term planning.

The evolution of drought monitoring capabilities in the Contiguous United States reflects a remarkable transformation from sparse point-based measurements to comprehensive multi-sensor observation systems spanning 250 years (see Figure 5-1). Beginning with foundational observations including early ecological records (herbarium collections, General Land Office surveys from 1775), U.S. Geological Survey stream gauges (1889), and the Cooperative Observer precipitation network (1890), the monitoring infrastructure has expanded through three distinct technological eras. The first era is the in situ gauge era (late eighteenth century through early 1970s), dominated by long, continuous but spatially sparse point measurements of precipitation, streamflow, groundwater, and vegetation composition. The second era is the satellite remote sensing era (beginning in the 1970s with missions such as Landsat), which introduced spatially continuous mapping of land surface and vegetation conditions but with relatively limited hydrologic variable coverage and record length. The third and current era is the integrated multi-sensor Earth system era (from the early 2000s onward), in which satellite observations, global reanalyses (e.g., ERA5-Land), and dense in situ networks are combined into coordinated, multiproduct drought monitoring and modeling frameworks across the United States. Figure 5-1 illustrates the temporal coverage and spatial extent of major data sources across six hydrological components (precipitation, streamflow, evapotranspiration, soil moisture, groundwater, and vegetation), organized by measurement footprint from point observations (<1 km^2) through fine-resolution satellite products (<10 km^2) to moderate-resolution reanalysis ($<1\times10^3$ km^2) and coarse-resolution gravimetric systems ($>1\times10^4$ km^2). This progression reveals both the opportunities and fundamental constraints that shape contemporary drought assessment under nonstationarity. While the post-2000 era provides unprecedented spatial coverage and variable diversity, enabling spatially explicit characterization of flash droughts, agricultural water stress, and vegetation response, historical trend analysis remains constrained to point-based measurements with sparse spatial representation. The longest continuous records (precipitation networks: 135 years; stream gauges: 136 years; groundwater observing wells: 125 years) provide invaluable temporal depth for detecting secular changes and characterizing low-frequency variability, yet their point-based nature limits spatial attribution of observed trends. Early ecological records (herbarium collections, General Land Office surveys, historical phenology observations) extend this temporal perspective back 250 years but remain spatially discontinuous. Conversely, comprehensive satellite coverage (Moderate Resolution Imaging

Spectroradiometer [MODIS]: 25 years; SMAP soil moisture: 10 years; Sentinel-2: 10 years) enables detailed spatial analysis but provides limited statistical power for distinguishing climate trends from decadal variability. This temporal-spatial trade-off necessitates the multiproduct integration frameworks and standardized indices discussed in subsequent sections, which seek to reconcile historical depth with contemporary spatial breadth while accounting for nonstationarity in both climate forcing and observational systems.

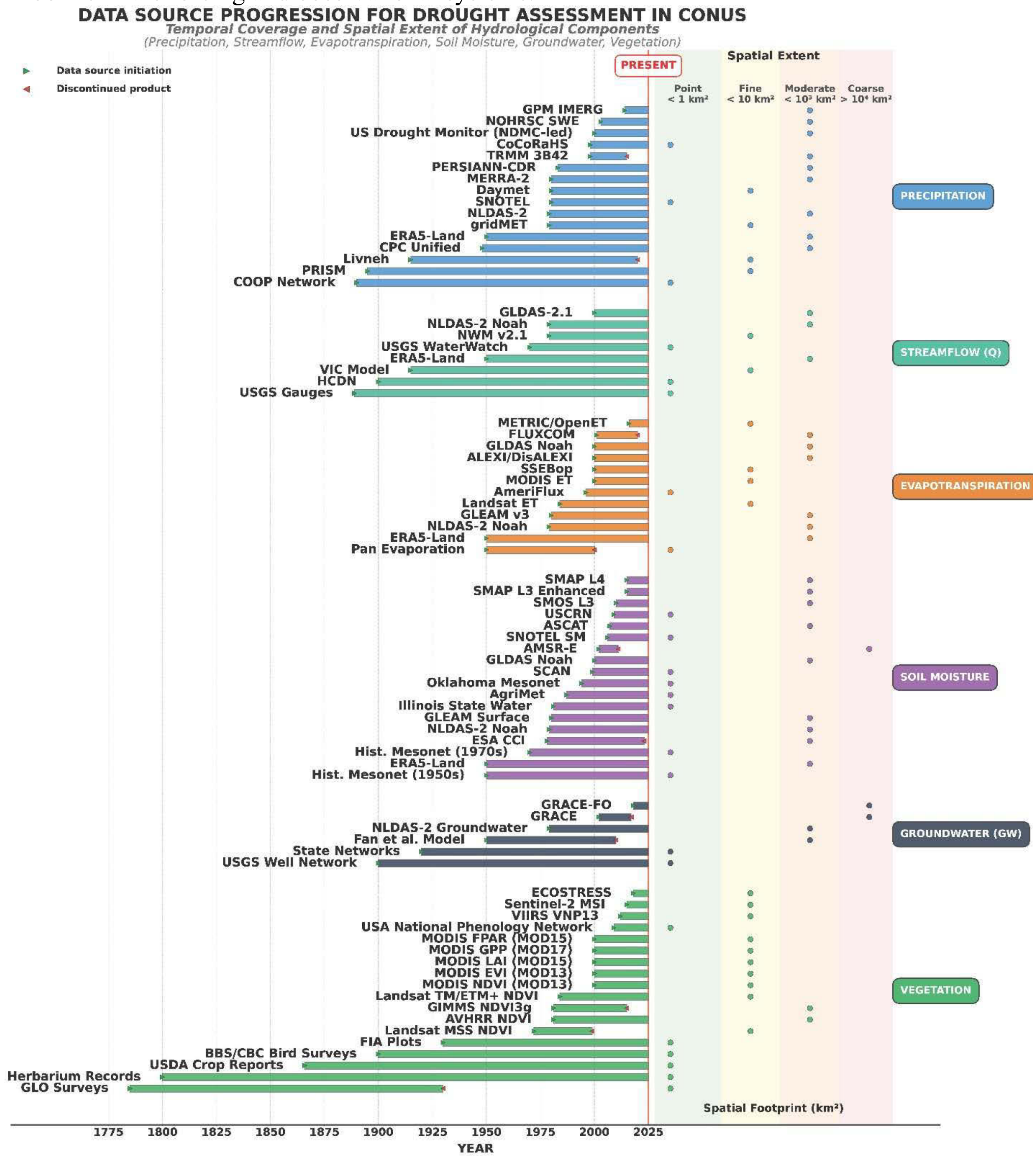


FIGURE 5-1 Data source availability for drought assessment under nonstationarity: Contiguous United States (CONUS) Hydrological Observing Systems (1785–2025).
NOTE: Spatial extent is encoded using four combined visual channels: bar color shading and opacity (darker and more opaque for finer resolution), hatching pattern (cross-hatch for point, diagonal lines for fine, none for moderate, dots for coarse), bar width (thicker bars indicate finer spatial footprint), and a right-side spatial extent panel with a log-scale axis (km^2) and color-coded zone bands (green: point, <1 km^2; yellow: fine, <10 km^2; orange: moderate, <10^3 km^2; red: coarse, >10^4 km^2). Green triangles denote data source initiation; red triangles indicate discontinued products.
SOURCE: Marshall, S.R.O., et al. (under review) 2026.

Continuity of Satellite Earth Observation Systems

Satellite Earth observations have become foundational to operational drought monitoring since their initiation in the 1970s. Contemporary missions provide global coverage of precipitation (GPM-IMERG), vegetation status (MODIS, Landsat, Sentinel-2), soil moisture (SMAP, SMOS [Soil Moisture and Ocean Salinity]), terrestrial water storage (TWS) (GRACE/GRACE-FO), and evapotranspiration (GLEAM) from multiple platforms. These satellite records now span sufficient duration (i.e., up to 25 years for MODIS, 10 years for SMAP, and 23 years for GRACE) to characterize interannual variability and support operational decision systems. Yet this progress faces a critical vulnerability, in which many missions are approaching or have exceeded their designed operational lifespans. Gaps in continuity, particularly for missions such as GRACE, SMAP, and Landsat, would fundamentally compromise the ability to detect, attribute, and respond to drought under conditions of nonstationarity. Sustained, long-term funding for satellite Earth observation continuity is therefore essential, and mission overlap periods, in which successor satellites are launched and cross-calibrated before predecessor decommissioning, should be treated as operational requirements rather than planning aspirations.

The Aqua satellite illustrates both the opportunity and the risk inherent in this dependence. The Aqua satellite, launched in 2002 with a design life of 6 years, has operated for over two decades while four of its instruments continue to deliver high-quality data on Earth's water cycle (e.g., ocean evaporation and temperature, atmospheric water vapor, precipitation, snow cover) (Parkinson, 2022); Terra, launched in December 1999, similarly continues operations more than 25 years after launch with all five instruments still providing valuable observations on Earth's biogeochemical and energy systems using five sensors that observe the atmosphere, land surface, oceans, snow and ice, and energy budget (Woodcock et al., 2023). SMAP, designed for a 3-year nominal mission, has operated for over 10 years and provides soil moisture data unique in accuracy and coverage for monitoring floods, droughts, wildfire, and food security; GPM, launched in 2014 with a 3-year design life, remains operational but faces fuel depletion around 2027 (Woodcock et al., 2023). An independent NASA Senior Review panel noted that these capabilities "greatly exceed the original missions for the sensors," yet several flagship missions, including Terra, Aqua, and Aura, are "rapidly approaching passivation" (i.e., the removal of all stored internal energy), and securing funding to sustain missions beyond their design lives remains a persistent challenge (Woodcock et al., 2023).

The consequences of mission discontinuity are not hypothetical; the approximately 1-year gap between the end of GRACE operations in October 2017 and the launch of GRACE Follow-

On in May 2018 disrupted the TWS record, requiring statistical reconstruction methods to bridge the data gap (Humphrey and Gudmundsson, 2019; Li et al., 2020). More broadly, the United States lacks a systematic framework for identifying, prioritizing, and funding sustained Earth observations, with precipitation, soil moisture, streamflow, and snowpack among the variables without plans for continued satellite monitoring (KISS Continuity Study Team, 2024). These gaps between missions create discontinuities in time series that undermine trend analysis, degrade baseline characterizations, and introduce inconsistencies in operational drought classification systems such as the U.S. Drought Monitor (USDM), which synthesizes multiple satellite inputs.

Similar continuity challenges arise for in situ streamflow observation networks. The U.S. Geological Survey and state cooperator stream-gauge programs have experienced cycles of expansion and attrition as funding priorities shift, leading to decommissioning of long-record stations and persistent gaps in headwater and small-basin coverage. Loss of gauges with multidecadal daily records reduces the ability to quantify trends in low flows and floods, detect nonstationarity in drought and flood frequency, and evaluate changes in baseflow and snowmelt timing at scales relevant for water management decisions. Stabilizing support for both benchmark reference gauges and operationally critical stations, and implementing transition strategies rather than abrupt site closures, is therefore essential to maintain a robust streamflow foundation for drought assessment.

Conclusion 5-2: Many Earth-observing missions are approaching or have exceeded their designed operational lifespans (e.g., Aqua and SMAP) and several flagship missions are rapidly running out of energy. Gaps between missions (e.g., GRACE and GRACE Follow-On) create discontinuities in time series that undermine trend analysis, degrade baseline characterizations and assimilation in land models, and introduce inconsistencies in drought assessment and classification. Sustaining these critical Earth observations is essential for accurate and timely drought assessment.

Recommendation 5-2: To ensure continuity and support proactive planning, NASA and USGS, in coordination with NOAA, should develop explicit mission succession strategies with multidecadal funding commitments to preserve critical Earth observation records, thereby avoiding gaps in records essential for drought detection and assessment. This includes incorporating explicit prelaunch cross-calibration protocols with predecessor systems, overlapping periods enabling robust inter-sensor comparison, and prioritizing long-term homogeneity essential for detecting climate signals under nonstationarity.

Operational Monitoring and Emergency Response

Operational drought management, exemplified by systems such as the National Integrated Drought Information System (NIDIS) and the U.S. Drought Monitor, requires high-frequency, spatially explicit information with minimal latency (Stahl et al., 2016; Vicente-Serrano et al., 2022). The USDM (Svoboda et al., 2002), produced weekly through synthesis of multiple data sources and expert assessment, provides drought severity classifications that trigger agricultural assistance programs, water use restrictions, and disaster declarations (Hatami Bahman Beiglou et al., 2021). The operational value of such systems depends not only on accuracy but also on timeliness, interpretability, and consistency with established decision frameworks.

Recent advances have introduced machine learning approaches to automate and forecast drought classifications, reducing latency and enabling probabilistic predictions (Brust et al., 2021). These methods leverage the principle that recent anomalies in hydrology and meteorology drive near-term changes in drought conditions, using recurrent neural networks to forecast USDM categories based on simulated meteorology and satellite-observed soil moisture. Such innovations point toward operational systems that provide continuous, probabilistic information rather than discrete classifications, better reflecting the inherent uncertainty in drought assessment and evolution (Hatami Bahman Beiglou et al., 2021). However, these approaches also introduce trade-offs. Because the algorithms are trained on historical examples, rare or unprecedented extremes may be underrepresented in the training data, leading to over-smoothing of outliers and reduced sensitivity to emerging regimes. Careful model validation against independent extreme events, transparent uncertainty characterization, and continued expert judgment therefore remain important companions to data-driven drought forecasts.

Effective operational monitoring increasingly recognizes that physical indicators alone are insufficient, and that incorporating impact data, Traditional Ecological Knowledge (TEK), and local observations alongside hydroclimatic indicators helps ensure that monitoring systems reflect conditions experienced by communities, ecosystems, and land managers. The integration of impact data documenting observed consequences for water supply, agriculture, ecosystems, and human livelihoods provides essential validation that monitoring systems reflect real-world conditions rather than purely statistical anomalies (Enenkel et al., 2020; Stahl et al., 2016). This integration remains challenging due to the qualitative, heterogeneous nature of impact reporting, but initiatives such as the European Drought Impact Report Inventory and the U.S. Drought Impact Reporter have begun to systematize documentation, allowing quantitative analysis of relationships between physical indicators and societal consequences (Stahl et al., 2016).

Long-Term Planning and Preparedness

Long-term drought planning operates on fundamentally different temporal scales and information requirements than operational monitoring. Water resource planning models, infrastructure investment decisions, insurance programs, and regional adaptation strategies require stable baseline climatology, explicit quantification of uncertainty, and mechanistic understanding of drought processes rather than purely empirical relationships (Brunner et al., 2020; Zhang, Cheng et al., 2025).

The challenge of nonstationarity is particularly acute in this context. Planning frameworks traditionally rely on historical records to characterize the range of conditions that infrastructure must accommodate. Under a changing climate, however, historical records may systematically misrepresent future conditions (Schwarz et al., 2025), because the statistical properties of past droughts no longer reliably bound the range of conditions that infrastructure and water systems will face. Adjusting historical data to reflect current climate states, while preserving information about variability structure, is one approach to this problem; water resource planning models in California, for instance, have adopted methods that modify historical hydrology to account for contemporary temperature and evaporative demand while maintaining realistic spatial and temporal patterns (Schwarz et al., 2025).

Climate change impact assessments provide forward-looking perspectives essential for long-term planning but introduce their own uncertainties. Ensemble projections and interannual to decadal predictions from multiple global and regional climate models span wide ranges of future drought frequency, severity, and duration (Xu et al., 2024). Model weighting approaches that account for both historical performance and inter-model independence have demonstrated potential to reduce projection uncertainty by 26–31 percent for long-term future periods, providing more constrained guidance for adaptation planning than unweighted multi-model means (Brunner et al., 2020; Q. Zhang et al., 2025). However, even constrained ensembles retain substantial uncertainty, particularly for regional drought projections, underscoring the need for adaptive management strategies that can respond to evolving conditions.

The integration of drought hazard information with exposure and vulnerability data represents another critical dimension of planning. Socioeconomic drought risk assessments require combining biophysical drought indicators with information on population distribution, agricultural land use, water infrastructure, economic dependencies, and other social, institutional, and cultural conditions that modulate adaptive capacity (Enenkel et al., 2020; Worku et al., 2019). This integration enables identification of populations and sectors at greatest risk and supports targeting of preparedness investments and adaptation assistance.

EVALUATION FRAMEWORKS FOR DROUGHT PRODUCTS

The expansion and improvement of satellite missions, climate models, reanalysis systems, and derived drought products over recent decades provides unprecedented observational capacity but also presents challenges for product selection and interpretation. Rigorous, transparent evaluation frameworks are essential for characterizing product performance, identifying conditions under which particular products excel or struggle, and supporting informed integration of multiple products (Beck et al., 2021). As introduced earlier for the World Meteorological Organization's (WMO) drought evaluation framework, such structured approaches provide a template for systematically assessing emerging satellite and model-based drought products.

Direct validation against in situ measurements remains the foundation of product evaluation where such data are available (van der Velde et al., 2021; Wu et al., 2020). For soil moisture products, this typically involves comparison of satellite retrievals or model estimates against ground-based sensors, quantifying bias, correlation, and error (residual/deviation) magnitude. However, direct validation faces inherent challenges related to scale mismatch between point measurements and satellite footprints, spatial representativeness of ground networks, and temporal alignment of observations (Wang et al., 2021). Careful experimental design, including consideration of sensor placement, spatial sampling density, and temporal averaging, is required to ensure that validation results reflect product performance rather than scale incompatibilities. In the Western United States, these challenges are particularly acute in forested terrain, where in situ soil moisture observations beneath canopy are sparse and provide limited constraint for calibrating satellite and modeled estimates. Recent U.S. Forest Service efforts to measure and model soil moisture in complex terrain, and to develop a coordinated soil moisture monitoring network with standardized soil profile characterization at sensor locations, illustrate ongoing progress toward addressing these gaps.

In data-sparse regions or where no single gold-standard reference exists, hierarchical validation methods become essential. Triple collocation analysis, which estimates random error (residual/deviation) variances across three independent datasets under assumptions of uncorrelated errors, enables global scale intercomparison without requiring absolute truth (Gruber et al., 2019). Application of triple collocation to SMAP, SMOS, and ASCAT soil moisture products confirmed SMAP's generally superior performance with root mean square errors near 0.040 m^3/m^3 compared to 0.107 for SMOS, though regional variations are substantial

(Wu et al., 2020). Such analyses support ensemble construction and weighting strategies that leverage complementary strengths across products.

Temporal consistency represents another critical evaluation dimension, particularly for products intended to support trend analysis or change detection. Climate data records must maintain stable bias characteristics and error distributions over time to enable reliable identification of decadal signals above instrument drift and calibration effects (Popp et al., 2020). The Global Climate Observing System has established stability requirements ensuring that long-term trends can be distinguished from spurious artifacts, and recent work demonstrates that multi-sensor climate data records can meet these targets when retrievals and ancillary datasets are harmonized across sensor transitions (Devasthale and Karlsson, 2023). For drought assessment under nonstationarity, where distinguishing secular trends from natural variability is significant, temporal consistency is as important as instantaneous accuracy.

Cross-product consistency evaluation, examining agreement across independent products in both space and time, enables identification of structural deficiencies and supports optimal information combination (Beck et al., 2021; Fang et al., 2024). Regions or periods where multiple independent products agree provide higher confidence in assessed conditions than those where products diverge. Systematic analysis of disagreement patterns can reveal underlying causes, such as retrieval challenges in specific land cover types, model biases under particular meteorological conditions, or inadequacies in observational networks that affect assimilation systems (van der Velde et al., 2021). This diagnostic capacity supports both product improvement and informed user decisions about which products to use in which contexts.

Integration Pathways toward Multiproduct Drought Assessment

The preceding sections have established that nonstationarity challenges traditional drought assessment approaches, that diverse data sources offer complementary perspectives but individual limitations, and that rigorous evaluation frameworks can characterize product performance. These foundations motivate a fundamental question: how can heterogeneous drought data (including TEK and local observations) be coherently integrated to provide more reliable, comprehensive assessment than any single product alone? Operational tools such as the U.S. Drought Monitor illustrate how combining quantitative indicators with expert judgment and locally derived knowledge can yield assessments that are both scientifically grounded and responsive to conditions experienced on the ground.

Multiproduct integration strategies have emerged as a central focus of modern drought science, driven by both necessity and opportunity (Beck et al., 2021). Necessity arises from the recognition that no single data source is optimal across all regions, timescales, and drought types. Opportunity arises from the proliferation of satellite missions, reanalysis systems, and impact and knowledge sources, including TEK and local experience that provide overlapping but complementary information. Effective integration must address several challenges: reconciling different spatial and temporal resolutions, accounting for distinct measurement physics and error (residual/deviation) characteristics, harmonizing across different periods of record, and transforming diverse physical quantities onto comparable scales.

The evolution of satellite soil moisture datasets exemplifies both the opportunity and the challenge. ERA5-Land is a land surface reanalysis product that estimates four-layer volumetric soil moisture at 9 km resolution from 1950 onward based on atmospheric inputs to the land model, offering temporal depth and vertical structure essential for understanding root-zone dynamics and long-term trends (Muñoz-Sabater et al., 2021). However, as a reanalysis product, it inherits model biases and uncertainties. SMAP L3 Enhanced provides surface soil moisture at 9 km resolution with exceptional accuracy from 2015 onward, offering high-quality recent observations but limited temporal depth (Abbaszadeh et al., 2019; Entekhabi et al., 2010). GLEAM 4.2a provides both surface and root-zone soil moisture at 0.1-degree resolution from 1980 onward through a model-based water balance that assimilates satellite surface soil moisture observations, which are closely related to or derived from the European Space Agency Climate Change Initiative (ESA-CCI) soil moisture record, offering intermediate temporal coverage and explicit root-zone estimates (Miralles et al., 2011). The ESA-CCI provides harmonized multidecadal surface soil moisture from 1980 onward at 0.25-degree resolution through merging of active and passive microwave retrievals, offering the longest satellite-based record but with lower accuracy during sensor transition periods (Gruber et al., 2019).

Each of these products has distinct strengths, e.g., ERA5-Land for long temporal continuity, SMAP for accuracy and low latency, GLEAM for root-zone perspective and evapotranspiration linkage, ESA-CCI for multidecadal trends and sensor intercomparison. However, effective integration must leverage these complementary strengths while mitigating individual weaknesses. The fundamental challenge is that these products report different physical quantities (e.g., surface versus root-zone moisture, different depth integrations), use different units (volumetric versus percentage of saturation), and have different error (residual/deviation) characteristics and climatology. Direct averaging or comparison is therefore inappropriate without transformation to a common framework.

Implementation for Multiproduct Synthesis

This subsection summarizes a practical workflow for combining multiple soil moisture products into standardized indices, rather than presenting a new case study, and highlights how the resulting ensemble can improve drought monitoring under nonstationarity. Practical implementation of standardized soil moisture indices for multiproduct drought assessment follows a systematic workflow designed to enable both individual product analysis and ensemble synthesis. For each product (ERA5-Land, SMAP L3 Enhanced, GLEAM, ESA-CCI), soil moisture time series are extracted for relevant layers and locations. Rolling temporal means are computed for accumulation periods of 1, 3, 6, 9, 12, and 24 months, transforming instantaneous observations into timescale-specific indicators that align with meteorological, agricultural, and hydrological drought processes (Dai et al., 2024; Liu et al., 2021).

Both Soil Moisture Index (SMI) and Empirical Standardized Soil Moisture Index (ESSMI or, more commonly, ESMI) are computed for each product, layer, and accumulation period using a fixed baseline period of 1991 to 2020. This 30-year baseline aligns with WMO standards and provides sufficient sample size for stable distribution estimation while focusing on recent climate conditions relevant to contemporary drought assessment (Cammalleri et al., 2022). The standardization transforms heterogeneous soil moisture values onto a common standard normal scale, allowing direct comparison across products despite differences in measurement physics, spatial resolution, units, and climatology.

The resulting standardized indices support multiple integration pathways. Individual product indices can be analyzed to assess product-specific drought signals, revealing where and when each product indicates anomalous conditions. Cross-product comparison identifies regions and periods of agreement and disagreement, with concordance across multiple independent products increasing confidence in drought classification (Beck et al., 2021). For example, if ERA5-Land, SMAP L3 Enhanced, GLEAM, and ESA-CCI all show very low ESMI values at the 3-month accumulation period for the same region and time, the ensemble signal supports classifying conditions as severe soil moisture drought with higher confidence than any single product alone, whereas disagreement flags areas where additional scrutiny or local information is needed. Thus, ensemble averaging or weighted integration based on product performance metrics from validation studies can provide synthesized drought indicators that leverage complementary strengths across products while mitigating individual weaknesses (Gruber et al., 2019; Wu et al., 2020).

The dual-index approach, computing both SMI and ESMI, provides valuable diagnostic information beyond drought monitoring itself. Convergence between the empirical and parametric indices indicates that the mathematical distributional assumption underlying SMI is reasonable for the location, season, and timescale under consideration. Divergence, particularly in the distribution tails where extreme droughts reside, signals non-Gaussian behavior that may reflect complex soil moisture dynamics, retrieval challenges, or model biases warranting further investigation (Carrão et al., 2016; Palagiri and Pal, 2024).

Multiproduct integration using standardized indices addresses several critical challenges in operational drought monitoring under nonstationarity. First, it reduces dependence on any single product, mitigating impacts of sensor failures, data gaps, or product-specific biases that inevitably affect individual systems. Second, it enables incorporation of products with different temporal coverage, allowing long-term reanalysis products to provide climatological context while short-term satellite products contribute high-accuracy recent observations. Third, it facilitates detection of emerging drought conditions through ensemble agreement, where concordance across multiple products provides confidence that observed anomalies reflect real conditions rather than product-specific artifacts (Fang et al., 2024).

The standardized indices also support analysis of drought propagation across the water cycle, a process that may be changing under nonstationarity (Dai et al., 2024). By computing indices at multiple accumulation periods, the transition from short-term meteorological drought to longer-term agricultural and hydrological drought can be quantified and monitored. Changes in propagation timescales, which recent research suggests are occurring in some regions as temperature-driven evaporative demand alters the coupling between precipitation deficits and soil moisture depletion, can be detected through analysis of cross-timescale relationships in standardized indices (Dai et al., 2024; Van Loon, 2015).

Conclusion 5-3: Land models and reanalysis systems provide spatially continuous, temporally consistent estimates of drought-relevant variables, but inconsistencies in long-term trends and anomaly magnitudes across different models complicate their integration in operational monitoring and, more critically, undermine confidence in distinguishing climate-driven changes from model structural artifacts under nonstationarity.

Recommendation 5-3: To improve model-based drought product interoperability and compatibility, NOAA and NASA, in collaboration with the broader hydrological modeling community, should establish guidance on standardized modeling output specifications and model multiproduct integration and validation methods. Additionally, to strengthen attribution of observed drought changes to climatic drivers, NOAA and NASA should support intercomparison studies quantifying model-to-model uncertainty under diverse climatic and land surface conditions.

Synthesis and Looking Ahead

Drought assessment under nonstationarity demands data infrastructures that are temporally consistent, spatially extensive, and methodologically sophisticated. The erosion of stationarity necessitates careful selection of assessment periods that balance statistical stability with contemporary relevance, thoughtful extension of observational records through paleoclimate reconstruction and reanalysis, and explicit attention to temporal and spatial sampling considerations that match observation systems to drought processes of interest. Operational monitoring requires high-frequency, low-latency data with clear interpretability, while long-term planning demands stable baselines, quantified uncertainty, and mechanistic understanding of drought drivers and propagation pathways.

The proliferation of satellite missions, reanalysis systems, and derived drought products over recent decades provides unprecedented observational capacity but also presents challenges for product selection, evaluation, and integration. No single data source is optimal across all regions, timescales, and drought types. Effective drought assessment therefore requires multiproduct integration strategies that leverage complementary strengths while mitigating individual weaknesses. Although this section focuses on soil moisture, similar standardization approaches can be applied to other drought-relevant variables such as precipitation, evapotranspiration, and terrestrial water storage. Standardized soil moisture indices, particularly the ESMI developed by Carrão and colleagues (2016) and the SMI proposed by Palagiri and Pal (2024), provide rigorous frameworks for transforming heterogeneous datasets onto common analytical scales that enable direct comparison, ensemble synthesis, and probabilistic interpretation.

These integration approaches represent necessary evolution in drought science, enabling assessment systems that are more reliable, transparent, and resilient to individual product failures or gaps than any single-product approach. The methodological foundations, comparative analysis, and implementation strategies detailed in this chapter provide a basis for operational application and continued research refinement. Subsequent chapters will demonstrate these methods through case studies, spatial analyses, and temporal trend assessments, illustrating how multiproduct integration enhances both scientific understanding and operational capacity for drought assessment in a climate system no longer governed by historical precedent.

6
Drought Indicators, Indices, and Nonstationarity

This chapter evaluates how drought indicators and indices are constructed and used under climate nonstationarity, with emphasis on key analytical choices (data, timescales, statistical standardization, and reference periods). It examines how those choices alter drought classification and uncertainty, considers system-specific interpretation and offers recommendations for transparent documentation and risk-aligned decision support.

DROUGHT INDICATORS AND INDICES

The present chapter considers the diagnostic measures and methods used to quantify, monitor, and assess drought, as well as how nonstationarity undermines or complicates these efforts. Diagnostic measures used in drought assessment, whether called indicators, metrics, or indices, aim to capture features of drought to allow for a delineation of its characteristics (magnitude, extent, duration), as well as their comparison across time and/or space. Because drought is multivariate in nature (often integrating meteorological, hydrological, and climatic processes on different timescales; McKee et al., 1993; McKee et al., 1995), it can be assessed using many variables (see Chapter 5), any one of which could offer a different perspective on a drought event, its drivers, or the responses of the ecohydrological/social system. Sometimes these measures agree; for example, when runoff and soil moisture exhibit coincident declines. Sometimes they do not; for example, when groundwater levels are at or above "normal" despite ongoing precipitation deficits. Furthermore, the timescale over which these measures are computed may flip the directionality of the same drought index (e.g., 30-day precipitation accumulations may be greater than normal, while 60-day aggregations are less than normal). As such, drought monitoring and assessment have pragmatically adopted a convergence-of-evidence–type approach (discussed in the "Convergence of Evidence" section below), assimilating multiple sources of drought information in making a claim about drought status and its features and impacts.

The most basic form of drought information is the *indicator*: a raw variable or parameter that describes a hydrometeorological state such as precipitation, temperature, soil moisture, streamflow, or groundwater level (Svoboda and Fuchs, 2016). Indicators require expert knowledge to interpret within a local climatic context or may be used to reflect extreme conditions in absolute terms (e.g., streamflow of 40 cubic feet per second, CFS, or a daily high temperature of 104°F). Alternatively, a drought *index* (or *indices*) is a computed numerical representation of drought severity (Svoboda and Fuchs, 2016) derived from an indicator(s). A drought index typically seeks to represent current conditions relative to some expectation (such as precipitation percent of normal) and are most often presented in standardized units (such as percentiles or quasi-gaussian standard normal deviations) in order to align with common thresholds defining drought severity (see “From Indicators to Indices: The Role of Standardization and Drought Severity Thresholds” section below). Numerous drought indices are used worldwide and constitute the most common tools employed in operational drought assessment (Svoboda and Fuchs, 2016).

The design of any drought index involves a series of analytical choices that determine how information about climate anomalies is translated into a quantitative depiction of drought severity or other characteristics, such as onset, termination, and spatial and temporal extent. These choices include (1) the variables/data source selected, (2) the spatial and temporal resolution of data, (3) the timescale used to analyze a hydrometeorological indicator, (4) the statistical framework applied to describe departures from normal conditions, and (5) the reference period used to define those normals. All of these analytical choices are critical in current operational drought assessment frameworks and can have significant implications for the perception of drought severity for any given region or time period.

As an example, drought severity (and/or recovery) will appear quite different if assessed using precipitation deficits versus groundwater anomalies (i.e., *variable selection*) due to the temporal lag in drought propagation through the hydrologic system (see Figure 2-1). While both depictions provide a lens through which drought conditions can be assessed, they ultimately represent different drought drivers impacting different systems or sectors. Furthermore, the same variable from different datasets can yield different depictions of drought based solely on the accuracy and/or bias of one dataset over another (Trenberth et al., 2014). As such, the datasets and variable(s) chosen to construct drought indices have a major impact on how drought is represented. Reconciling these differences can be a real challenge for the drought assessment practitioner (discussed in the “Convergence of Evidence” section below).

The *spatiotemporal resolution of data* can also affect interpretation: spatially coarse datasets can smooth local extremes and obscure strong environmental gradients, while high-resolution gridded or station data may reveal spatial heterogeneity critical for local management decisions (Mardian, 2022). An example of this spatial complexity is the presence of markedly different soil moisture states within the same agricultural field or along a single hillslope (Western et al., 2002; Vergopolan et al., 2022). While high-spatial-resolution data may be valuable for local analysis, regional drought assessment systems typically operate at coarser spatial scales, creating a practical trade-off between local detail and regional consistency. Furthermore, high-resolution datasets are generally more difficult to produce in near-real time, a constraint that can limit their integration into operational drought assessment frameworks. Similarly, the temporal resolution of the data, whether (sub)daily, weekly, or monthly, can emphasize either rapid-onset droughts (Otkin et al., 2018) or slow, cumulative deficits (Sreeparvathy et al., 2025). In this sense, resolution choices are not merely technical decisions or explicit dataset constraints, but they also affect which processes, impacts, and risks are most relevant to capture in a given assessment.

The *timescale* over which drought conditions are analyzed affects drought severity interpretation. Shorter timescales (e.g., 20 days) may better capture shallow soil moisture (Hoylman et al., 2024) or rapidly evolving flash drought dynamics where conditions deteriorate quickly (Otkin et al., 2018), whereas longer timescales (e.g., 365 days) highlight cascading hydrologic impacts deeper into the critical zone (Baez-Villanueva et al., 2024). This sensitivity reflects differences in system memory, whereby drought signals propagate and persist over different timescales across hydrological, ecological, and social systems (Van Loon et al., 2024).

The *statistical framework* used to define drought severity shapes how drought severity is interpreted, whether drought severity is based on a fitted probability distribution (e.g., parametric) or on empirical transformations (see, for example, the Standardized Precipitation Evapotranspiration Index [SPEI] and the Evaporative Demand Drought Index [EDDI] formulations; Beguería et al., 2014; Hobbins et al., 2016, respectively). This complexity arises from decisions about which probability distribution is most appropriate for the variable of interest and/or how empirical probabilities should be estimated from finite samples. In the case of parametric approaches, substantial research has examined which probability distributions are most appropriate for specific hydroclimatic variables (Vicente-Serrano et al., 2010; Vicente-Serrano et al., 2012; Stagge et al., 2015; Vicente-Serrano and Beguería, 2016), yielding robust scientific debate over appropriateness and uncertainty (discussed further in the “Uncertainty in Drought Indices” section below). Regardless of the specific distribution chosen, parametric approaches estimate drought severity as a function of both rarity *and* magnitude (e.g., departure from normal), allowing standardized values to reflect how extreme an event is relative to the parameterized distribution. Alternatively, some empirical, rank-based approaches represent severity based on the ordering of observations, explicitly constraining the possible range of severity by the number of observations in the reference period (Wilks, 2011). As a result, the most extreme (e.g., driest) observation within a reference period will map to the same standardized value regardless of its absolute magnitude, rendering these approaches insensitive to the extremeness of outliers beyond their rank. This feature may be advantageous in some cases, as for when a significant outlier “pulls” a parameterized distribution away from the true distribution impacting estimates of probability elsewhere in the indicator space (e.g., sample uncertainty, discussed further in the “Uncertainty in Drought Indices” section below), but may also obscure the severity of a given event.

Once these analytical choices are specified, computation of a drought index requires defining the historical context, commonly referred to as a *reference period*, against which current conditions are evaluated (see Chapter 4). This step is foundational: it establishes what is considered normal and therefore anchors the probabilities, rankings, and categorical thresholds used to define drought severity to a specific historical period. Unlike many other analytical choices, reference period selection anchors statistical drought characterization to a specific climate history, effectively defining assumptions about (non)stationarity, uncertainty, and risk.

The choice of reference period has many considerations, including whether specific historical events should be incorporated and/or how to tailor the reference period to suit the purpose of a specific drought assessment. For example, should the 1930s Dust Bowl be used to contextualize contemporary droughts or should a more recent climatic normal be used? Do certain sectors/systems require different reference periods to produce a relevant drought assessment? How should considerations about system-specific dynamics (such as adaptive capacity, vulnerability, and exposure) be captured? The answers to these questions depend on the intent of any specific assessment framework or process and the context they wish to reflect. As climate conditions evolve, the assumptions embedded in these choices become increasingly important. Choices about variables, scales, statistical methods, and reference periods collectively shape how drought is interpreted, compared, and acted upon.

ANALYTICAL CHOICES UNDER NONSTATIONARITY

While not every analytical decision in drought assessment explicitly assumes a stationary climate, most are influenced by expectations of relative stability in the underlying hydroclimate system. As a system evolves, with rising temperatures, shifting precipitation regimes, and changes in land and water management, those expectations become less reliable (see Chapter 4). Past research suggests that nonstationarity can alter which variables most effectively capture dryness, the temporal and spatial scales at which anomalies emerge, the most relevant timescales for analysis, the statistical methods used, and the utility of historical records as benchmarks for current or future conditions. In some cases, such as fitting probability distributions in order to standardize indicators, the assumption of stationarity is explicit, and failing to account for changing conditions directly violates the statistical foundations of these methods (Milly et al., 2008). At the same time, acknowledging nonstationarity does not eliminate the need for, nor invalidate the value of, drought indices; rather, it underscores the importance of constructing those indices in ways that preserve interpretability while better reflecting evolving conditions. The following sections examine how nonstationarity may affect some of the analytical choices that are present in the formulation of any drought index.

Nonstationarity may alter how variables are chosen and interpreted in drought assessment (Vicente-Serrano et al., 2025). Historically, drought assessment has often relied on precipitation deficits as a primary signal of onset and severity, although Wilhite and Glantz (1985) argued decades ago that drought cannot be fully understood through precipitation alone. This is especially true now in a warming world, where the processes that govern water availability and ecosystem response are changing rapidly (Zhuang et al., 2024). Rising temperatures and increased atmospheric evaporative demand, for example, amplify the role of energy-driven processes in drought development (Gebrechorkos et al., 2025), particularly for agricultural, ecological, and snow-dominated hydrological systems (Vicente-Serrano et al., 2020; Vicente-Serrano et al., 2025; Udall and Overpeck, 2017). How these atmospheric anomalies translate into drought severity depends on the dynamic state of hydrologic storage, shaped by catchment memory and responses to prolonged drought (Van Loon et al., 2024; Chen et al., 2025). Atmospheric indicators therefore capture potential stress, while hydrologic and ecological variables (such as soil moisture, streamflow, and vegetation indices) reflect how that stress is buffered, propagated, or amplified through the land surface and biosphere under real-world management and storage constraints. As a result, drought indicators that capture changing meteorological drivers and interactions, integrate multiple variables, or explicitly estimate hydrological and ecological states will become more valuable to quantify the impacts of nonstationarity on drought dynamics. One illustration of this shift is the growing use of operational soil moisture models for drought monitoring (White and Case, 2014; Green et al., 2021; Gibbons et al., 2023) and recognition of their superiority over traditional drought indices for predicting soil moisture drought (Hoylman et al., 2024). Compared with purely meteorological indices, these products can provide near-real time estimates of subsurface conditions and implicitly integrate antecedent forcing, reducing reliance on manually selected accumulation timescales and better aligning indicators with agricultural and ecological impacts.

Nonstationarity also complicates both the selection and interpretation of timescales in drought metrics and indices. In many regions, hydroclimate is becoming more variable (Stevenson et al., 2022), with shifts in intensity of precipitation events (Lamjiri et al., 2020) and changing seasonality (Zhang et al., 2021). Traditional indices such as the Standardized

Precipitation Index (SPI; McKee et al., 1993) begin by aggregating daily (or sub-daily) precipitation over fixed windows, or timescales (e.g., 30 days), and then comparing those totals to a historical reference distribution (defined by the reference period) for the same accumulation period. Under changing (nonstationary) event dynamics, however, two 30-day periods with identical precipitation totals can correspond to very different hydrologic realities: a few short, high-intensity storms may generate substantial runoff and limited infiltration, whereas persistent, lower-intensity rainfall may more effectively recharge soil moisture and shallow groundwater (i.e., effective precipitation). From the perspective of the index (SPI), these periods are identical, yet they can pose very different risks for crops, ecosystems, and water supply. As nonstationarity alters storm intensity, intra-seasonal variability, and processes such as infiltration and snow–rain partitioning, fixed accumulation windows calibrated under past conditions may no longer align with the dominant mechanisms governing drought impacts. Choosing timescales in a nonstationary climate therefore requires explicit consideration of changing event dynamics, including concepts such as effective precipitation, the emergence of flash drought and the response times of the system of interest, rather than relying solely on historically conventional windows for meteorological, agricultural, or hydrologic drought.

Finally, the choice of reference period plays a central role in contemporary drought assessment when using traditional drought indices in a nonstationary world, yet remains an area where practices vary considerably (Hoylman et al., 2022; Lisonbee et al., 2025). Because traditional probabilistic methods assume that the underlying distribution of a climate variable is stationary through time (Milly et al., 2008), the period selected to estimate that distribution directly influences how drought severity is quantified. Shorter, more recent reference periods tend to reflect contemporary climate conditions and may better represent current expectations of normal (Hoylman et al., 2022). However, shorter records reduce the number of samples available for estimating the parameters of a probability distribution, increasing statistical uncertainty, particularly for the higher order moments of a distribution (Guttman, 1994). Longer periods of record provide greater confidence in statistical parameterization but implicitly assume that the underlying climate system has remained stable, which may no longer be (or may never have been) valid in regions undergoing change. Therefore, while longer records may reduce statistical uncertainty in parameter estimation mathematically (under the assumption of stationarity), they can do so at the cost of accurately representing the climate regime relevant to present-day drought risk. The appropriate balance between statistical robustness and climate relevance likely depends on the rate, or velocity, of change in the variable of interest.

Under nonstationarity, this trade-off becomes consequential because shifts in precipitation and atmospheric demand distributions can cause long reference periods to blend past and contemporary climate conditions in ways that distort the perceived severity of current events (see Figures 6-1 and 6-2). In some regions, drought may appear more severe than warranted from a contemporary perspective where conditions have trended drier, or less severe where the climate has become wetter (Hoylman et al., 2022; Sofia et al., 2024; Nie et al., 2025). From a risk perspective, this matters because the reference period defines the benchmark against which hazard, exposure, and vulnerability are interpreted. When that benchmark lags behind the evolving climate or the adaptive capacity of the system of interest, drought metrics may no longer reflect contemporary risk. For this reason, reference periods in a nonstationary climate are best treated as adaptable parameters, selected intentionally and reevaluated as conditions and decision contexts evolve, rather than fixed climatologies assumed to remain valid over time.

Figures 6-1 and 6-2 illustrate one practical way to visualize nonstationarity in drought-relevant climate variables using moving 30-year climatologies. In each example, the left panels summarize how July to September normals, defined as the median value (and the inter-quartile range [IQR] represented as whiskers) of a summed parameter over the 3-month timescale given a 30-year reference period, evolve over time for precipitation, reference evapotranspiration (ET_o; based on the Penman Montieth approach), and the resulting potential water balance ($P - ET_o$). These are the key components of the SPEI, and in this case represent the underpinnings of a 3-month SPEI formulation. The right panels show how the full generalized (log) logistic distribution of potential water balance (Beguería et al., 2014) shifts as the reference window advances through time (one year at a time). Together, the figures highlight that nonstationarity can manifest in different directions depending on place: Blaine County, Idaho, shows a clear drift toward drier conditions (declining precipitation, rising ET_o, and an increasingly negative water balance, or deficit), whereas Palm Beach County, Florida, trends toward wetter summer conditions overall (increasing precipitation, relatively constant ET_o and an increasingly positive water balance). In both cases, the shifting probability distributions emphasize that drought characterization is sensitive not only to changes in the central tendency, but also to how the frequency and severity of anomalies evolve as the normal climate itself moves (e.g., changes to the higher statistical moments, or tails, of the distribution). For example, the same deficit of -510 mm in Blain County, Idaho, would be classified as a D3 (Extreme Drought representing a ~1 in 20-year event) using the 1961–1990 reference period, but only represent a D1 (Moderate Drought representing a ~1 in 8-year event) based on the 1991–2020 reference period. Alternatively, in Palm Beach County, Florida, the same deficit of -26 mm would be classified as a D1 (Moderate Drought representing a ~1 in 10-year event) using the 1961–1990 reference period, but represent a D3 (Extreme Drought representing a ~1 in 34-year event) based on the 1991–2020 reference period. These differences have potentially significant implications for drought response and relief efforts, especially those programs directly triggered by thresholds, such as the Farm Service Agency's Livestock Forage Disaster Program (LFP; 7 U.S.C. § 9081[1]). More discussion of drought thresholds can be found in the "Drought Severity Thresholds" section below.

[1] https://uscode.house.gov/view.xhtml?req=(title:7%20section:9081%20edition:prelim)

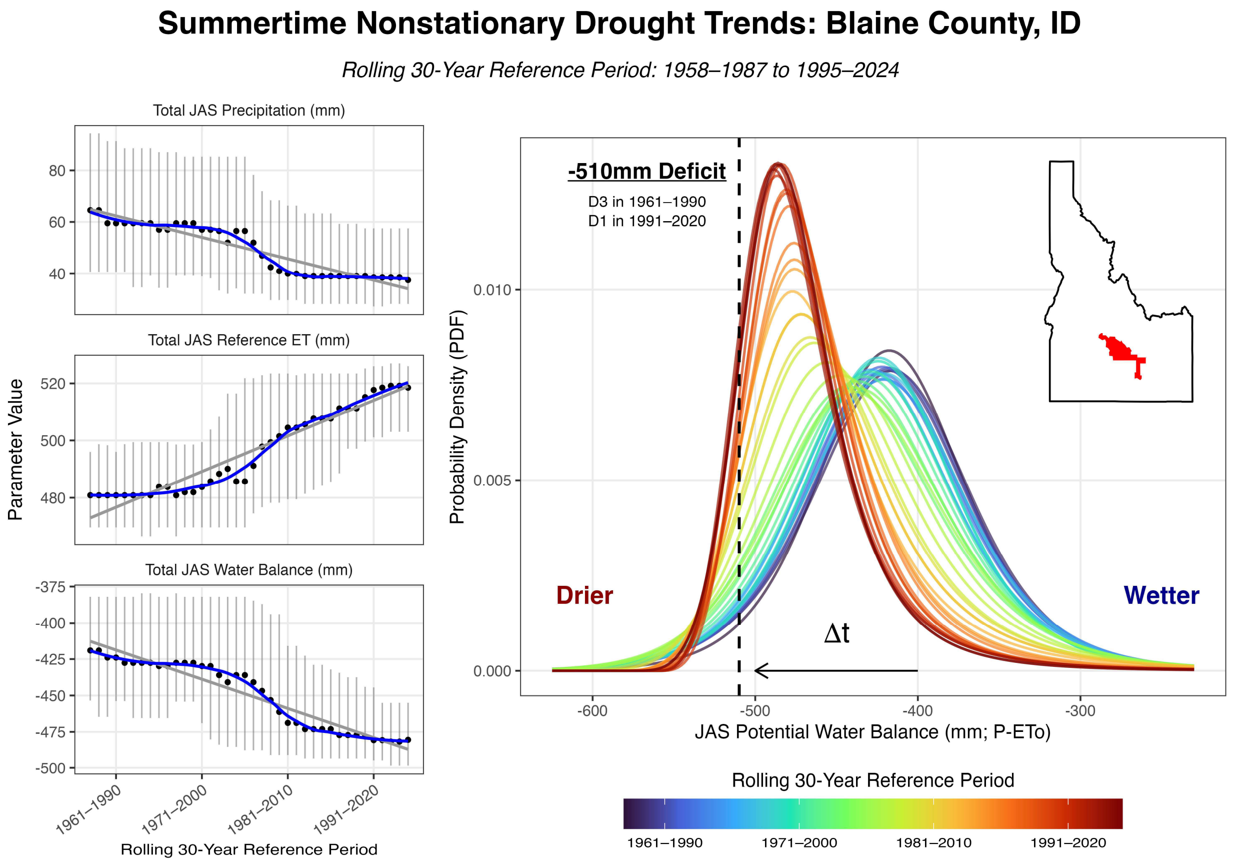


FIGURE 6-1 Nonstationary drought trends in Blaine County, Idaho, based on moving rolling 30-year climatologies reference periods.
NOTE: Rolling 30-year medians with whiskers representing the inter-quartile range (IQR) of July–September total precipitation, reference evapotranspiration (ET_o), and potential water deficit ($P - ET_o$) show declining moisture supply, increasing atmospheric demand, and intensifying deficits since the mid-20th twentieth century (left). Shifting probability density functions of potential water deficit (right) illustrate a systematic drift toward drier conditions across successive 30-year periods, highlighting how nonstationarity alters drought characterization relative to fixed historical baselines.
SOURCE: Committee-generated, based on data from the from the TerraClimate dataset (Abatzoglou et al., 2018). CC BY 4.0.

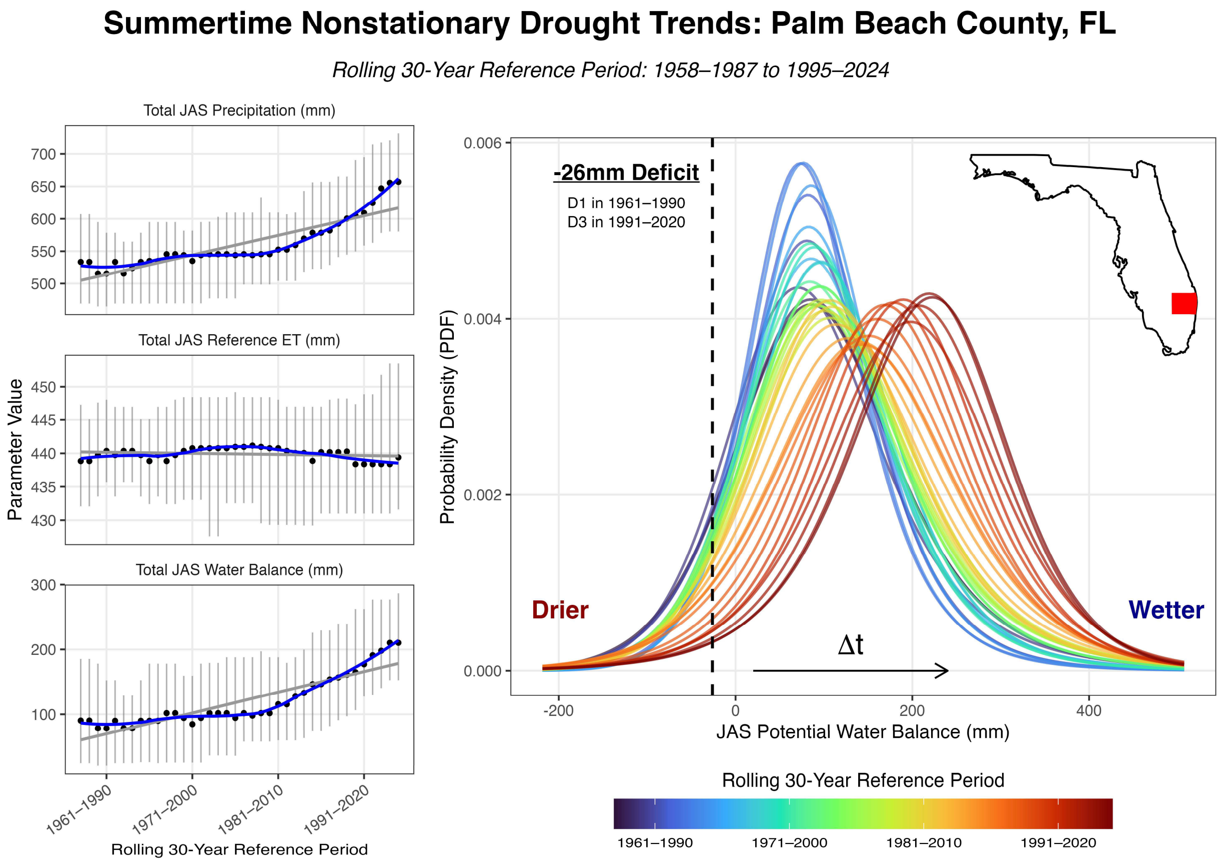


FIGURE 6-2 Nonstationary drought trends in Palm Beach County, Florida, based on moving 30-year climatologies.
NOTE: Rolling medians with whiskers representing the inter-quartile range (IQR) of July-September total precipitation, reference evapotranspiration (ET_o), and potential water deficit ($P - ET_o$) indicate increasing moisture supply alongside relatively constant atmospheric demand, resulting in a net shift toward wetter conditions over time (left). Probability density functions of potential water deficit (right) shift systematically toward wetter states across successive 30-year periods, illustrating how nonstationarity can alter drought characterization relative to fixed historical baselines.
SOURCE: Committee-generated, based on data from the from the TerraClimate dataset (Abatzoglou et al., 2018). CC BY .4.0

Beyond adapting reference periods for a changing climate, a growing body of work has pursued the development of explicitly nonstationary statistical formulations for drought indices. These approaches relax the assumption that the parameters describing a probability distribution are fixed in time by allowing one or more parameters (e.g., location, scale, or shape) to vary as functions of covariates such as time, temperature, climate modes, or anthropogenic influences. Generalized Additive Models for Location, Scale, and Shape (GAMLSS; Rigby and Stasinopoulos, 2005) provide a flexible framework for this purpose, enabling drought indices (including SPI and SPEI among others) to be reformulated under nonstationary probability models (e.g., Wang et al., 2015; Rashid and Beecham, 2019; Bazrafshan et al., 2022; Li et al., 2026). In these formulations, drought severity remains probabilistically interpretable, but probabilities are conditioned on evolving conditions rather than a fixed historical baseline (see Figure 9-3 as an example of this approach). Applications have shown that nonstationary indices can alter estimates of drought duration, severity, and termination, in some cases suggesting the occurrence of more frequent but shorter events compared to stationary counterparts (Bazrafshan et al., 2022). While such methods offer a more sophisticated way to account for nonstationarity, they represent a practical implementation challenge, introducing additional modeling choices, computational burden, data requirements, and interpretive complexity, underscoring the need for transparency and careful alignment between method, decision context, and risk tolerance.

Conclusion 6-1: Reference periods under the context of nonstationarity should be treated as adaptable parameters, updated or reevaluated as conditions change and/or flexible to apply to specific systems and decision framework, rather than fixed climatologies assumed to remain valid over time.

Recommendation 6-1: NOAA, USDA, USGS, affiliated regional climate centers, and national drought assessment partners such as the National Drought Mitigation Center (NDMC) should develop flexible methods to examine drought information with different reference periods in consultation with drought data providers, practitioners, and end users. This could include producing multiple datasets concurrently using different reference periods (e.g., the last 30 years, the most recent climate normal period, and the full period of record) or enabling dynamic generation of drought indices using user-defined reference periods. In doing so, methods should balance flexibility for system-specific applications with the need for consistent, transparent, reproducible, and comparable assessments of drought conditions across space and time.

DROUGHT SEVERITY THRESHOLDS

Drought indices, while valuable for their inherent probabilistic interpretability, are often translated into categorical classifications to facilitate communication with stakeholders and support decision frameworks that prefer discrete thresholds (such as the convergence-of-evidence approach described below). Table 6-1 extends Table 2-1 and presents a classification scheme that partitions the standard normal scale (as well as percentiles) into drought categories (note: these can be extended symmetrically to pluvial classes as well). This scheme is used commonly by the U.S. Drought Monitor (USDM), the North American Drought Monitor (NADM), and other international drought monitoring efforts.

TABLE 6-1 A Modified Drought Classification Schema for the USDM Drought Categories

Category	Description	Example Percentile Range for Most Indicators	Values for Standardized Precipitation Index and Standardized Precipitation-Evapotranspiration Index
	Normal or wet conditions	x > 30	x > -0.524
D0	Abnormally Dry	30 ≥ x > 20	-0.524 ≥ x > -0.842
D1	Moderate Drought	20 ≥ x > 10	-0.842 ≥ x > -1.281
D2	Severe Drought	10 ≥ x > 5	-1.281 ≥ x > -1.644
D3	Extreme Drought	5 ≥ x > 2	-1.644 ≥ x > -2.054
D4	Exceptional Drought	x < 2	x < -2.054

NOTE: This table follows the drought classification framework used by the U.S. Drought Monitor but expresses the standardized thresholds using mathematically exact normal-distribution quantities rather than rounded approximations. This distinction is important because commonly used rounded values (e.g., -1.6 or -2.0) do not correspond exactly to the stated percentile thresholds under a standard normal distribution and can therefore produce slight inconsistencies in drought classification.
SOURCE: Adapted from the U.S. Drought Monitor. (https://droughtmonitor.unl.edu/About/AbouttheData/DroughtClassification.aspx) The U.S. Drought Monitor is jointly produced by the National Drought Mitigation Center at the University of Nebraska–Lincoln, the United States Department of Agriculture, the National Oceanic and Atmospheric Administration, and the National Aeronautics and Space Administration. Map courtesy of NDMC.

Standardized drought thresholds are useful because they offer a common way to classify droughts and make their severity more interpretable by the public. They also aid practitioners in interpreting how severe a given event is based on many lines of inference and diverse datasets (see “Convergence of Evidence” section below). These categories are also used to describe how rare a drought event is, and therefore, inform people on how they might conceptualize disaster response and/or preparations for future events. For example, a standardized drought index value of -2.054 indicates conditions expected to occur approximately 2 percent of the time under the reference climatology, or roughly once every 50 years. If impacts occur during a sufficiently rare event such as this, it may be sensible that response efforts focus primarily on disaster mitigation. In contrast, if impacts occur during much more common events (say ~1 every 10 years), a focus on adaptation may be of merit. This recurrence interval framing supports risk communication and enables a simpler understanding of the probabilistic likelihood of any particular event.

Classification thresholds gain operational meaning through calibration against observed impacts in specific sectors and regions (see Chapter 7). For example, Moderate Drought (D1) thresholds might be associated with reduced surface water availability that affect outdoor recreation (such as fishing closures) or water diversions, whereas Extreme Drought (D3) thresholds may correspond to declining groundwater levels in wells or disruptions to municipal water supply. In hydrological applications, thresholds may be linked to streamflow or reservoir storage percentiles, while agricultural applications often calibrate drought categories relating soil moisture percentiles to crop stress or yield losses (Stahl et al., 2016). This calibration process connects standardized statistical measures to real-world consequences, enhancing the relevance and interpretability of drought classifications for decision-makers. In many drought management plans, this relation between drought categories, impacts, and action are used for important decisions, like declaring emergencies, providing disaster aid, restricting water use, or supporting farmers.[2]

Under nonstationarity, however, these probabilities should be interpreted with caution: if the climate system is changing, the frequency of extreme conditions may differ from that implied by historical baselines (see Figures 6-1 and 6-2), a fundamental challenge that underscores the importance of regular baseline updates and parallel analysis using multiple reference periods. Therefore, when reference periods are updated to reflect contemporary climate conditions (and, by extension, contemporary return intervals), the historical relationship between drought categories and observed impacts may weaken, reducing the reliability of past impact analogs for present-day decision-making. At the same time, changing reference periods do not eliminate the possibility that the absolute magnitude of dryness may intensify under climate change. Even if percentile-based classifications are recalibrated to reflect contemporary conditions, warming-driven increases in atmospheric demand and shifts in precipitation regimes may produce physically drier conditions than those experienced historically. In this sense, the same physical conditions may be classified as less rare under updated baselines even as the absolute conditions driving dryness increase (see Chapter 9).

Figure 6-3 illustrates that drought severity classifications derived from standardized or percentile-based thresholds (see Table 6-1) are not solely a function of short-term variability but are strongly shaped by the underlying climate dynamics and the choice of reference period. Here, drought classifications shown in the right panels are derived from the distribution of the simulated drought indicator in the left panels using an expanding reference climatology. Following an initial 30-year baseline, drought categories for each subsequent year are computed relative to the longest period of record available at that time. For example, drought classes assigned in year 40 are based on a 40-year reference period, whereas classifications in year 100 are based on the full 100-year record. This approach mirrors common recommendations (Guttman, 1994; Svoboda and Fuchs, 2016) in which drought severity is evaluated against the longest available historical context (period of record), while also illustrating how evolving baselines interact with nonstationary climate behavior to influence drought frequency and severity.

[2] See, for example, https://drought.mt.gov/response-actions.

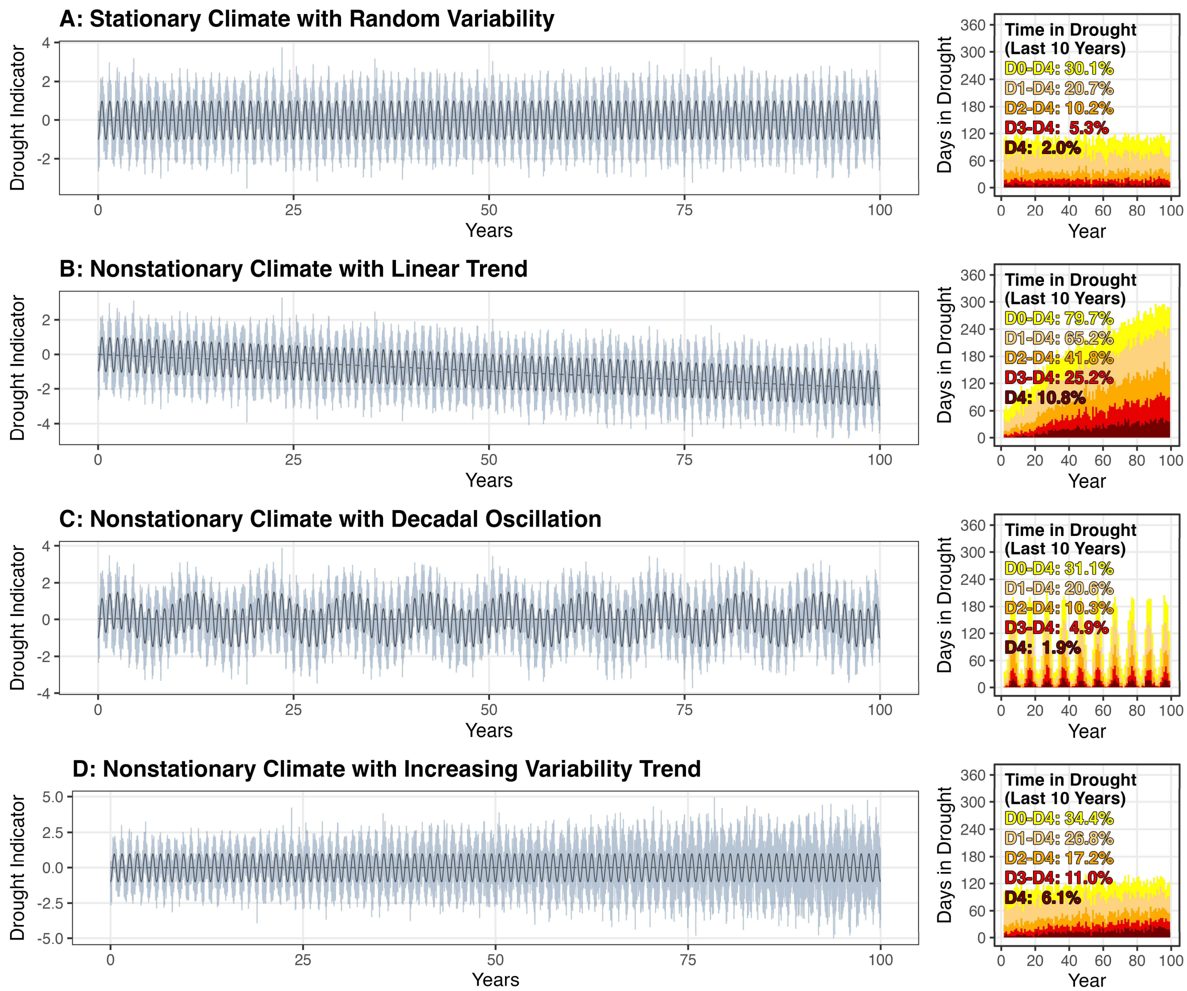


FIGURE 6-3 Synthetic examples illustrating how nonstationarity influences drought characterization under a percentile-based classification framework.
NOTE: Daily time series (left panels) show simulated "drought indicator" values representing a variable of interest over a 100-year period, with a seasonal reference signal (black line) overlaid to highlight changes in the underlying hydroclimate. Right panels summarize annual days in drought by category (D0–D4) using parametric percentile-based thresholds consistent with the U.S. Drought Monitor schema, along with cumulative percentages of time spent in drought over the final 10 years. Panels illustrate (A) stationary climate variability, (B) a linear drying trend (-0.02 standardized units per year), (C) a repeating decadal oscillation, and (D) increasing variability through time.
SOURCE: This figure is adapted from Nie et al. (2025), but modified to (i) extend the simulation period from 30 to 100 years; (ii) apply an expanding reference climatology with a minimum 30-year baseline; (iii) express drought classification using percentile-based metrics based on the expanding climatology rather than fixed reference distributions highlighting how evolving baselines affect drought frequency, severity, and interpretation under nonstationarity; and (iv) evaluating the impact of an oscillating climate forcing (panel C) compared to a shift in seasonality. CC BY-NC 4.0.

In the stationary case (panel A), drought categories occur with frequencies broadly consistent with their nominal probabilistic definitions and expectations, and the cumulative time spent in drought remains stable over time. In contrast, nonstationary conditions fundamentally alter how often thresholds are met. Under a linear drying trend (panel B), increasingly large portions of the distribution fall into drought categories as time advances, leading to systematic inflation of drought frequency and severity even though the same percentile-based thresholds are applied. The result is a frequency and duration of classified drought conditions that far exceed the expected nominal probabilistic definitions. The decadal oscillation case (panel C) demonstrates how internally driven low-frequency variability can generate pronounced, episodic clustering of drought categories without a long-term trend; note that the range of the oscillation shown in the graphic may be greater than in most observed variables. Finally, increasing variability alone (panel D) increases the frequency of both moderate and extreme drought classifications by widening the distribution, despite no change in the mean state.

In fact, there is evidence that changing drought frequency and severity classifications in the presence of static percentile-based thresholds are already becoming a challenge for federal drought disaster assistance programs. For the U.S. Department of Agriculture's (USDA) Livestock Forage Disaster Program, simulations show that federal government expenditures on the program are projected to increase by 45 to 135 percent by 2100 due to more frequent triggering of the USDM-based eligibility thresholds when using common drought methods (Hrozencik et al., 2024), imposing risk on future federal budgets. If the metrics used to classify drought in the LFP are updated to reflect nonstationary conditions, the projected federal expenditures would also be reduced. However, such updates would also modify the frequency with which producers qualify for payments under the same absolute conditions, underscoring the need to distinguish between episodic drought disasters and longer-term adaptation challenges in regions where severe dry conditions are becoming increasingly common.

In practice, all of these behaviors (and combinations thereof) may be expressed across space, time, and indicators. For example, some locations or variables may exhibit relatively monotonic changes in the mean state, as illustrated in panel B, while others may be dominated by internally driven low-frequency variability associated with regional or large-scale climate modes, as in panel C. At the same time, these signals may be superimposed on changes in variability alone (panel D), which alter the shape of the underlying distribution without shifting its mean. Furthermore, changes to mean state or variability (similar to panel B or D) may occur in nonlinear ways, exacerbating this problem over time. When combined, trends, oscillations, and changes in variance (among other manifestations of nonstationarity) modify the probabilistic structure of drought indicators in complex ways, affecting the frequency, duration, and severity of threshold exceedances. As a result, the interpretation of standardized or percentile-based drought classifications becomes increasingly contingent on both the nature of the underlying climate dynamics and the reference framework used to define normal conditions. These considerations underscore the need for the drought community to align definitions of drought for various monitoring intents and systems of interest in order to ensure consistency across analysts and alignment with the broader value structures of society.

FROM INDICATORS TO INDICES: THE ROLE OF STANDARDIZATION

Standardization provides a framework for integrating heterogeneous drought indicators across variables, products, regions, and timescales. However, any standardized index reflects implicit decisions about the underlying datasets, reference periods, and statistical methods that shape how drought severity is ultimately perceived. Beyond transforming raw data into comparable units, standardization also offers an opportunity to make the underlying analytical choices in drought assessment transparent and consistent. When decisions such as reference period selection or statistical formulation (e.g., parametric vs. nonparametric methods) vary across datasets or practitioners, drought severity estimates can diverge even when based on similar (or even the exact same) underlying information. Explicitly documenting and, where appropriate, harmonizing these choices can therefore improve consistency and comparability across drought assessments.

Standardization has become a core organizing principle in drought monitoring because it enables diverse indicators to be expressed on comparable probabilistic scales (e.g., percentiles or standard normal units). The SPI popularized this approach for precipitation anomalies and helped establish a widely adopted framework that has since been extended to many other drought-relevant variables (McKee et al., 1993; Svoboda and Fuchs, 2016). However, while the outputs of drought indices are often standardized, many of the analytical choices that shape those outputs remain inconsistently applied or insufficiently documented (Laimighofer and Laaha, 2022).

This inconsistency matters operationally because it can hinder synthesis, obscure uncertainty, and complicate communication with decision-makers as drought monitoring systems expand to incorporate many indices (Zargar et al., 2011; AghaKouchak et al., 2015; Mukherjee et al., 2018). For example, commonly cited papers underpinning the derivation of SPI suggest that “sample sizes of at least 60 should be used to estimate the tails of a distribution; the smaller the sample size, the more unreliable the probabilities become” (Guttman, 1999; based on Guttman, 1994). This suggestion is then echoed in international recommendations (WMO, 2012): “Ideally, one needs at least 20–30 years of monthly values, with 50–60 years (or more) being optimal and preferred (Guttman, 1994).” In practice, adopting a “full period of record” approach across station or gridded products may violate assumptions of stationarity and can yield spatially inconsistent effective reference periods where record lengths vary. One example of this is data from neighboring meteorological stations that may be standardized against markedly different climatological contexts (e.g., ~30 vs. ~100 years), leading to classification differences that arise from arbitrary differences in data record lengths rather than hydroclimatic conditions.

Importantly, standardization should not be interpreted as a guarantee of uniformity, objectivity, or correctness. While standardized methods place diverse indicators on a common scale, they do not eliminate the need for judgment about which variables, timescales, and reference periods are appropriate for a given system or decision context. The diversity of analytical choices involved in drought index computation therefore underscores the importance of transparent documentation and reporting of these decisions. These challenges are further amplified in a nonstationary climate, where departures from assumed stationarity can cause standardized metrics to misrepresent contemporary risk when reference periods or distributional assumptions are no longer valid. Standardization therefore functions best as a facilitating framework rather than a prescriptive solution, but only when assumptions are well documented. It enables comparison, synthesis, and communication, but must be complemented by explicit consideration of nonstationarity, system-specific sensitivity, and adaptive capacity, as well as decision intent of the analyst.

Ultimately, choices about how and what to standardize implicitly encode judgments about which systems and impacts matter most, making standardization not only a technical exercise but also a reflection of societal priorities and risk tolerance. When used in this way, standardized methods can support diverse drought assessment approaches and risk-based interpretation, while still allowing flexibility to adapt methods as climate conditions and management needs evolve. Here, transparency can be achieved via explicit documentation of data provenance, reference period design, distributional assumptions, parameter estimation methods, handling of zero or censored values, and any adjustments for nonstationarity or uncertainty. Without such documentation, differences among standardized drought products may reflect methodological artifacts rather than true differences in hydroclimatic conditions.

Conclusion 6-2: Strengthening standardization around analytical methods, reference period design, and metadata transparency is a necessary step toward more consistent, reproducible, and risk-aligned drought assessment in a nonstationary climate.

Conclusion 6-3: Transparent documentation of analytical methods, reference periods, and uncertainty is essential for ensuring that drought metrics are interpretable, comparable, and appropriately applied as climate conditions evolve.

Recommendation 6-2: NOAA, USDA, USGS, and affiliated regional climate centers, in coordination with academic and practitioner communities, should develop and adopt shared standards for documenting and publishing metadata associated with drought metrics, including methods, reference periods, and uncertainty.

CONVERGENCE OF EVIDENCE

Once the array of analytical choices needed to define drought indices are determined (and documented), the exercise of drought assessment can begin. The convergence-of-evidence approach used in operational drought assessment reflects the recognition of both the multivariate nature of drought and the practical reality that no single measure can capture all relevant drivers or depictions of abnormal water availability across different systems, timescales, and regions. Convergence of evidence allows practitioners to differentially weigh specific indicators and indices reflecting different types of droughts simultaneously (e.g., meteorological, agricultural, hydrological, ecological, and socioeconomic drought), recognizing that different drought impacts manifest depending on context.

A key strength of the convergence-of-evidence approach is its flexibility and conceptual simplicity. It enables drought assessments to incorporate diverse data sources with differing spatial and temporal resolutions, modeling approaches or sector-specific foci, and generate assessments that adhere to standardized systems (such as the U.S. Drought Monitor) in different regions, despite using different data. It also allows for expert judgment to reconcile situations in which indicators diverge, such as when near-term precipitation deficits have ended but soil moisture or streamflow remains low (e.g., meteorological vs. hydrological or agricultural drought). This approach has been widely adopted in operational contexts, where timely decisions are required despite incomplete data, evolving conditions or region-specific considerations.

At the same time, the convergence-of-evidence approach is inherently difficult to formalize. Because this approach relies on expert synthesis rather than fixed decision rules or more formal quantitative frameworks (e.g., statistical or machine learning–based approaches), its outcomes are generally considered impossible to reproduce consistently. For example, different analysts may reasonably weigh the same set of indicators differently, leading to variation in drought classification. This heterogeneity is not necessarily a flaw in itself, but it does complicate efforts to assess uncertainty, compare assessments across space and time, or evaluate how drought classifications would change under alternative assumptions, such as different reference periods. Nonstationarity may further complicate convergence-of-evidence–based approaches. As climate conditions shift, historical relationships among indicators may weaken, and expert heuristics developed under past climate regimes may become less reliable. Similarly, impact reports may reflect evolving system exposure or vulnerability rather than changes in hydroclimatic hazard alone. In these contexts, convergence of evidence can obscure whether observed changes in drought classification reflect true shifts in risk, changes in system sensitivity, or an emergence of novel climate states.

Efforts to develop more structured, transparent, and reproducible approaches to drought assessment should seek to better document how multiple indicators, impact reports, expert judgment, and other forms of knowledge are integrated into drought classifications. The goal is not to eliminate the current expert-driven, convergence-of-evidence approach, but to make the analytical steps underlying drought determinations more transparent, reproducible, and testable. By clearly documenting assumptions, the quantitative frameworks used in modern drought assessment can promote greater consistency across regions and time, facilitate comparison among assessments, and provide a structured basis for evaluating how classifications might change under alternative reference periods or nonstationary conditions. At the same time, such frameworks should complement, rather than replace, other ways of knowing, including Indigenous Knowledge, Traditional Ecological Knowledge (TEK), local expertise, and lived experience, all of which can provide critical context for interpreting drought conditions and impacts.

> *Conclusion 6-4: Efforts within the drought assessment community should continue to explore transparent and reproducible approaches to drought assessment while recognizing that expert judgment, local expertise, Indigenous and Traditional Ecological Knowledge, and other ways of knowing provide critical perspectives not fully captured by purely quantitative approaches.*

SYSTEM-SPECIFIC PERSPECTIVES

Operational drought assessment is increasingly asked to serve multiple purposes at once, namely, to communicate (1) how severe current conditions are for affected systems, and (2) how rare those conditions are relative to an assumed historical baseline. Under nonstationarity, these purposes can diverge because the probability distribution used to define normal is itself evolving, while system exposure, vulnerability, and adaptive capacity are also changing. As a result, drought classifications become conditional statements; conditional not only on the indicator and method but also on the system context and the reference framework used to define risk.

A system-specific perspective can cast drought fundamentally as a risk problem, where impacts emerge from the interaction of the hazard, exposure, and vulnerability (see discussion of these terms in the “Risk and Decision Framing in Drought Assessment” section in Chapter 1). Importantly, each of these components can be nonstationary, as can the ability to adapt to drought hazard and exposure. This implies that a drought category derived from a fixed reference period may remain statistically well-defined yet become progressively less aligned with contemporary risk as hazards shift, exposure changes, and adaptive strategies evolve.

From this perspective, reference periods can be tailored to the system of interest, such as agricultural production, ecological resilience, or water-supply reliability, so that drought classifications reflect the risks most relevant to that system rather than a one-size-fits-all climatology. The appropriate reference period depends on both the character of nonstationarity (e.g., trend-driven drying, seasonal shifts, changes in variance, low-frequency oscillations, or human-modified regime change) and the adaptive capacity of the system of interest. Systems capable of rapid adjustment (e.g., some agricultural and operational decision contexts) may benefit from baselines that emphasize contemporary conditions, whereas systems with long memory or slow recovery (e.g., many ecological and hydrologic storage systems) may require longer historical context to remain interpretable. In all cases, the baseline choice affects whether drought categories primarily communicate rarity (return period under the baseline) or severity (degree of stress relative to contemporary expectations), and these interpretations can become increasingly incompatible as the climate changes.

A practical implication is that drought monitoring frameworks may need to support parallel reference period views of the same indicator to maintain both interpretability and decision relevance. A framework like this could both report drought classification relative to a long-term, fixed reference period for long-term comparability, alongside a contemporary or evolving baseline tailored for system-specific, risk-aligned decision support. Because such choices can materially alter drought classifications and trigger thresholds, they must be accompanied by transparent documentation of reference period design, rationale, and intended use. In a nonstationary climate, failure to document and periodically reevaluate these assumptions risks conflating methodological artifacts with real changes in drought hazard and can misalign response triggers with contemporary system risk.

Conclusion 6-5: Reference periods that align with risk profiles of specific systems are needed to inform shared drought assessment and decision-making. Such reference periods should be developed with engagement of all affected communities.

Recommendation 6-3: NOAA, USDA, and USGS, in collaboration with state and federal agencies (including the USDA Climate Hubs and NCEI's Regional Climate Centers), should convene key communities affected by drought to identify reference periods that align with risk profiles of specific systems, to better inform decision-making for each system.

UNCERTAINTY IN DROUGHT INDICES

The uncertainty associated with drought indices is difficult to quantify in operational contexts and arises from multiple, interacting sources. Some sources of uncertainty originate in the underlying datasets themselves (Trenberth et al., 2014), such as precipitation estimates from gridded products or modeled soil moisture from land surface models. Additional uncertainty is introduced through the physical or empirical models used to derive secondary variables, such as reference evapotranspiration computed using different formulations (e.g., Thornthwaite-Mather vs. Penman-Monteith; Thornthwaite and Mather, 1955, 1957; Allen et al., 1998). Standardized drought indices also inherit statistical uncertainty associated with sampling variability, distribution choice, and parameter estimation when fitting probabilistic models to finite records. Finally, these uncertainties vary as a function of space and time, further complicating the task of quantifying uncertainty in real-time, operational contexts. While drought assessors may implicitly account for these uncertainties through expert judgment or convergence-of-evidence approaches, they are rarely quantified explicitly or attributed to specific components of the drought index formulation. As a result, uncertainty in drought classifications is commonly treated subjectively rather than analytically, even though it can materially affect estimates of drought frequency, severity, and duration.

In a retrospective context, variability in the underlying datasets used for drought analysis can lead to substantial differences in assessed drought severity at regional to global scales. For example, Trenberth et al. (2014) show that differing conclusions about drought trends can stem from the choice of precipitation dataset alone, with variations in station coverage and data continuity exerting a strong influence on estimated drought signals and, in some cases, producing contrasting interpretations of how drought severity has changed. Similarly, Stern et al. (2022) show that no single historical climate dataset necessarily performs best for all variables, with different products exhibiting strengths and weaknesses depending on the variable of interest, thereby complicating dataset selection and optimal application in operational settings. Consistent with these findings, Hoffmann et al. (2020) show that uncertainties arising from input data selection are often larger than the differences between commonly used drought indices themselves (SPI, SPEI, PDSI [Palmer Drought Severity Index]), particularly during drought extremes, implying that data choice can dominate drought assessment outcomes regardless of the index used. Finally, these differences among commonly used high-resolution climate datasets can propagate into large discrepancies in modeled hydrological variables (e.g., streamflow, snowpack, evapotranspiration), underscoring that dataset selection alone can substantially shape drought and water-resource assessments even when analyzing the same historical period and/or indicator (Stern et al., 2022).

As atmospheric evaporative demand increases under climate change, the choice of reference evapotranspiration formulation becomes increasingly consequential (Beguería et al., 2014). Comparisons among ET_o models indicate that the more comprehensive, physically based Penman–Monteith approach generally provides more realistic estimates of atmospheric demand than temperature-only formulations such as Thornthwaite–Mather (Sheffield et al., 2012). Use of simplified, temperature-based methods can therefore lead to systematic overestimation of drought severity, particularly where changes in humidity, wind speed, or radiation modulate evaporative demand. Consequently, ET_o model choice represents a nontrivial source of uncertainty in SPEI, especially in water-limited regions and at longer accumulation timescales (Beguería et al., 2014). Although different ET_o formulations often yield highly correlated SPEI time series, meaningful differences in drought magnitude and inferred trends emerge when non-temperature controls on evaporation are important.

Sampling uncertainty arises because standardized drought indices are estimated from finite historical records, which introduces uncertainty in distribution parameter estimates and propagates directly into the resulting standardized values. Bootstrap-based analyses show that point estimates of SPI or SPEI can be associated with wide confidence intervals, particularly for rare events and shorter records, such that drought classifications may shift across standard severity thresholds (Hu et al., 2015). Building on this, Vergni et al. (2017) demonstrate that sampling-related uncertainty varies systematically with record length, accumulation timescale, index type (e.g., SPI versus SPEI), and whether parametric or nonparametric formulations are used. They further show that expressing uncertainty in terms of return periods can improve interpretability and provide a clearer indication of estimate reliability. Similarly, Laimighofer and Laaha (2022) show that record length and observation period strongly control the magnitude of uncertainty in SPI and SPEI estimates and can be sufficient, on their own, to alter drought classifications. Importantly, these analyses generally assume a stationary climate when evaluating the effects of sample size and record length, an assumption that becomes increasingly problematic under nonstationarity and complicates the interpretation of uncertainty derived from historical samples.

Distinct from sampling uncertainty, parameterization uncertainty reflects uncertainty introduced by the statistical structure of the drought index itself, independent of record length. This includes choices about the probability distribution used to represent the variable of interest, the number of parameters used to characterize that distribution, and how specific data features (such as zero values or skewed tails) are handled. For example, SPI is most commonly computed using a two-parameter Gamma distribution, which cannot explicitly represent zero precipitation and therefore requires additional assumptions (e.g., mixed or censored distributions; Stagge et al., 2015), introducing structural ambiguity in the lower tail of the distribution (Wu et al., 2007). In some cases, as for when there is a large proportion of zero precipitation samples, these mixed distribution solutions to the zero-inflation problem can result in an index never predicting drought.

Comparative studies have shown that distribution choices (e.g., Gamma, Pearson Type III, generalized logistic, Tweedie or generalized extreme value) can yield materially different standardized values for the same underlying event, particularly for extremes most relevant to drought classification (Stagge et al., 2015; Svensson et al., 2017). Laimighofer and Laaha (2022) demonstrate that distribution choice is often one of the dominant contributors to total variance in SPI and SPEI estimates, rivaling or exceeding sampling uncertainty in some contexts, while differences among parameter estimation methods and goodness-of-fit tests tend to play a secondary role. Because parameterization uncertainty persists even for long records, and especially when the assumptions of stationarity are violated, it cannot be reduced simply by increasing sample size and represents a structural source of uncertainty that is rarely propagated or reported in operational drought monitoring.

Applications for Droughts in the United States

In this recent decade, the extension of standardization to soil moisture has been found to more effectively reduce uncertainties in calculating precipitation-based drought-related indicators (also known as top-bottom approach). Specifically, soil moisture is physically bounded by porosity, exhibits strong spatial heterogeneity related to soil texture and land cover, and is measured or modeled with varying depths and physical principles across products (Rawls et al., 1982; Saxton and Rawls, 2006). Additionally, soil moisture represents the stabilized water stored in land that directly reflects current wetness conditions, enabling rapid and accurate detection of drought or flash drought events without the temporal lag inherent in hydrological flux measurements. This advantage comes from its unique ability to capture the immediate water status of the soil column while avoiding the substantial uncertainties associated with quantifying water losses through evapotranspiration, runoff, and deep percolation processes.

It is worth acknowledging explicitly that every choice embedded in this framework involves judgment. The selection of which products to include, which accumulation periods to prioritize, which baseline period to use, and which severity thresholds to apply are all consequential decisions shaped by scientific convention, available data, and context. This is not a weakness; it is the nature of drought monitoring. Standardization reduces certain measurement incompatibilities, but it does not eliminate interpretive subjectivity. TEK and local observations offer complementary perspectives that are not captured by remote sensing or reanalysis, including long-term place-based experience with how drought manifests across specific landscapes, crops, and communities. Integrating these knowledge systems with satellite-derived indices strengthens drought assessment in ways that purely technical standardization cannot.

Two complementary approaches to soil moisture standardization have emerged from recent works, each addressing these challenges differently. First, Carrão et al. (2016) developed a nonparametric approach (i.e., Empirical Standardized Soil Moisture Index, or ESMI) using Kernel Density Estimation (KDE) with logit transformation to address boundary bias, enabling flexible adaptation to local distribution shapes without imposing parametric assumptions. ESMI uses data-driven density estimation to map observed soil moisture values to cumulative probabilities, then transforms these probabilities to standard normal scores. This approach is particularly valuable when soil moisture distributions are non-Gaussian, multimodal, or otherwise complex, as the kernel density estimation adapts to the actual data structure. The logit transformation employed by Carrão and colleagues maps the bounded interval to the unbounded real line, eliminating boundary bias that would otherwise distort density estimates near the physical limits of soil moisture (Carrão et al., 2016). Meanwhile, Palagiri and Pal (2024) proposed an alternative parametric approach (i.e., SMI) using the Gamma distribution with truncation and renormalization, building directly on the established SPI and SPEI frameworks. Specifically, SMI fits a two-parameter Gamma distribution to baseline period observations using maximum likelihood estimation, applies truncation to confine probability mass to the physically meaningful range, and transforms cumulative probabilities to standard normal scores. The renormalization procedure ensures that all probability mass is allocated within the specific interval, improving accuracy of drought intensity estimation particularly in distribution tails where extreme droughts reside (Palagiri and Pal, 2024). This approach offers computational efficiency and interpretability within the familiar SPI and SPEI frameworks, though performance depends on how well the Gamma distribution represents actual soil moisture behavior in a given location and season.

Both approaches transform soil moisture observations, regardless of source, to unitless standard scores that can be interpreted probabilistically and compared across products, regions, and timescales. Generally, negative values indicate drier-than-normal conditions, positive values indicate wetter-than-normal conditions, and the magnitude reflects severity in terms of standard deviations from the climatological mean. This transformation enables direct comparison of drought signals from ERA5-Land, Soil Moisture Active Passive (SMAP), Global Land Evaporation Amsterdam Model (GLEAM), and European Space Agency Climate Change Initiative (ESA-CCI) despite their different measurement physics, spatial resolutions, and temporal coverage. The standardization can be computed on temporally aggregated series at multiple accumulation scales (i.e., 1, 3, 6, 9, 12, and 24 months) to capture drought processes across meteorological, agricultural, and hydrological drought events, following established multi-scalar drought index methodology (Dai et al., 2024; Mckee et al., 1993).

The methodological demonstration comparing the nonparametric ESMI and parametric SMI highlights fundamental differences in how ESMI and SMI treat probability distributions, boundary conditions, and classify extreme levels (see Figure 6-4). First, the data-driven ESMI approach constrains standardization within the observed historical envelope, using empirical percentiles that reflect actual data magnitude and variability. In contrast, SMI extends probability mass beyond observed bounds through parametric tail extrapolation inherent to distribution fitting methods (e.g., Gamma distribution), providing a wider range of extremes in both tails. While this extension may theoretically help capture compound drought events with rapid inter-arrival times, it produces two critical limitations: (1) it might assign unrealistically low probabilities to extreme droughts that have actually occurred due to the nature of mathematical distribution methods, and (2) it systematically underestimates drought intensity compared to the nonparametric ESMI approach by extending the distribution tails beyond physically realistic soil moisture bounds, between 0.05 (extreme dry) and 0.6 (close to water saturation in soil).

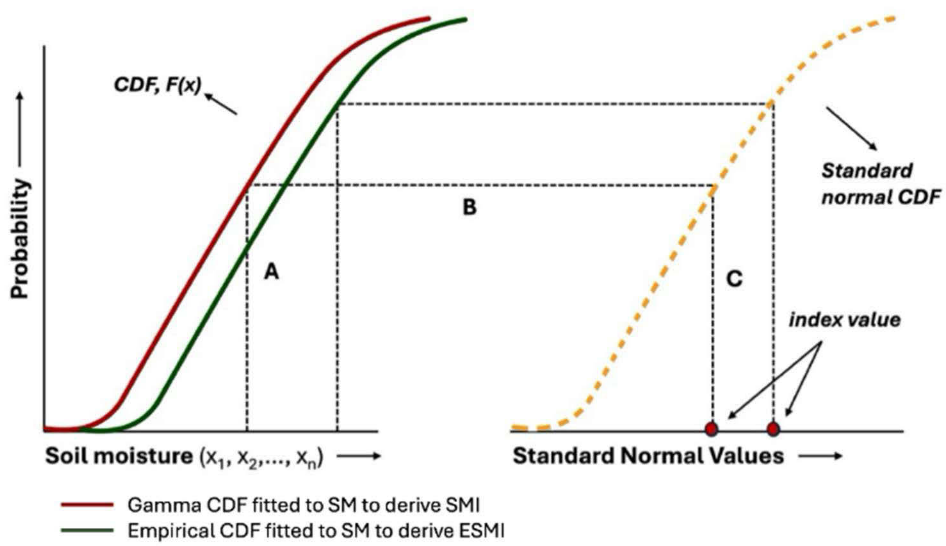


FIGURE 6-4 The computation procedure of nonparametric ESMI and parametric SMI indices. NOTE: The curves on (A) represent the CDF, F(x) fitted to SM observations ($x_1, x_2, \ldots, x_n$). The dashed curve (C) is the standard normal CDF. The non-exceedance probability is determined for SM observations in stage (A), followed by transforming these values to standard normal variables in stage (B), and the ESMI and SMI values (C) (with extreme classifications introduced by McKee et al., 1993, see Table 6-2).
SOURCE: Figure regenerated from Palagiri and Pal (2024). CC BY-NC 4.0.

The choice between ESMI and SMI reflects a fundamental tension in drought monitoring: whether to prioritize fidelity to the observed climate (ESMI) or continuity with established parametric frameworks (SMI). ESMI's empirical approach ensures that "extreme" classifications correspond to genuinely rare historical conditions, making impact probabilities more interpretable from observed precedent. However, as mentioned above, this approach cannot extrapolate to conditions more extreme than those captured in the historical record, potentially underrepresenting risk in rapidly changing climates with short observational record.

On the other hand, SMI's parametric approach allows theoretical extension into unobserved tail regions, which may be valuable for planning scenarios and risk assessment when extrapolation is necessary. However, the validity of such extrapolation depends critically on whether the mathematical distributional assumption holds in the tails, where data are sparse by definition. Divergence between ESMI and SMI in extreme classifications serves as a diagnostic: concordance suggests that the parametric assumptions are reasonable, whereas systematic divergence indicates distributional inadequacy or nonstationarity that requires further investigation.

For multiproduct integration across satellite and reanalysis datasets with heterogeneous error characteristics, ESMI offers greater flexibility and robustness. For operational systems prioritizing computational efficiency and continuity with established SPI/SPEI-based workflows, SMI may be preferred. Using both indices in parallel provides complementary perspectives and enhances diagnostic capability, particularly in data-sparse regions or under nonstationary conditions where distributional assumptions are uncertain.

The integration of multivariable datasets could provide a robust framework for monitoring complex hydrological extremes, a capability demonstrated through the analysis of the severe July 2012 flash drought over central North America. Specifically, ESMI is found to offer a distinct advantage in characterizing drought stress when used alongside precipitation data from Climate Hazards Group InfraRed Precipitation with Stations data (CHIRPS) v3 and temperature data from Climate Hazards Center InfraRed Temperature with Stations (CHIRTS) (see Figure 6-5(c)). While the precipitation deficits shown in Figure 6-5(b) highlight the meteorological forcing, with very low rainfall during the peak drought deficit in July, ESMI reveals the compounded severity of the drought, with index values in the central Great Plains dropping significantly to between -1.5 and -2.0, as well as beyond -2.0 in some regions (see Figure 6-5(a)). The temporal evolution of this event, detailed in Figure 6-5(c), confirms the statistical sensitivity of ESMI to rapid-onset flash conditions. Specifically, following a convergence of peak annual temperatures (T_{max}) and a sharp reduction in precipitation (below 50 mm/month) in July, the ESMI z-score degraded rapidly from a near-neutral state (z-score of approximately -0.5) in early spring to a severe low of approximately -1.7. This response highlights the index's ability, as well as the capabilities of CHIRPS and CHIRTS, to capture the synergistic effects of heatwaves, dry conditions, and rainfall reduction on soil water availability, which would be valuable for drought monitoring and forecasting.

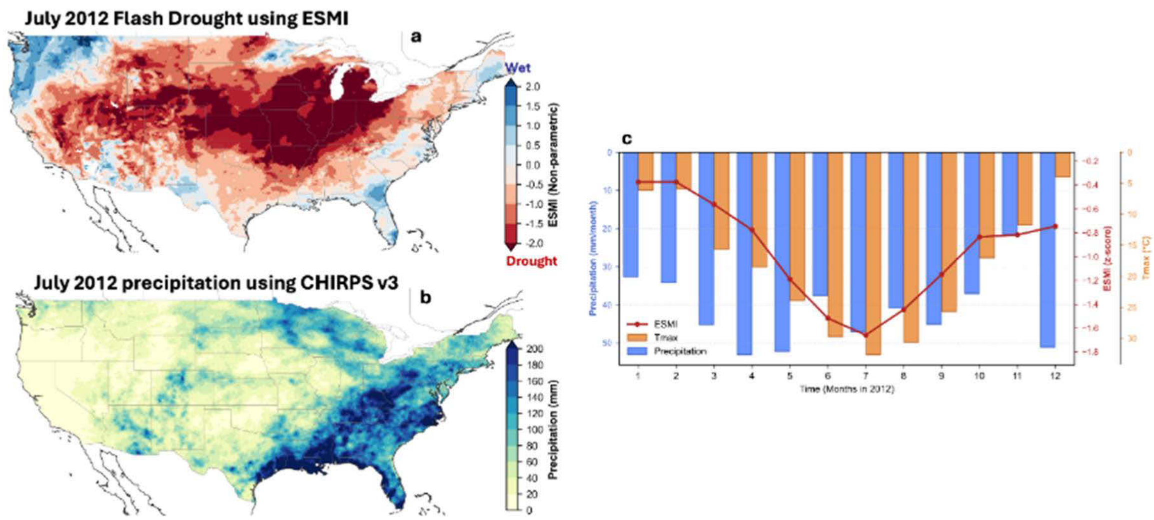


FIGURE 6-5 Application of monthly (a) ESMI, (b) CHIRPS, and (c) CHIRTS datasets for the July 2012 drought over North America.
NOTE: In (a), red color represents dry/drought conditions, blue color represents wet conditions. CHIRPS can be accessed on the CHC data server (https://data.chc.ucsb.edu/products/CHIRPS/v3.0), while CHIRTS can be downloaded via CHC data server (https://www.chc.ucsb.edu/data/chirts-era5).
SOURCE: Tran et al. (unpublished manuscript) 2026.

Moving beyond traditional top-down approaches (e.g., precipitation/ET-based metrics), it is important to prioritize soil moisture-derived indices (i.e., ESMI and SMI) for operational drought mapping. Soil moisture, in this case, can serve as the memory of the terrestrial water cycle, offering a more direct assessment of plant-available water than atmospheric proxies alone. This includes fuel moisture, a critical variable for fire management that responds to the same soil and vegetation water deficits captured by soil moisture indices and that drives wildfire risk in drought-affected landscapes. This shift is currently enabled by the maturation of satellite missions such as the ESA-CCI and NASA's SMAP. Indeed, these missions provide the essential and valuable top-layer soil moisture inputs and long-term historical climatology required to calculate robust anomaly-based indices. Also, by leveraging these active and passive microwave datasets, false alarms and lags during water processes, commonly found in drought monitoring, can be reduced significantly to provide more accurate, physically based decision support for agricultural, water resources, and fire management applications.

Looking toward the future, the development of drought monitoring and prediction can evolve from observation to prediction through the application of artificial intelligence/machine learning (AI/ML) (Oyounalsoud et al., 2024; AghaKouchak et al., 2022; Kikon and Deka, 2022). The next generation of disaster forecasting can rely on advanced deep learning architectures (e.g., Graph Neural Network, GNN) to model nonlinear climate interactions and predict drought propagation on a global scale. Also, a prerequisite for training these advanced models is high-quality, standardized global training data. To this end, the global-scale ESMI and SMI datasets currently being developed by Tran et al. (in preparation, 2026) will serve as a foundational ground-truth layer. By utilizing this upcoming global record, researchers can train ML models to recognize complex teleconnections and soil moisture memory patterns, ultimately enabling the operational forecasting of drought onset weeks or even months in advance.

OPPORTUNITIES TO LEVERAGE AI/ML IN DROUGHT SCIENCE

Artificial intelligence and machine learning methods offer exciting opportunities for advancing drought science and the process of drought assessment. However, as with any emerging technology, its role should be carefully defined and tested with extensive validation. While AI/ML may fit into numerous components of the drought assessment pipeline, there are four historical and emerging arenas that contextualize its opportunity well. These include assessment automation, state variable prediction, forecasting, and data synthesis.

ML has been used to create automated drought mapping applications that attempt to mirror the decisions and processes of national assessment systems. For example, Brust and others (2021) use historical representations of drought (as defined by the USDM) along with meteorological/remotely sensed information to train ML models with the goal of generating automated USDM-style maps. Importantly, this approach can be applied to real-time prediction as well as to forecasts with up to 12-month lead times. While useful, these models, and the USDM itself, should not be interpreted as estimating an objective ground truth for drought. This is because the USDM (and therefore the predictions of models trained on the USDM) represent a human-generated synthesis of information that seeks to best represent drought at a given point in time given the information available and evolving monitoring practices. As new data products become available, different analysts contribute, and/or impact information changes, different representations of the same conditions could emerge with any single realization being equally plausible and/or defensible. Therefore, an ML approach such as this would be expected to reproduce how drought has historically been assessed, but not necessarily how drought should be assessed given perfect information and synthesis approaches. This distinction is especially important under the context of nonstationarity, where past classifications may encode assumptions about baselines, impacts, or vulnerabilities that no longer hold.

A more physically focused application of AI/ML is to improve the estimation and prediction of drought-relevant state variables, such as soil moisture, streamflow, snowpack, vegetation stress, groundwater, and evaporative demand. In many cases, these are the variables, states, and fluxes that decision-makers care about directly, yet they are sparsely observed, extremely heterogeneous in space and time, and difficult to model in real time. This is an emerging application of these models; however, ML has been shown to dramatically improve predictions of streamflow (Nearing et al., 2020; Arsenault et al., 2023; Nearing et al., 2024) by leveraging flexible methods to ingest diverse information and datasets such as process-model simulations, in situ observations, remote sensing, meteorological forcing, soils, terrain, and vegetation information. By estimating hydrological states more directly, AI/ML can reduce reliance on meteorological indices as imperfect proxies for agricultural, ecological, or hydrological drought conditions. In this role, AI/ML can strengthen drought assessment by improving the underlying information available to analysts rather than simply automating the final classification.

Another AI/ML application showing great promise is in drought forecasting and early warning. Recent studies demonstrate that ML models can skillfully predict hydrologic drought conditions and streamflow deficits at subseasonal-to-seasonal timescales (Hammond et al., 2025). This application is particularly useful for drought practitioners and watershed managers as it allows for more proactive approaches for managing drought. At the same time, forecasting systems trained on historical data inherit assumptions embedded in the training period, including historical relationships among climate variables, impacts, and drought classifications. As nonstationarity intensifies, AI/ML drought forecasting systems may therefore require continual retraining, explicit treatment of shifting hydroclimatologies, and careful evaluation under conditions outside the range of the historical record. AI/ML forecasting systems should therefore be viewed as evolving decision-support tools whose performance and interpretation depend strongly on the stability, representativeness, and transparency of the data and assumptions on which they are trained.

AI/ML may also support convergence-of-evidence approaches, although this application requires caution and careful governance. For example, AI/ML and Large Language Models, or LLMs, could help organize diverse datasets, identify converging/conflicting signals among indicators, summarize impact reports, flag regions where classifications are particularly sensitive to reference periods, and document how different lines of evidence contributed to an assessment. These tools may be particularly useful in operational settings where analysts must quickly synthesize large volumes of spatial data, model output, field reports, and impact information under time constraints. With appropriate caution and careful formulation, hybrid approaches leveraging both human-expert knowledge and AI/ML data synthesis/reporting could make convergence-of-evidence assessments more consistent, transparent, and reproducible. However, these tools should not replace expert judgment, local expertise, Indigenous and TEK, or practitioner experience. Their value may be greatest when they help analysts see more evidence, understand uncertainty, and document reasoning more clearly while preserving the contextual knowledge that remains essential to drought assessment.

Special care is advised, particularly during the ongoing period of rapid AI/ML innovation and as the use of AI/ML is adopted more widely, to ensure methodological transparency, reproducibility, and an avoidance of bias. In particular, AI/ML can produce results absent understanding, which could undermine scientific advances while also perpetuating inequalities and unfairly affect people if not wielded carefully (e.g., Ferrara, 2024; González-Sendino et al., 2024; Cuesta, 2026; Jarrahi et al., 2026). Good governance and sustainable and ethical use of AI/ML are important in ensuring an overall net benefit to society (Gaffney et al., 2025).

7
Drought Impacts, Impact Data, and Nonstationarity

This chapter focuses on drought impacts, explicitly defined as an indicator of the potentially harmful outcomes of drought. Drought impacts are highly variable between systems (e.g., ecological vs. hydrological) and communities (e.g., Indigenous peoples vs. municipal water users), and the current infrastructure for collecting, reporting, and assessing drought impacts similarly varies across regions, sectors, and drought types. Nonetheless, drought impacts are an essential element of drought assessment and are affected by nonstationarity both in the manifestation of the hazard itself and in societal and ecological changes shaped by dynamic vulnerabilities and adaptation decisions.

DROUGHT IMPACTS

Drought impacts are different from indicators and indices in important ways. Drought indicators are raw variables or parameters that describe a hydrometeorological state such as precipitation, temperature, soil moisture, streamflow, or groundwater level. By comparison, in environmental contexts, an impact is the direct or indirect effect that a hazard or disaster has on a particular system, place, or people and culture (Lindell, 2013). This can include damage or destruction to property, livelihoods, and environments, and it can reflect a reduction in the capacity for people—individuals, families, and communities—to maintain their standard of living and mental or physical health (Lackstrom et al., 2014). In drought, an impact extends beyond the social world to include effects on the health of landscapes, species, and ecosystem services. Impacts reflect the susceptibility to or actual harm from drought to a specific system and can be modulated by its onset, severity, duration, and mitigation efforts. An impact, then, is an expression of exposure combined with the adaptive capacity of an individual, group, or system to mitigate drought that results in harm to the system of interest (Lackstrom et al., 2013). An indicator of drought on a river system, for example, might include reduced river flows, while an impact to a river system might be fish kills or municipal water restrictions that result from reduced river flows. A system of structures, networks, and regulations (e.g., dam releases or recreation closures), however, might intervene in a drought to reduce damage to riparian areas, support fish and other species, and insulate downstream agriculture and tourism industries from economic losses. Impacts, then, are an important indicator of harm within the complex interaction of the hazard, exposure, and adaptive capacity of a system when affected by drought. For this report, the committee has adopted the following definition for drought impacts:

> *Drought impacts are the direct and indirect effects of a drought, resulting from the combination of a geophysical condition and human or nonhuman system vulnerability.*

For further clarity, Figure 7-1 provides examples of indicators, indices, and impacts for different drought types. Following this framework, unusually dry soil or low stream levels are not, by themselves, drought impacts, but instead are indicators of potential drought conditions. In these situations, indices would be statistical representations of the drought severity and/or rarity such as the Soil Moisture Volatility Index, or SMVI (Osman et al., 2024) or a streamflow percentile. Impacts in these cases would be, for example, the deleterious effect of dry soils on crop yields or fish kills caused by low stream levels.

Drought Indicators, Indices, and Impacts

Drought Type	Indicators	Indices	Impacts
Meteorological	Precipitation, ET	SPI, EDDI	N/A
Agricultural	Soil Moisture, Crop Greenness, ET	SMVI, VegDri, NDVI	Crop Yields, Irrigation Water Use
Ecological	Greenness, ET, Sap Flow, Wetted Riffle	NDVI, EVI	Flora/Fauna mortality, reproduction, growth
Hydrological	Streamflow, Water Table, Groundwater, Reservoir Level	Flow percentiles, Action Trigger Levels	Water Use Restrictions, Release Changes, Auxiliary Water Sources
Socioeconomic	Market Volatility, Geopolitical Stability, Food-Water-Energy Prices	Socioeconomic Drought Index, Time-Weighted Water Deficit and Backward Index	Higher Food-Energy-Water Prices, Poor Health Outcomes, Geopolitical Conflict

FIGURE 7-1 Examples of drought indicators, indices, and impacts for different drought types.

Drought impacts also serve other functions. Impacts inform drought products like the U.S. Drought Monitor (USDM) and have been used for decades to calibrate and validate numerical and physical drought models, including the Palmer Drought Severity Index. In this way, drought impacts can act as user knowledge as an expert heuristic to benchmark geophysical and numerical drought indices. Through a combination of scientific and on-the-ground observations, impacts can be combined to reflect a snapshot of a current or ongoing drought, which may help communities understand the environmental and societal effects of a drought (Lackstrom et al., 2017). Importantly, many governmental and policy entities use impacts as a trigger to determine what resources are needed and for whom (e.g., pasture damage triggering open haying in state-owned lands or deer disease and kills triggering a reduction in hunting tags made available). Impacts may likewise point to gaps in observation and monitoring systems that might otherwise permit individuals, groups, and organizations or agencies to employ mitigation strategies to enable future adaptive capacity.

Conclusion 7-1: Impacts are complicated manifestations of drought, but they are nonetheless critical to the entire drought assessment process.

Drought Impacts: Stakeholder Perspectives

For those who have lived in a particular place for generations and have developed a deep relationship with it, drought impacts are more than indicators in a hazard cycle. Impacts can reflect the overall health of peoples' relationship with their ecosystem, including misalignments between them. Perception of impact magnitude can also signify people's calibration to long-term experience of "normal," which can manifest with descriptors like "worst I've ever seen." This is certainly true for Tribal peoples whose identity and culture are tied to place. But it can also be true for agricultural producers who depend upon the orderly coming and going of seasons for their livelihoods. Water managers, ecologists, and natural resource managers may be more able than Tribes and agricultural producers to set aside drought impacts when they go home at the end of the workday, but drought nonetheless affects them.

Tribes

For Tribes, Native Hawaiians, and Alaskan Natives, drought impacts may be best understood in the context of an approach to the environment embodied not by traditional Western scientific practices but by knowledge systems like Traditional Ecological Knowledge, or TEK, which is characterized by a comprehensive and integrative approach to human and natural systems. Indigenous peoples who have inhabited regions of the United States for centuries, for example, have developed long-term observations of past social-ecological interactions and often reveal important insights into changes in species diversity, ecological processes, land management outcomes, and public health. Importantly, although characterized in traditional scientific narratives as subjective, TEK holds significant value in its deep-time perspective, which as many studies have detailed, "may be leveraged to define baseline conditions, establish restoration targets, track global change impacts, and serve as an early warning system of large-scale ecological state transitions" (Souther et al., 2023). Incorporating TEK and related perspectives may allow drought assessment frameworks to become more useful and usable to Tribes and Native communities, integrating them into their lived experiences with drought. Such frameworks may likewise expand timelines for early drought detection and reshape the nature of impacts that are collected to include more indirect impacts (e.g., mental or public health) or impacts that are difficult to measure (e.g., community relationships with the ecosystem). The National Integrated Drought Information System (NIDIS) Tribal Drought Engagement Strategy 2021–2025 (Bamford et al., 2020) documents collaborative work between NIDIS and Tribes in the Missouri River Basin and Midwest in support of enhanced and inclusive drought early warning.

Agricultural Producers

When drought limits water availability, crops suffer from reduced plant growth, yields, and crop quality. Rainfed agriculture is affected through reduced precipitation. Irrigated agriculture is affected if drought reduces snowpack, streamflow, or groundwater recharge, all of which can prevent replenishment of stored water supplies. In rangeland livestock systems, drought reduces summer forage availability, as well as yields of the irrigated hay crops that are often required to feed livestock over the winter months when forage resources are not available due to harsh weather conditions. These drought impacts reduce farm/ranch income, which in turn can affect the broader economy in rural, agriculture-dependent communities through reduced harvest and processing activities and reduced spending by directly affected farm/ranch households.

A dry year creates uncertainty for agricultural producers. A row crop farmer wonders whether crop sales will be enough to cover the operating loan they received from the bank at the start of the growing season. A rancher wonders whether their livestock will gain enough weight grazing on rangelands with reduced grass availability. They also wonder whether the lower yields on their alfalfa and other hay crops will lead to a feed deficit for their livestock over the harsh winter months; and if so, how far they will have to travel (and pay) to purchase replacement hay. These impacts can cascade to increased food prices, possibly resulting in increased food insecurity locally and nationally.

If the drought is severe, the farmer wonders whether the negative impacts of drought will be enough to trigger federal financial assistance to help them manage their losses. The livestock producer wonders if they need to sell cows whose genetics they may have spent years refining, even though rebuilding the herd in the future will be expensive. In the Western United States especially, these agricultural producers also observe the drier grass and feel the dust around them, which increases their stress around heightened wildfire risk. An agricultural producer may be able to weather a drought year, but two or three such years will begin to wear on their financial reserves and their mental health (Yazd et al., 2019; Linder et al., 2025). Such strain on producers can have indirect impacts, such as negative mental health outcomes (OBrien et al., 2014), especially for those in rural areas.

Water Resource Managers

Water managers at municipal utilities and other public water supply systems are responsible for supply, treatment, and distribution of water to their customers. The built infrastructure facilities that they operate (reservoirs, canals, drinking water, and wastewater treatment) allow them to manage a certain level of variability in year-to-year water supply availability and customer water needs. When drought lasts longer or is more severe than the built infrastructure was designed for, drought impacts begin to emerge. Water managers may need to impose frequent water use restrictions that inconvenience their customers or consider cost decisions such as leasing agricultural water for short-term response. In more extreme cases, communities may experience shortfalls that threaten human health. Reduced streamflow may increase water temperature, creating challenges for nuclear and thermal power plants that rely on water to cool plant reactors. Reduced streamflow can also lead to water quality impairment in wastewater treatment systems that rely on high dilution. Drought may also harden the soil, preventing infiltration and leading to greater runoff and flood risk.

Natural Resource Managers

Reductions in water flow and volume in rivers, streams, and lakes can lead to habitat fragmentation and biodiversity loss. Wetlands can diminish in size, reducing habitat for numerous aquatic species, amphibians, and migratory birds. Normal migration patterns of aquatic and terrestrial species can be disrupted. Water quality is also often compromised by drought. Decreases in water flow and volume can lead to higher water temperatures and increases in algal production. Pollution present in water bodies is also less easily diluted when water flows and volume are low (Mosley, 2015). Especially during prolonged periods of drought, threats to natural systems from drought can be exacerbated by increased extractions for agricultural and municipal water uses.

Conservation policies to protect plant and animal species have generally been designed for a stable climate, yet climate change is shifting habitat and growing conditions. Protected areas may no longer support the plant and animal species for which they were established. Plants may shift their range, and animal species that have historically been protected may move to new areas that lack legal protections, in search of water or more desirable climate conditions. Wildlife may find their migration patterns disrupted in time or space, whether by drying wetlands, wildfire, or shifting timing in food source availability. Further, wildlife and natural resource managers can find ecosystem restoration more challenging when historical conditions are no longer attainable due to climate change. Ecosystem transformation has emerged in recent decades to support healthy and productive ecosystems in the face of significant climate and environmental change (Jackson, 2021). Natural resource managers are confronted with myriad decisions in this process, many under deep uncertainty and resource limitations (Crausbay et al., 2022). From these significant challenges have risen multiple, effective frameworks for guiding natural resource management decisions toward ecological transformation. One of the most prominent is the resist-accept-direct (RAD) framework (Schuurman et al., 2020), which characterizes decisions on a spectrum between the categories of resisting change, accepting change, and directing change.

RISK FRAMEWORK FOR IMPACTS

Drought impacts, by their very nature, are partly determined by humans and human actions. Returning to the risk-informed drought assessment framework introduced in Chapter 1, the risk of a drought impact can be framed as an interaction among the drought hazard and the system's exposure and adaptive capacity. The drought hazard is a physical meteorological or hydrological process described in previous report chapters, and drought is often characterized with indicators and indices. Agricultural, water resource, cultural and social, and economic or market systems exposure and adaptive capacity are human constructs, and are largely determined by decisions in policy, planning, and engineering. For example, the same meteorological conditions (i.e., the hazard) could elicit a significant drought impact for an undersized or outdated water supply system compared to an adequately sized system (i.e., the exposure or adaptive capacity). In this case, the relationship between a geophysical indicator, like precipitation anomalies, and a drought impact will be very different between the two water systems because of the systems' different exposures and adaptive capacities. For ecological systems, exposure and adaptive capacity can be complex mixes of human and nonhuman constructs that can be determined by decisions in policy, planning, and management, but are also determined by nonhuman factors such as biodiversity, ecological synergies, and species-level disturbance and stress resilience (Crausbay et al., 2022). It is therefore critical that advances in drought impact reporting and data collection account for the inherent dependence of impacts on exposure and adaptive capacity from both human and nonhuman causes.

> *Conclusion 7-2: System exposure and adaptive capacity are important parts of the risk of drought impacts, and changes in either can affect the likelihood and/or severity of a drought impact. Therefore, along with drought impact data, drought assessment should*

regularly collect and report information on changes in a system's drought exposure and/or adaptive capacity.

Risk-informed drought decision-making relies on drought impact information to understand current conditions but also relies on documented drought hazard-impact relationships to predict potential future impacts for both emergency management and long-term planning applications. The risk of a drought impact can change with an increase or decrease in a system's exposure and/or adaptive capacity, irrespective of any changes in the drought hazard (examples include growing human demand for water resources, ecological shifts that increase disturbance impacts, and others described in Ashraf et al., 2021; Hadley et al., 2021; Rodíguez-Flores et al., 2023; Coder et al., 2025). Therefore, drought assessment frameworks need to be proactive in updating system-specific attributes of exposure and adaptive capacity so that they can properly assess, forewarn, and communicate the potential of a drought impact corresponding with a particular drought hazard. For example, if a water supply reservoir increases its storage capacity through expansion or dredging, it may increase its adaptive capacity to drought and therefore decrease the risk of a water supply drought impact. This information on changes in system exposure and/or adaptative capacity are equally important to document and communicate as changes in a drought hazard itself. Local and state governments and agencies can address this challenge of estimating drought impact risk via changes in exposure and/or adaptive capacity through regular and robust data collection including public and commercial water use, water resource health assessments, and ecosystem drought resilience assessments, as well as through planning such as regional water supply planning, hazard mitigation planning, and stress-test and tabletop drought exercises.

Conclusion 7-3: Assessment of drought impacts requires information on drought conditions as well as the status and adaptive capacity of affected systems to inform operational drought response and long-term planning, but mechanisms for collecting and using such data do not exist consistently across the United States. State government agencies (e.g., natural resource, agriculture, and environmental protection agencies) in collaboration with local governments may be best positioned to undertake collection of data and planning that are relevant to drought exposure (e.g., water use, stream gauge, and low flow measurements) and adaptive capacity across systems (e.g., through water supply and hazard mitigation plans) and use of that information to reduce drought impact risk (e.g., tabletop exercises of existing drought plans).

DROUGHT IMPACT DATA, COLLECTION, AND REPORTING

Drought impact information is widely used for local- and state-level drought assessment, including triggering specific mitigative actions. For example, the Missouri Drought Mitigation and Response Plan uses drought indicators and indices to determine the state's drought phase and to scope potential mitigative actions; however, the plan uses drought impacts to determine which mitigative actions should be enacted (Missouri DNR, 2023). Drought impact data are also used to establish relationships with geophysical indicators such as precipitation anomalies and indices like the Palmer Drought Severity Index. Strong and reliable relationships between drought indicators and impacts are necessary to effectively predict, forewarn, and assess drought impacts in a systematic and scientifically robust way. The connection between physical drought indicators and their societal and ecological consequences is neither automatic nor uniform across regions and sectors. Traditional drought monitoring has focused primarily on physical anomalies, with limited systematic documentation of impacts. This gap impedes calibration of monitoring systems to real-world relevance and obscures understanding of which physical conditions translate into which types and magnitudes of consequences (Enenkel et al., 2020).

Many peer-reviewed studies over the past few decades (see, e.g., Bachmair et al., 2015; Stagge et al., 2015; Parsons et al., 2019; Kchouk et al., 2022) have worked to establish relationships between drought indicators and impacts with varying levels of success. However, innovation in drought impact prediction and assessment with more easily measurable and quantifying indicators has been impeded by the continued lack of systematic and holistic drought impact data collection and cultivation. Advances in artificial intelligence (AI) and machine learning (ML) and participatory design in recent years have greatly improved the collection, useability, and actionability of drought impact data and the incorporation of expert knowledge. Large language models (LLMs), in particular, have shown promising benefits in more exhaustively collecting and synthesizing drought impact information (Shang et al., 2025; Wang et al., 2025), which could help fill in significant impact information gaps to improve all phases of drought assessment. However, continued work is needed by the entire drought impact community to expand and standardize impact collection so that drought assessment activities are grounded in accurate and representative drought impact information.

Drought Impact Data

Drought impact data are invaluable for all parts of drought assessment and are necessary to understand and predict relationships between geophysical indicators and social, economic, and environmental repercussions of drought. However, the diversity and complexity of drought impacts, even within one geographic region, have impeded the development of a systematic framework by which impacts can be easily and consistently integrated in drought assessment. Nevertheless, impact data have been an important component of drought assessment in the United States for decades. Drought impact information is collected by state, local, and Tribal scientists and officials through regular contact with individuals and groups representing public and private sectors that are affected by drought.

The diversity of drought impact reporting capacity, responsibility, and interest between state, Tribal, and federal entities has created a complex patchwork of drought impact reporting pipelines, which has resulted in some states or sectors having more efficient and effective drought impact reporting than others. The myriad drought impacts are reported to different organizations, including University Extension and state departments and agencies. Some local-level federal offices such as the Natural Resource Conservation Service (NRCS) and Farm Service Agency (FSA) have collected drought impact information; however, this effort has largely been the individual offices' decision without task from federal U.S. Department of Agriculture (USDA). Each of these organizations have different ways of collecting, reporting, and using the impact information, often with varying degrees of documentation and protocol. Some entities have developed systems to facilitate effective drought impact data collection, including web-based tools for individuals and organizations to report drought impacts. For example, Montana developed a statewide drought impact reporting system to streamline the impact data collection process and to better inform drought decision-making. The National Drought Mitigation Center (NDMC) has similarly developed a nationwide tool for drought impact and condition reporting, the Condition Monitoring Observer Reports on drought (CMOR, Smith et al., 2021) tool. While drought impact data largely remain much more inconsistent and disorganized, CMOR and state-level impact data collection services have improved impact information flow into drought assessment in recent years. Similarly, citizen science initiatives, such as the Community Collaborative Rain, Hail, and Snow (CoCoRaHS) network have grown self-reported drought impact systems that have greatly benefited drought monitoring and post-event assessment (Lackstrom et al., 2017)

Agricultural impacts of drought arguably have the most refined and systematic impact data collection frameworks in the United States, largely facilitated by the USDA. Agricultural impacts, such as disrupted or delayed field work, stunted crop growth, elevated irrigation demands, poor pasture conditions, and decreased yields, are reported by agriculture special interest organizations such as state farm bureaus and crop associations. Weekly crop and soil condition and progress have been regularly reported during growing seasons for several decades, in a reliable and accessible format that permits relatively easy drought assessment and scientific research. Equally reliable annual reports of indemnity payments by federal government programs have similarly facilitated advancements in the understanding of the socioeconomic impacts of agricultural drought on high-value crops and production systems across the United States.

Impacts to water resources and other hydrological data collection and cultivation are often available for use in drought assessment. Drought impacts to hydrology and water resources are tracked and data collected by federal, state, Tribal, and local governments as well as by semiprivate or private water management groups, and private citizens. For example, drought impacts to public supply water reservoir levels may be reported by the Army Corps of Engineers, one of many state agencies, or local municipalities, depending on the ownership and management of the water body. In these cases, the regular stream stage or reservoir level data collected and reported by federal or state governments must be married to the stage or level at which an impact may occur (such as reduced water intake capacity for potable water supply) to predict, forewarn, or assess the hydrological drought impact. The U.S. Geological Survey (USGS) and National Oceanic and Atmospheric Administration (NOAA), in collaboration with state agencies and local governments, have taken great strides in standardizing this important surface water resource impact information to help guide management decisions and actions; however, more work and coordination are needed to improve the reliability and actionability of hydrological drought impact information. Furthermore, human-induced changes in water demand or supply in surface water systems can reduce the predictability of water supply impacts from drought, and therefore the indicator-impact relationships must be regularly updated.

The inconsistent relationships between geophysical variables and hydrological or water resource drought impacts are even more complex for groundwater systems. Both unconfined and confined aquifer systems can be affected by drought through reduced recharge and increased water demand and dewatering. However, groundwater monitoring, modeling, and projection are challenged by a significant lack of measurements and geologic characterization coupled with rapid changes in water demand. The underlying geology largely determines the groundwater recharge rates following significant drought, and this information is difficult to obtain at the spatial scales needed for accurate water supply planning in groundwater-dependent regions. Furthermore, the longer timescales of groundwater drought response and recovery relative to the more rapid responses for agricultural and surface water responses and recovery can challenge traditional drought assessment systems and indicators. Recent and continued advances in large-scale groundwater resource monitoring via remote sensing, combined with more efficient AI-assisted modeling and advanced physics-based modeling, have the potential to greatly expand the ability to assess groundwater resources and their response to drought. It is important for drought assessment frameworks to develop the flexibility to incorporate the growing wealth of groundwater information as these innovations continue.

Private industries can also be an important source of drought impact information. Examples include reports from energy and power generation companies affected by reductions in power production from surface water-cooled power plants, transportation and logistics companies affected by reduced maritime traffic due to restrictively low river levels, and insurance and reinsurance companies affected by increased damage claims from crop loss or fire damages.

Ecological impact data collection is arguably the least well developed in the United States. This is partly due to the relatively recent acknowledgment of ecological drought as an important form of drought that is separate from agricultural drought, the complexity and varied timescales of ecological response to and recovery from drought, and the relatively indirect economic and social impacts and mitigation of ecological drought. Natural resource impacts, including to aquatic and terrestrial ecology, are reported by scientists and natural resource managers, as well as by recreation and outdoor enthusiasts. Ecosystem health and species collections are two examples of critical ecological drought impact data and are often collected by federal agencies such as the U.S. Forest Service and National Park Service, various state agencies, Tribal experts, local government units (e.g., forest preserves), university and nonprofit organization scientists, and private citizens. These data are critical for post-event drought assessment and scientific research on ecosystem drought vulnerability, as well as to inform ecosystem management and adaptation decisions from local to federal scales. One of the strengths of ecological drought information is the long legacy of species data collection across the United States, in some cases dating back centuries (Bellew and Boudreau, 2025). These records, while sometimes inconsistent, allow scientists to establish drought-ecosystem relationships that can transcend the multidecadal internal variability of the climate system, and establish a robust record of long-term change in ecological composition and health (Rocha-Ortega et al., 2021). Additionally, ecological information, such as tree rings and fire scars, provide useful information for regional drought risk assessment that spans farther into the past than any direct weather observations. However, there remain significant gaps in actionable ecological drought impact data. Remote sensing has helped reduce this information gap by providing virtually real-time indications of ecosystem response to environmental conditions; however, more work is needed to better establish reliable triggers and thresholds directly corresponding to drought impacts across different ecosystems and to support effective ecological transformation. These research and data needs are arguably greatest in the nation's most heterogeneous ecosystems: urban areas. Drought can have significant impacts on urban ecology, including reducing ecosystem services of green infrastructure such as tree cooling potential. The plethora of microscale environments and inconsistent human intervention in urban areas limit the potential usability of traditional remote sensing tools for ecological drought impact information collection. One advantage of urban environments is the high density of potential reporting sources. Advancements in citizen science ecological monitoring and reporting, in particular, have helped fill gaps in urban ecological drought monitoring, and these citizen reports have been used in recent urban drought assessments (e.g., Lackstrom et al., 2017; Brown and Williams, 2019).

Other Approaches to Collecting Impact Data

Recent initiatives have begun to address this deficit of impact data through systematic impact documentation. The European Drought Impact Report Inventory, containing nearly 5,000 impact reports from 33 countries, reveals the same prioritization of agricultural and public water supply impact reports, which dominate documented drought consequences (Stahl et al., 2016). The National Drought Mitigation Center's Drought Impact Reporter has similarly collected impact information from traditional and social media, government and private sector statements, citizen science initiatives and other sources, and provides these reports in a consistent and easily accessible format (Smith et al., 2014). Global assessments using geocoded disaster databases demonstrate that correlations between physical drought indicators and reported impacts vary by region and impact type, with hazard metrics derived from land reanalysis showing stronger relationships in some contexts than others (Kageyama and Sawada, 2022).

Emerging methods for automated extraction of impact information from social and news media offer potential for near-real-time impact monitoring at unprecedented spatial and temporal resolution (Shang et al., 2024). The Social Drought dataset, comprising over 1.5 million social media posts aligned with expert-verified news articles and U.S. Drought Monitor classifications, demonstrates proof of concept for integrating conventional meteorological data with unconventional social media signals to provide holistic understanding of drought impacts. However, significant challenges related to data quality, representativeness, algorithmic bias, and interpretation remain before such approaches can be operationally integrated (Shang et al., 2024). While recent advances have been made in the collection of drought impacts from social and traditional media, including through crowd-sourcing, there has been relatively little advancement in the ability to process, interpret, and communicate these huge datasets to support effective drought decision-making.

The operational value of impact data extends beyond validation of physical monitoring systems. When drought severity classifications can be explicitly linked to impact thresholds, decision-makers can establish consistent triggers for interventions, allocate resources based on demonstrated need, and communicate risk in terms that resonate with affected populations (Stahl et al., 2016). The drought classification scheme presented in Table 6-1, while defined on a standardized statistical scale, gains operational meaning through calibration against observed impacts in specific sectors and regions.

Conclusion 7-4: The growing wealth of drought impact information presents an opportunity to improve drought assessment at national, state, and local levels, especially as innovations and AI and other technology and science continue to be developed.

Recommendation 7-1: NIDIS should work with decision-makers, scientists, and the broader drought community to develop a set of best practices by which drought impacts data can be consistently and effectively used for all aspects of drought assessment, especially for state drought plans and other policy and action plans.

Drought Impact Data Collection and Use

Drought impacts are used both for internal state and local government decision-making and to inform nationwide drought monitoring and mitigation efforts. State agencies and organizations, including state climate offices, collect drought impact information through regular and sometimes mandated contact with local governments and agencies as well as private citizens. The information may be regularly collected irrespective of drought conditions or may only be collected and communicated when drought is recognized by the state. Many states have integrated drought impact collection and data into their drought preparedness and mitigation plans, and these plans have linked specific policy or regulatory actions to impacts. Similarly, local governments and decision-makers often look to drought impacts to inform mitigative actions, including water conservation measures and burn bans.

Drought impact data are also used by private industries and can sometimes significantly affect economic markets. This is especially the case with agricultural drought impact data, including crop progress and yield information that are regularly collected and reported by the USDA. Agricultural drought impacts are also critical for traditional (i.e., not parametric) insurance programs offered by state and federal governments and by private insurers. Because drought often reduces on-farm income, these programs are vital for agricultural production and profitability during and following drought years.

U.S. Drought Monitor

The U.S. Drought Monitor incorporates objective drought indices and indicators based on geophysical data as well as drought impacts information. The drought indices and indicators are based on historical data that have been converted into a percentile format that is directly relatable to the USDM Dx categories and are available every week nationwide; they are the primary tool used to determine the Dx status. However, the drought impacts data are not provided on a consistent weekly basis for all states and do not have the required historical record for conversion into a percentile format; consequently, they cannot be consistently incorporated in the same way drought indices and indicators are and must be evaluated based on local expert knowledge.

USDM authors use drought impact reports two ways. The first is to highlight areas that need to be examined in more detail with objective indicators. This typically happens when an area is not yet in a drought or abnormally dry status but is experiencing stress as indicated by the impact information, likely due to developing flash drought (for flash drought, impacts frequently lead the indicators). The second way is to refine a Dx status when the objective drought indices and indicators yield different signals (i.e., for different timescales [e.g., long-term vs. short-term], different sectors [e.g., agricultural vs. hydrological], or different products [e.g., soil moisture derived from in situ observations, remote sensing, and/or models]).

The key to the USDM methodology is the convergence-of-evidence approach. Ideally, the decision to assign a Dx status is dependent on the various objective drought indices and indicators "converging" to a particular drought state. This is also true for drought impacts information. In most cases, the impacts that are being experienced should be consistent with what the indices and indicators are saying (the exception being flash drought as noted above).

Impacts information is being collected and summarized by NDMC and CMOR, but better, more comprehensive, and standardized impacts reporting is needed: impacts information across a spectrum (e.g., when it is dry, when it is wet, and in between) and context (e.g., does it always look this dry in July, or is it an anomaly?).

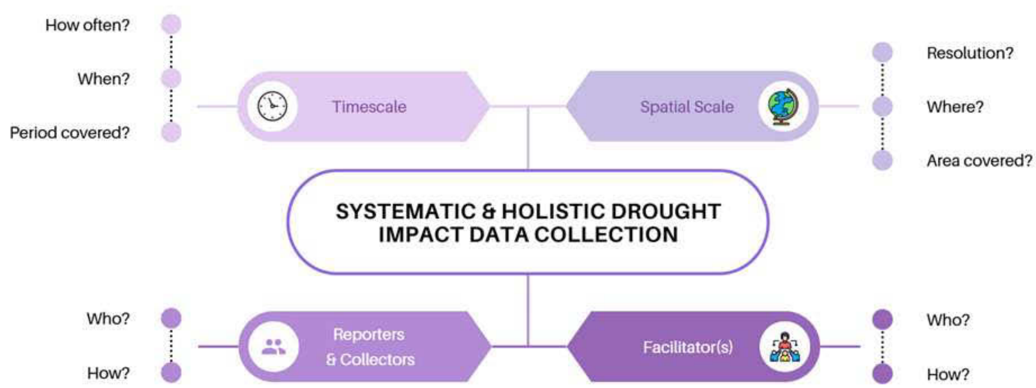
Conclusion 7-5: The current infrastructure for collecting and communicating drought impacts is inadequate and impact data are not collected evenly across drought impact types (e.g., less actionable impact information for ecological drought), which has created uneven emphasis for drought assessment and response on some systems (e.g., agriculture) over other systems (e.g., wetlands) that are impacted by drought.

Recommendation 7-2: NIDIS should facilitate the development or improvement of systems for systematic collection, reporting, and integration of drought impacts

consistently across sectors, regions, and interests, for multiple uses, including drought assessment, adaptation, and other decision-making. In this work, NIDIS should collaborate with the U.S. Department of Agriculture (agriculture and forest), Department of Interior (coastal, ecological, water resources), Department of Homeland Security (drought response/resilience, national security), Bureau of Land Management (fire, rangeland), Health and Human Services (public health), Environmental Protection Agency (water resources, air and water quality), and Tribal communities, as well as the broader drought community.

INCORPORATING IMPACT DATA INTO DROUGHT ASSESSMENT

Impact data are already incorporated in most aspects of drought assessment. However, the process by which this is done is inconsistent across states, regions, sectors, and drought events. Even within the U.S. Drought Monitor, impact data are not provided consistently in time or space, which forces the author to determine if and how they will use the patchwork of drought impact reports and data available. Furthermore, the current disorganized system of drought impact data cultivation impedes scientific understanding of relationships between drought indicators and impacts and effective prediction, early warning, and communication of those impacts. Therefore, proper incorporation of impact data into drought assessment requires expansion and improvement of systematic drought impact reporting across systems, regions, and interests. The required attributes of such a drought impact reporting system include (1) sufficient impact report frequency and spatial resolution for prediction, early warning, monitoring, and (ideally) impact mitigation; (2) sufficient timescales and periods of record to establish robust and reliable relationships between drought indicators and impacts; (3) dedicated and well-resourced groups of reporters and data collectors across the country; and (4) an entity or entities that can lead the facilitation of a nationwide drought impact data system. It is expected that the specific details of these four attributes will differ between drought types (e.g., surface water resources vs. forest ecology); however, all four attributes are necessary for successful incorporation of drought impact data into assessment (see Figure 7-2).



Timescale	Spatial Scale	Reporters & Collectors	Facilitator(s)
• Frequent enough for monitoring and early warning • Repeat time within resource limits • Relevant time for impact • Established legacy of reports for research, assessment, & posterity	• Fine enough for early warning and monitoring • Reasonable scale within resource limits • Reports in areas known to be affected by drought • Relevant spatial area for impact	• Interest holders with capability and capacity • Robust collection and reporting methods • Number of reporters reasonable within resource limits • Established relationships and engagement	• Groups/Agencies with relevant missions and mandates • Robust facilitation methods • Publicly available with reasonable latency • Historical data for assessment

FIGURE 7-2 Attributes of a system that can properly incorporate impact data into drought assessment.

The USDA's National Agricultural Statistics Service (NASS) provides a good example of this type of impact reporting system. NASS is in ongoing contact with USDA local and regional offices, Extension, state agriculture agencies, and individual farmers and producers, and they use this engagement to regularly collect information on crop and livestock progress, condition, and production. This system has most of the necessary attributes for drought impact data reporting and incorporation, namely that crop conditions and yields are reported at sufficient time intervals for both drought monitoring and post-event assessment; the impacts are recorded at either county or state level (which is often sufficient for agricultural drought assessment); and there is a long record of impact data stretching back decades in most places. The data are also easily available and accessible for all aspects of drought assessment. These attributes are present because USDA has been able to develop and sustain relationships with individuals and groups who are reporting and collecting impact information, and because USDA has had support to establish and maintain this impact data collection infrastructure.

While the USDA NASS data and reporting system is far from perfect, it is an example of a successful means of systematically and consistently collecting and cultivating impact data for drought assessment and can serve as a general model with which to develop similar drought impact reporting systems for other sectors and drought types. Another example of interagency collaboration toward a broader goal of hazard mitigation is the National Interagency Coordination Center (NICC),[1] which coordinates resources and support for wildland fire across

[1] https://www.nifc.gov/nicc

the United States. Whether ecological impacts, water resource impacts, or nonagricultural economic impacts, effective drought impact reporting and data systems must have each of the four attributes listed: timescale, spatial scale, reporters and collectors, and system facilitators (see Figure 7-2). Following this blueprint, drought impact collection, reporting, and data cultivation can be more easily standardized and compared across drought events and geographic regions and can more easily facilitate science research advancements in drought prediction, early warning, and monitoring.

Conclusion 7-6: Current drought impact reporting systems do not capture consistent or comprehensive drought impact information across time, geography, or drought types, which limits the usefulness of impact data to drought assessment and decision-making.

Nonstationarity

Drought impacts are strongly determined by the drought hazard and the exposure and adaptive capacity of the system of interest. All three of these components of drought impact risk can experience nonstationarity in both time and space. Therefore, drought assessment that explicitly uses impact data must account for nonstationarity in the geophysical hazard and or indicator used to characterize drought, and any potential nonstationarity in the exposure or adaptive capacity of the system of interest. Nonstationarity or changes in human practices that alter either a system's exposure or adaptive capacity change the drought-impact relationship and therefore the underlying risk of a drought impact, which is one aspect of anthropogenic drought (AghaKouchak et al., 2021). Similarly, drought can cause long-term changes in ecosystem structure and function, which themselves affect the exposure and adaptive capacity of the ecosystem (Müller and Bahn, 2022). Changes in the drought hazard or a system's exposure or adaptive capacity can also elicit new or newly discovered drought impacts, such as vector-borne diseases like Dengue (Lowe et al., 2021) and West Nile virus (Erazo et al., 2024), which have been linked to drought and hydroclimatic variability.

Just as emerging or newly discovered drought impacts can be an effect of nonstationarity, so, too, can changes in the characteristics of more familiar impacts, such as impacts to agricultural production and electricity generation. For example, based on observed nonstationarity in agricultural loss data, some analyses have recommended that federal crop insurance programs adopt shorter loss histories for setting premiums while using longer time series to capture extreme events (Coble et al., 2011). Similarly, in its 2022 Integrated Resource Plan, the Pacific Gas and Electric Company (PG&E) moved from using a 30-year historical average hydroelectric generation conditions to a 15-year average for which the impacts of climate change are more apparent (PG&E, 2022).

An ideal drought impact collection and reporting system should be flexible enough to respond to new or newly realized impacts and emerging threats.

Conclusion 7-7: Changes in human and nonhuman systems create nonstationarity in drought impacts and can change the impact-indicator relationship.

Conclusion 7-8: Drought impact collection and reporting systems need flexibility to respond to new or newly realized impacts and emerging threats.

8
Framework for Incorporating Nonstationarity into Drought Assessment

VISION

Given the challenges raised by nonstationarity that have been discussed in the preceding chapters, drought assessment should increasingly be designed around a two-pronged drought analysis framework that delineates and addresses the specific needs of (1) short-term operational assessments for activities like emergency management and (2) long-term planning assessments for activities like adaptation, depending on the application. A nonstationary drought analysis framework should start from the decisions it is designed to support, not purely from the statistical machinery.

At the shortest horizons, key decisions include insurance payouts, contract triggers (e.g., of parametric insurance contracts), regulatory oversight, state- and local-level policy decisions, and damage compensation based on drought severity categories. For these operational/emergency management applications, the priority is stability, transparency, and regulatory and stakeholder acceptance of the indices used to make decisions.

A sensible vision for this short-term operational drought assessment is to rely on contemporary baseline periods on the order of 30 years (± 10 years depending on the type of drought assessment, systems of interest, and decision frameworks), to keep the reference climatology aligned with contemporary conditions, but to avoid overly complex time-varying parameterizations that require much longer data records. (Figure 8-1 shows a conceptual illustration of baseline choice in drought assessment; in this figure, the blue line indicates constant mean). In practice, this means using well-established indicators (e.g., Standardized Precipitation Index [SPI] or Standardized Precipitation Evapotranspiration Index [SPEI]) calibrated on a moving or periodically updated baseline, with careful documentation of how baselines are selected and refreshed so that terms of use remain clear and reproducible for all parties. Given the relatively short baseline period in this framework, the contemporary baseline could reasonably be treated as stationary (blue line in Figure 8-1). This approach aligns with the so-called updated stationary analysis (Luke et al., 2017), in which the latter portion (e.g., ~30 years) of a nonstationary time series is modeled under a stationary assumption. Furthermore, using a shorter baseline can improve responsiveness to evolving climate conditions, but it also increases sampling uncertainty and can reduce the stability of percentile-based thresholds, underscoring the need to balance responsiveness with robustness when selecting the baseline length.

At the other end of the spectrum are long-term planning decisions in water resources management, environmental restoration, critical infrastructure decisions, ecosystem conservation, and climate adaptation more generally. These long-term planning decisions must consider how drought hazard may evolve over years to many future decades. Here, the vision shifts toward explicitly nonstationary probability models that allow distribution parameters to change over time and with physical covariates. Baselines need to be longer, ideally 60 years or more (75 ± 25 years), and should integrate observational records, reanalyses, and climate model output to capture a wide range of variability and trend behavior (red line indicating changing mean in Figure 8-1). While the baseline is typically derived from the historical record, it may also incorporate future predictions and projections depending on the purpose and design of the modeling framework (see the long-term reference period in Figure 8-1).

Long records, including paleoclimatic records, matter here for two reasons. First, long-horizon decisions are exposed to low-frequency climate variability and regime shifts (e.g., due to climate change, multidecadal ocean–atmosphere variability, land-cover change, slow groundwater and ecosystem responses, and other factors) that cannot be characterized reliably with short baselines. Second, robust estimation of tail risk and return levels for rare, high-impact droughts requires enough data to constrain extremes and avoid overfitting trends to short-term fluctuations. As a result, drought assessment to inform long-term planning should use the full available record and explicitly account for nonstationarity across the entire period, rather than a regular resetting of the reference frame to a recent window. In other words, the goal is not simply to update a baseline, but to model how the drought distribution has changed and may continue to change, conditional on physically meaningful drivers. For example, planners might use nonstationary frequency analysis of a standardized drought index where the distribution parameters (e.g., location, scale) evolve with global temperature, regional circulation indices, or greenhouse gas concentrations, then propagate these evolving distributions into design criteria for reservoirs, groundwater management rules, and environmental flow requirements (Ragno et al., 2019; Katz et al., 2013; Renard et al., 2006).

Adopting a nonstationary framework is required to meet the challenge of climate change and natural variability, 1) based on the high-confidence knowledge that temperatures will continue to increase as long as greenhouse gases continue to be added to the atmosphere and 2) given that the same human-caused climate change will in some cases force changes in precipitation, both in regional monotonic drying or wetting trends and in altering variability patterns on interannual to multidecadal timescales (IPCC, 2021). This report recognizes the need for increased climate research to support drought assessment and adaptation to drought (see Conclusion 3-5), and it is already clear that both human-forced change and internal climate system processes will change drought risk in nonstationary ways over decadal and longer timescales. Even in cases where uncertainty exists regarding the cause of observed decadal to multidecadal precipitation change (e.g., in the headwaters of the Colorado River and Rio Grande [e.g., Seager et al., 2023, Kuo et al., 2025; Klavens et al., 2025; Todd et al., 2025]), the paleoclimate record makes it clear that multidecadal droughts can persist for decades to centuries (Gangopadhyay et al., 2022; Williams et al., 2022a), and likely even longer (e.g., Todd et al., 2025). This knowledge can be critical for adaptation efforts, for example, in ensuring sustainable water use or ensuring that communities are safe from catastrophic wildfire impacts.

Adopting this nonstationary framework has downstream implications for the economic evaluation methods on which long-term decisions rely. Federal and state agencies use cost-benefit analysis built on stationary climate assumptions: discount rates applied to benefit streams assumed to follow historical hydroclimate distributions, and infrastructure performance evaluated against a fixed reference climate. Under nonstationarity, however, these methods systematically underestimate the benefit of building flexibility into adaptation decisions and the costs of switching from one adaptation pathway to another when conditions evolve differently than expected (Haasnoot et al., 2020). Frameworks that explicitly evaluate sequences of investment options, rather than single static investments against a stationary baseline, are increasingly used in adaptation planning internationally, but are not yet standard in U.S. federal agency practice. A drought assessment framework designed for long-term planning is incomplete without paired updates to the economic evaluation methods used to act on it.

Practical Considerations Associated with this Vision

Building on the two-pronged approach toward drought assessment based on application and timescale described above, this section discusses practical considerations and choices that must be made when implementing the framework, including the use of additional covariates and variables, and persistence of trends. A framework for incorporating nonstationary considerations into drought assessment needs to have flexibility for application across a wide range of settings with different drought drivers and manifestations. Drought assessment, particularly for long-term planning, should also accurately capture current understandings of future trends.

Additional covariates. While temporal nonstationarity is often modeled as a function of time, other physics-based nonstationary covariates (e.g., land use and land cover (LULC); local water demand; temperature) can also be considered (i.e., modeling changes in drought severity or frequency as a function of changes in LULC or temperature).

Additional variables. Any drought-relevant variable (e.g., precipitation, snowpack status, soil moisture, groundwater, evapotranspiration) or drought indicator can be used within this framework (y-axis in Figure 8-1).

Trend persistence. When modeling future droughts by extrapolating a nonstationary trend inferred from historical observations, the modeler should explicitly consider whether that trend is expected to persist. This is often a strong assumption and should be evaluated using future climate model predictions and projections as well as theory and observational evidence (e.g., whether the inferred trend can physically continue to increase, given constraints on atmospheric moisture supply, land-surface feedbacks, or groundwater depletion). From a practical viewpoint, the future can be represented either with a stationary assumption (e.g., a constant mean; dotted blue line in Figure 8-1) or with an explicitly nonstationary specification (e.g., a changing mean; dotted red line in Figure 8-1).

Applying This Vision

The committee recommends adopting a decision-first, two-pronged drought assessment framework that explicitly links baseline choice and statistical assumptions, and methods, to the decision context for both short-term operational drought assessments used for emergency management, and longer-term assessments designed to support long-term planning.

For short-term operational assessments aimed at predicting subseasonal-to-seasonal changes in drought conditions (prediction and early warning), characterizing current drought conditions (monitoring), analyzing the characteristics of a recent drought event (post-event assessment), or assessing potential changes in regional to local drought characteristics under the current climate (projection), the community should standardize an updated stationary approach based on contemporary baselines (e.g., 30 years ± 10 years, depending on the type of drought assessment, systems of interest, and decision frameworks), with clear rules for baseline refreshing, documentation, versioning, and reproducibility.

For long-term planning drought assessments designed for multiyear expectations of drought conditions and impacts (prediction and early warning), for analysis of recent drought events in the context of a region's or location's long-term drought history (post-event assessment), and for long-term planning and drought impact mitigation (projection), the framework should emphasize explicitly nonstationary models that use the full available observational record (including the paleoclimatic record), and model-based predictions/projections and allow statistical parameters to evolve with time and/or physically meaningful covariates (e.g., temperature, circulation indices, water demand, LULC).

Because appropriate methods and baselines are decision dependent, this framework should be co-developed and maintained by a consortium spanning (1) the research community (to advance methods, data, including paleoclimatic data, diagnostics, uncertainty quantification, and open-source reference implementations); (2) operational agencies and practitioners (e.g., water agencies, drought monitoring systems, infrastructure owners) who can define decision requirements and operational constraints; and (3) standards and regulatory stakeholders (e.g., professional societies, guidance-setting bodies, insurance regulators) to ensure transparency, stability, and acceptance for high-stakes applications.

Box 8-1 describes additional considerations for an improved national drought assessment framework.

BOX 8-1
Considerations for a National Drought Assessment Framework

Examples of useful components of a more application-tailored drought assessment framework:

Decision-specific guidance: shared guidance specifying baseline lengths, update frequency, documentation standards, and reporting requirements for short-term and long-term drought assessment, specific to the application at hand.

Reference implementations: open-source, modular toolkit implementing both tracks (updated-stationary and explicitly nonstationary), with consistent outputs (e.g., return levels, exceedance probabilities, category thresholds) and standardized uncertainty reporting.

Benchmarks and stress tests: benchmark datasets and stress tests across hydroclimatic regimes to evaluate sensitivity to baseline length, covariate choices, and assumptions about trend persistence (i.e., stationary vs. nonstationary).

Governance and change management: operationalize governance for updates (i.e., who updates baselines, how changes are communicated, and how legacy decisions remain comparable), aligned with end-user needs and regulatory constraints.

Impact data infrastructure: comprehensive drought impact data system by systematically collecting, standardizing, and sharing impact data (e.g., crop losses, well failures, supply disruptions, ecosystem threshold exceedances, and inflation-adjusted economic losses). This system would support impact-based studies, enable decision-specific nonstationary drought models, and strengthen the validation of indicator-based assessments.

Because this framework is explicitly decision focused, federal and state agencies assessing changes in drought should adopt it as a common guideline and then tailor it to their specific mandates and decision horizons (e.g., short-term operations vs. long-term planning). This includes selecting the drought-relevant variables and indicators that match the application (e.g., agricultural drought metrics vs. meteorological drought indicators, or hydrologic variables such as streamflow and groundwater), so the resulting products, including maps for different sectors, drought types, and time horizons, are fit for purpose rather than one-size-fits-all.

Conclusion 8-1: A framework for incorporating nonstationarity in drought assessment to inform decision-making should be designed around a two-pronged drought analysis framework that integrates (1) short-term operational/emergency management assessments and (2) long-term planning assessments, depending on the application.

Conclusion 8-2: For drought assessments used for short-term operational decision-making, an updated stationary approach based on contemporary baselines (e.g., 30 years ± 10 years, depending on the type of drought assessment, systems of interest, and decision frameworks) is appropriate, assuming it is implemented with clear rules for baseline refreshing, documentation, versioning, and reproducibility.

Conclusion 8-3: Drought assessments designed to support long-term planning (including post-event assessment, and projection) should be based on explicitly nonstationary models that use the full available observational record including paleoclimatic information (when available and relevant) and model-based predictions/projections. The assessment framework should allow statistical parameters to evolve with time and/or physically meaningful covariates (e.g., temperature, circulation indices, water demand, land use land cover). This framework for modeling evolving statistical parameters can be implemented using either traditional statistical approaches or emerging artificial intelligence and machine learning methods for representing nonstationarity.

Conclusion 8-4: Developing a shared approach to drought assessment under nonstationarity requires the engagement of a wide range of stakeholders, including from (1) the research community to advance methods, diagnostics, dynamical understanding, uncertainty quantification, and open reference implementations; (2) operational agencies and practitioners (e.g., water agencies, farmers, ranchers, forest and rangeland managers, wildfire managers, drought monitoring systems, and infrastructure owners) who can define decision requirements and operational constraints; and (3) standards and regulatory stakeholders (e.g., professional societies, guidance-setting bodies, and insurance regulators) to ensure transparency, stability, and acceptance for high-stakes applications.

Conclusion 8-5: An improved framework for drought assessment should include approaches that are increasingly tailored to specific conditions and decision contexts, as well as agency- and user-specific applications.

Recommendation 8-1: To support the development of a common drought assessment framework, NOAA/NIDIS should facilitate the establishment of a consortium that includes representatives from the research community, operational agencies and practitioners, and standards and regulatory stakeholders.

Recommendation 8-2: NOAA/NIDIS, in collaboration with other agencies such as USDA, should develop a common drought assessment framework that integrates approaches for both short-term operational and long-term planning applications. In this framework, short-term operational assessments should be based on

contemporary baselines, with clear rules for baseline refreshing, documentation, versioning, and reproducibility; and long-term planning assessments should be based on nonstationary models that use the full available observational record (including the paleoclimatic record) together with model-based predictions and projections, and that allow distribution parameters to evolve over time and/or with physically meaningful covariates.

Recommendation 8-3: NOAA/NIDIS should facilitate development, with a consortium of key drought sector representatives, of a set of application-specific guidelines, specifying baseline lengths, update frequency, documentation standards, and reporting requirements for short-term and long-term drought analysis, with complementary guidelines tailored to specific applications or sectors.

Recommendation 8-4: The drought assessment community should invest in research and development to strengthen convergence-of-evidence approaches by introducing more transparent, structured, and reproducible frameworks for selecting the baseline period and integrating multiple indicators. These efforts should aim to formalize how the baseline period is selected and how indicators are combined, weighted, and interpreted, based on expert judgment and domain-specific knowledge.

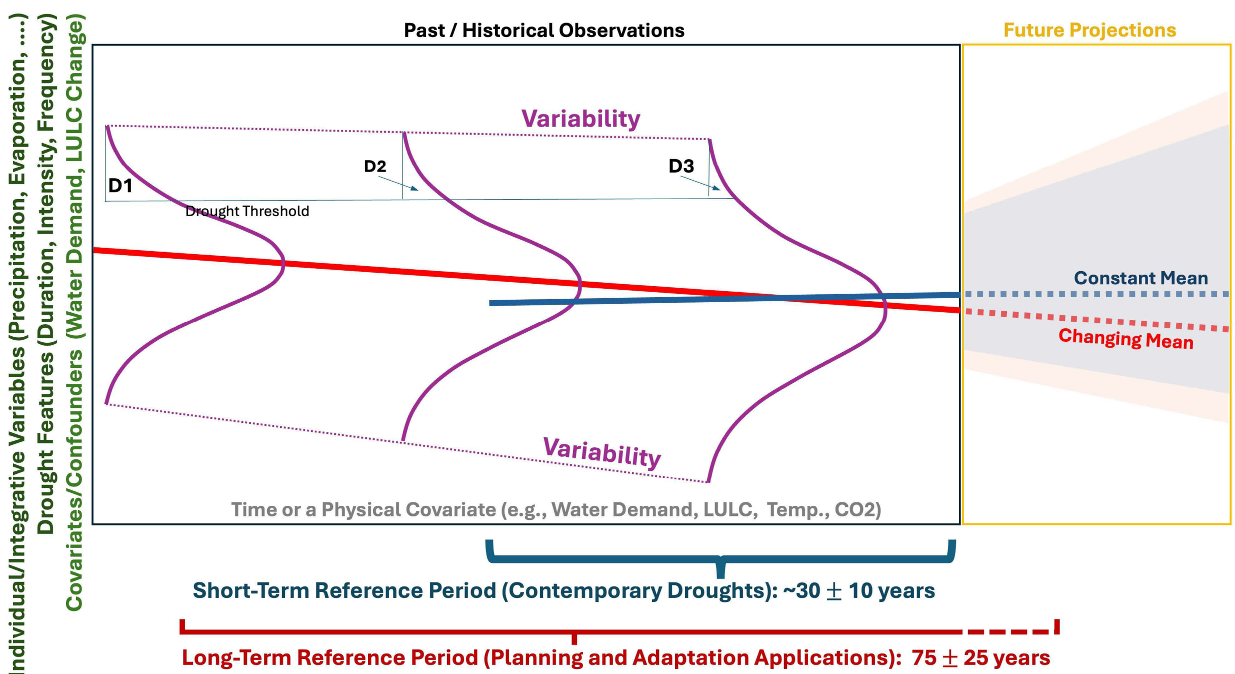


FIGURE 8-1 Conceptual illustration of baseline choice in drought assessment.
NOTE: The blue line represents an updated-stationary approach using a contemporary baseline with a constant mean, while the red line represents an explicitly nonstationary framework with a changing mean (and potentially other distribution parameters). The light blue and red shading represent uncertainty bounds from multi-model future projections. The y-axis denotes a generic drought-relevant variable or index, and the baseline length reflects the decision context (short-

term applications vs. long-term planning). Because of changes in the mean and/or variability over time (red line), a drought that was previously considered moderate (D1 on the U.S. Drought Monitor [USDM] scale) may become a more extreme event (e.g., D3) when evaluated relative to a shorter contemporary period (blue line). Changes in drought-related variables can be examined as a function of time or other variables (e.g., temperature, land use and land cover [LULC]).

IMPLEMENTATION

A core element of the proposed vision is a two-pronged, decision-first framework that links operational drought monitoring with long-term planning in a consistent way. For operational monitoring, assessment, and emergency drought response, the framework provides contemporary drought information anchored to a shorter, decision-relevant baseline, typically on the order of 30 years (± 10 years; see Figure 8-1). These indicators can drive triggers for relief programs, water use restrictions, and early warning alerts, and they should be produced at relatively high spatial and temporal resolution across diverse geographic regions and sectors. In parallel, the same underlying variables and indices are analyzed within an explicitly nonstationary context using longer baselines and physically meaningful covariates to produce evolving severity thresholds, return period estimates, and scenario-based projections for planning. The intent is a coherent system in which the indices used by emergency managers and the indices used by planners are mathematically consistent but interpreted differently depending on the decision horizon, baseline choice, and assumptions about nonstationarity (e.g., constant mean vs. changing mean, stationary vs. evolving parameters). This structure supports comparability across space and time, while still allowing tailored, decision-specific implementation.

Types of decisions and actions that need to be made. The framework should explicitly map drought metrics to the actions they are meant to support. At shorter horizons, key decisions include activation of drought declarations, allocation rules and shortage sharing, water use restrictions, emergency supply logistics, agricultural relief eligibility, and parametric triggers for insurance payouts, damage compensation, and disaster assistance. In these contexts, the priority is stability, transparency, and operational reproducibility, so that triggers are defensible and consistent across jurisdictions and over time. At longer horizons, decisions include reservoir design and operating rules, groundwater sustainability plans, environmental flow requirements, ecosystem and watershed restoration, critical infrastructure design and retrofit, interbasin transfer planning, and investment prioritization across portfolios of drought risk reduction measures and adaptations. These decisions are exposed to multidecadal climate variability, trend behavior, and potentially deep uncertainty, so they require explicit treatment of nonstationarity and careful use of the full available record. Deep uncertainty refers to when future conditions are highly uncertain and stakeholders cannot confidently assign probabilities to different outcomes or agree on the best model, assumptions, or values to use in decision-making.

Application types, short-term vs. long-term. Short-term applications generally operate on seasonal to interannual horizons and are dominated by the need for actionable thresholds, clear triggers, and regulatory or contractual acceptance (e.g., drought categories used for relief eligibility, SPI or SPEI thresholds used in parametric instruments). A practical implementation is an updated-stationary approach, that is, using well-established indicators calibrated on a moving or periodically updated baseline, with strong version control and documentation so that outcomes remain traceable and reproducible. Long-term applications operate on decadal horizons and require explicit modeling of changing probabilities and evolving tails of risk distributions. Here, the framework shifts toward nonstationary probability models where distribution parameters may evolve with time and/or physical covariates (e.g., temperature, circulation indices, water demand, LULC), and where projections can be incorporated to assess plausible futures. This application approach should support scenario-based planning and robust decision-making, rather than relying on a single best-estimate extrapolation of historical trends.

Periods of record. Because baseline choice is decision dependent, the framework should formalize guidance on periods of record and how they are used. For operational triggers and near-term assessment, a contemporary baseline of ~30 years (± 10 years) is typically appropriate to keep the reference climatology aligned with current conditions, while avoiding overly complex time-varying parameterizations that require much longer records. Within this approach, the baseline can be treated as stationary or may include a trend, depending on the application and index design, but the key requirement is that the selection and update rules are explicit and auditable. For planning and design, longer records are essential. Baselines should be 60 years or more (e.g., 75 ± 25 years) where feasible, and should integrate observations, reanalyses, and climate model output to capture a wide range of variability, trend behavior, and physically plausible futures (see Figure 8-1). In this approach, the recommendation is to consider the full available record in an explicitly nonstationary framework, rather than relying only on a recent window, because long-horizon decisions are sensitive to low-frequency variability, regime-like behavior, and tail risk that shorter baselines cannot constrain reliably.

Practical Considerations. In implementation, nonstationarity does not need to be represented only as a function of time. Where appropriate, the framework can also incorporate physics-based covariates (e.g., land use and land cover; temperature, climatic/oceanic circulation patterns); that is, it can model changes in drought severity or frequency as a function of evolving LULC or warming rather than time alone. The chosen baseline then serves two complementary purposes, enabling evaluation of future droughts relative to contemporary conditions while still allowing comparisons against longer-term baselines needed for planning. The approach is also flexible with respect to what is modeled, since any drought-relevant variable (e.g., precipitation, soil moisture, groundwater, evapotranspiration) or drought indicator can be used within the same structure (y-axis in Figure 8-1). Finally, when future drought behavior is inferred by extending a historical nonstationary trend, the modeler should explicitly assess whether the trend is expected to persist, recognizing that this is often a strong assumption that should be tested using predictions, projections, and/or physical evidence (e.g., whether continued increases are physically plausible given constraints on atmospheric moisture supply, land-surface feedbacks, or groundwater depletion). From a practical standpoint, the future can be represented either with a stationary assumption (e.g., a constant mean; dotted blue line in Figure 8-1) or with an explicitly nonstationary specification (e.g., a changing mean; dotted red line in Figure 8-1).

Decision Framework

The proposed nonstationary drought framework is designed to expand evolving drought hazard information and the user-centric decision structures that are already in use, rather than replacing those structures. In practice, many public agencies and private actors operate with rule-based, threshold-driven protocols, where crossing a specified level of an index or metric activates a discrete action (e.g., drought declarations, conservation stages, contingency supplies, relief payments). For these applications, the framework supports systematic recalibration of triggers so that threshold meaning remains aligned with changing conditions, while the underlying governance and operating logic stays intact. In other words, users keep the same trigger architecture and familiar categories, but the reference used to interpret "severe" or "extreme" is updated in a controlled, documented way based on nonstationary evidence.

Other users rely on probabilistic and economics-based decision methods, where decisions are guided by quantified risk, trade-offs, and performance under uncertainty (e.g., risk-based design, adaptive pathways, robust decision-making, portfolio optimization, cost–benefit analysis). The literature on robust decision-making under deep uncertainty also describes opportunities for application of approaches such as multiple scenario development and resilience thinking in natural resource management (Polasky et al., 2011; Benson and Garmestani, 2011), including ways to improve deliberations among decision-makers in situations where probabilities are poorly characterized and about which stakeholders disagree (Lempert, 2003). For these contexts, the framework provides time-evolving probability distributions and risk metrics (e.g., changing exceedance probabilities, shifting return levels, scenario-conditioned severity–frequency relationships) that can be ingested directly by existing planning and financial tools. For example, a water utility can stress-test candidate strategies across multiple plausible nonstationary drought trajectories, including futures with accelerated drying or increased interannual variability. Insurers and reinsurers can evaluate how nonstationary severity–frequency assumptions affect pricing, reserves, and portfolio solvency, and can compare results across alternative views of trend persistence and uncertainty. Across both classes of decision-making, the goal is not to prescribe a single "best" decision rule. Instead, it is to deliver decision-ready drought information that is consistent, transparent about assumptions, and usable across a spectrum of applications, from operational triggers to multi-objective planning under deep uncertainty.

Impact-Based Drought Assessment

A decision-centered nonstationary drought framework should ideally treat impacts as first-class information, not merely as outcomes to be explained after the fact. Where impact data are available, they can be used to define drought risk in the most decision-relevant way: by modeling how the probability and severity of real-world consequences evolve over time and under changing climate and human conditions. In this approach, drought is not characterized solely by a hydroclimatic index (e.g., SPI, SPEI), but by an impact metric that directly matters to users (e.g., inflation-adjusted crop revenue loss, acreage fallowed, well failures, hydropower deficits, municipal shortage events, ecosystem stress indicators). A nonstationary model can then be built around the evolving distribution of those impacts, with parameters allowed to change through time and/or with physically and socioeconomically meaningful covariates (e.g., temperature, demand, land use, irrigation technology, groundwater depth). This reframes drought analysis from "How is the indicator changing?" to "How is the likelihood of harmful outcomes changing, and why?"

Agriculture provides a clear example. Many regions have multidecadal records of crop yields, planted area, and market value that can be converted to real (inflation-adjusted) economic outcomes. If these data are sufficiently consistent, one can model drought-related losses directly, rather than relying on a proxy indicator. For instance, a nonstationary impact model could estimate how the probability of yield losses exceeding a critical threshold evolves with rising temperatures, shifting precipitation regimes, and changes in irrigated area, while also accounting for adaptation (e.g., adopting more drought- or heat-resistant crop varieties or crops, irrigation expansion, improved efficiency). Similar impact-centered analyses are possible for other sectors:

hydropower generation shortfalls (e.g., energy deficits relative to differing demand scenarios), municipal supply restrictions (e.g., frequency of mandatory conservation stages), groundwater outcomes (e.g., well failure rates or depth-to-water thresholds), or ecosystem impacts (e.g., frequency of critically low environmental flows or habitat suitability exceedances). In each case, the outputs are immediately interpretable as evolving risk to a service, asset, or community outcome.

The primary challenge is that reliable, standardized, long-term impact data are often unavailable, fragmented across institutions, or inconsistent due to changes in reporting practices, economic conditions, infrastructure, and policy. Impacts are also shaped by exposure and vulnerability, which can change rapidly (e.g., shifting cropping patterns, population growth, new pumping regulations), making attribution and nonstationary inference difficult without careful metadata and covariate information. As a result, impact-based drought monitoring and assessment remain challenging in many regions, and operational systems often revert to hazard-based indicators because they are easier to produce consistently. Closing this gap will require deliberate investment in impact data infrastructure, including consistent reporting standards, open and interoperable databases, and sustained partnerships with sectoral agencies and stakeholders so that impact metrics can be used alongside hydroclimatic indicators to support robust, equitable, decision-relevant drought risk management.

National Assessment

Every part of the United States (all 50 states and U.S. territories) is at some risk of drought and aridification in the future; thus, nationwide long-term drought assessment is needed to build drought resilience across the country.

Conclusion 8-6: The entire United States is at risk of drought and aridification in the future, and this risk should be assessed at regular intervals in recognition that the understanding of nonstationarity (both climatic and otherwise) and drought dynamics changes in time. This regular assessment should focus on providing stakeholders with the information they need to increase resilience to future drought and aridification.

Recommendation 8-5: NOAA and its partners should carry out regular national drought assessment that facilitates long-term (seasons to decades) planning for all regions in the United States, whether they are currently experiencing drought or not. These long-term assessments should take into both natural and human-driven forms of nonstationarity, including natural and human-forced climate change, and should be designed to enhance resilience to possible future drought.

CHALLENGES AND UNANSWERED QUESTIONS

Implementing this vision requires closing gaps in data, indicators, impact understanding, decision tools, institutional practice, and governance, and it also raises a set of unresolved scientific, institutional, and ethical questions that must be addressed explicitly. A recurring theme is that nonstationary drought frameworks are decision dependent and cannot be developed in silos. Different agencies and users (private or government) should work with modeling teams to co-develop decision-specific frameworks that are transparent, defensible, and fit for purpose across regions and sectors.

Data Gaps and Consistency Challenges

The lack of long, homogeneous, and well-documented records of drought-relevant variables across many regions remains as a foundational gap. Robust nonstationary modeling often requires consistent time series of precipitation, temperature, evapotranspiration, soil moisture, groundwater, and streamflow, yet many observational records are short, fragmented, or affected by changes in instruments, station density, land use, and data processing practices. In addition, inconsistencies between observational datasets and reanalyses remain a practical barrier, particularly when drought characterization depends on derived variables (e.g., potential evapotranspiration, or PET) and when uncertainty estimates are not routinely provided or are difficult to interpret. There is also limited availability of merged, drought-tailored products that explicitly quantify uncertainty, document inhomogeneities, and provide consistent spatial coverage at decision-relevant scales. (See Chapter 5 for a detailed assessment of these data issues and Chapter 7 for information on drought impact data.)

Unanswered questions include: What constitutes a “sufficiently homogeneous” record for nonstationary drought inference in a given region? How should analysts reconcile conflicts between observational products and reanalyses, particularly when those differences are comparable to the inferred trend signal? How should uncertainty from measurement, interpolation, and reanalysis assimilation be propagated into drought categories and triggers?

Indicator Gaps, Including Operational Nonstationary Products

Most widely used operational drought indices still assume fixed historical baselines and stationary thresholds. There is no broadly adopted, standardized family of nonstationary drought indicators with clear guidance for calibration, updating, interpretation, and uncertainty communication. This gap is particularly acute for applications that require regulatory or contractual defensibility, where indices must be stable, auditable, and reproducible over time. (See Chapter 6 for a detailed discussion of drought indicators.)

A specific and high-priority gap is the absence of an operational aridity index (and related operational products) designed to explicitly reveal nonstationarity and trends. Closely related is the lack of routinely produced products that show how the character of drought is changing due to trends, including changes in duration, frequency, intensity, onset/intensification rates, seasonality, and multiyear persistence, and doing so consistently for both historical conditions and future projections. Such products would move beyond static snapshots and provide decision-makers with an interpretable view of how drought hazard is evolving, while still preserving transparency and avoiding false precision.

Unanswered questions include: Which indicators can be made operational while still capturing nonstationary behavior in a statistically defensible way? How should nonstationary indicators be “versioned” so that results remain comparable across time as baselines are updated? What is the best practice for expressing uncertainty and deep uncertainty in a way that is meaningful for operational thresholds?

Modeling and Methodological Gaps, Including Complexity vs. Robustness

Scientifically, there is no consensus on how complex nonstationary models must be in order to materially improve decisions, or how to balance flexibility against transparency and robustness. Different regions will face different dominant drivers of nonstationarity, different levels of data availability, and different sensitivities to covariate selection. As a result, a single national or global modeling template is unlikely to work everywhere. Another persistent challenge is deep uncertainty, both in future climate projections and in how human systems evolve (e.g., population, demand, groundwater development, land management). Translating these uncertainties into drought-relevant metrics that avoid false precision yet still support concrete choices remains a major research gap. Similarly, trend persistence assumptions are often implicit. When analysts fit nonstationary trends to historical data, the core question becomes whether those trends should be assumed to continue, stabilize, or reverse in the future, and on what physical basis.

Unanswered questions include: When does added nonstationary complexity demonstrably improve decisions relative to simpler updated-stationary approaches? What diagnostics should be required to justify model complexity, especially for high-stakes applications? How should analysts select covariates in a way that is physically interpretable and avoids overfitting? What constitutes sufficient evidence that an inferred historical trend is physically plausible to extrapolate?

Decision-Tool and Workflow Gaps

Many existing decision tools are built around stationary concepts, including fixed return periods, fixed drought categories, and thresholds derived from a single historical reference period. Tools often do not allow practitioners to explore how triggers, categories, and return periods shift under alternative baseline choices, covariate assumptions, or scenario-based futures. There is also a lack of modular, open, reproducible toolchains that connect the full workflow from inputs (observations, reanalyses, projections) to outputs (indices, thresholds, return levels, uncertainty, and decision-relevant summaries), with clear documentation of assumptions.

Unanswered questions include: What minimum functionality should decision-support tools provide to enable baseline sensitivity analysis and scenario testing? How should outputs be aggregated and disaggregated across scales without losing decision relevance (e.g., local irrigation district vs. multistate basin)? How should model outputs be translated into actionable policies when different sectors require different risk tolerances? What are the key communication or data literacy challenges associated with these decision-support tools?

Institutional and Governance Gaps, Including Planning Documents

Institutionally, decision processes and regulatory frameworks are still anchored to stationary concepts. Moving toward nonstationary triggers and evolving baselines will require changes in statutes, regulations, agency guidance, and contract language, alongside new norms for transparency and accountability. Governance is also underdeveloped: Who owns the baseline update process? How are updates communicated to avoid confusion and loss of trust? How are versions archived and audited? What constitutes acceptable change management when thresholds impact payouts, restrictions, or allocations? A major planning gap is that most state drought plans do not include future drought assessment, and while some hazard mitigation plans do, there is no consistent framework for embedding nonstationary drought risk and climate projections into long-term planning and preparedness. Future risk is often treated as optional, ad hoc, or relegated to appendixes rather than integrated into decision workflows and investment planning.

Unanswered questions include: What governance model ensures consistency across agencies while allowing decision-specific tailoring? How should planning documents incorporate future assessments in a way that is neither speculative nor dismissive? What are the standards for "acceptable" use of climate predictions and projections in operational planning and in legally or financially consequential decisions?

Ethical and Distributional Gaps

An important issue that deserves further study is how distributional impacts may arise when baselines and thresholds shift. For example, changes in drought indices, reference periods, or trigger thresholds could affect relief eligibility, insurance payouts, water restrictions, or enforcement in different ways across communities, farmers, and sectors. Understanding these effects can help ensure that alternative baseline choices and model structures are evaluated transparently and that potential implications for vulnerable groups are considered in the design and communication of drought assessment methods.

Unanswered questions include: Who bears the burden of changing baselines (e.g., communities that become "less eligible" for relief because thresholds evolve)? How should vulnerability and risk disparity criteria be operationalized in the design of triggers and benchmarks? What safeguards ensure that technical updates do not erode trust or create systematic inequities?

Co-Development, Communication, and Sustained Funding Gaps

Nonstationary drought science will only translate into resilience gains if it is co-developed with users and embedded in real decision environments. Yet many efforts remain research prototypes without pathways to operational adoption, sustained maintenance, or regulatory acceptance. Risk communication is another gap: stakeholders need to understand changing baselines, evolving probabilities, and trade-offs between decision framings, but baseline data literacy is unknown, and the field lacks widely tested communication strategies and visualization standards for nonstationary concepts. This points to a clear call to action. For researchers, priorities include building open, reproducible nonstationary drought toolkits; developing comparative assessments that show when added complexity improves decisions; identifying social science research and communication strategies; and conducting co-developed case studies in which baseline choices and model structures are evaluated with real decision-makers. For funding agencies, there is a need for programs that explicitly link methodological advances with testbed applications in agencies, utilities, and the private sector, and that support long-term, multidisciplinary collaborations rather than isolated, short-duration projects. While an agency such as the National Oceanic and Atmospheric Administration (NOAA) is often viewed as the primary federal entity for drought monitoring and prediction, other agencies may need to develop decision-specific frameworks tailored to their missions and operational requirements. For example, the U.S. Department of Agriculture (USDA) may require sector-specific drought metrics and triggers for agricultural programs in addition to the U.S. Drought Monitor, while the U.S. Geological Survey (USGS) and the U.S. Department of the Interior Bureau of Reclamation

(USBR) may prioritize approaches optimized for hydrologic drought assessment (e.g., streamflow, groundwater, and related impacts).

Unanswered questions include: What sustained institutional home should maintain operational nonstationary indicators and their documentation? What incentives and structures best support co-development across academia, agencies, and private actors? How can communication materials be tested and validated to avoid misinterpretation and false confidence?

Limited Drought Impact Data for Impact-Based Nonstationary Analysis

A key gap for decision-centered nonstationary drought analysis is the limited availability of consistent, long-term drought impact data. In principle, impacts (e.g., crop yield and inflation-adjusted revenue losses, well failures, drying of ponds that provide water for cattle, supply disruptions, ecosystem threshold exceedances) provide the most direct basis for estimating how drought risk is changing. In practice, impact datasets are often fragmented across agencies, inconsistently defined over time, sparse at decision-relevant spatial scales, and rarely accompanied by metadata needed to separate changes in hazard from changes in exposure and vulnerability (note that elements of risk, including exposure, vulnerability, and adaptive capacity, may change at different rates across sectors and impact types, and some drought impacts may be less sensitive to changes in adaptive capacity than others). This limitation constrains both impact-based decision support, scenario planning, and validation of indicator-based nonstationary frameworks. It also leaves important questions unanswered, including: Which impact metrics should be tracked consistently across sectors and jurisdictions? What standards and governance are needed to ensure stable reporting and reproducibility? How should impacts be normalized (e.g., inflation adjustment, exposure normalization, unequal resource allocation) to support robust nonstationary inference? Without targeted investment in impact data infrastructure and co-developed reporting protocols, nonstationary drought assessment will remain dominated by hazard proxies rather than outcomes that directly matter most to users. (See Chapter 7 for a detailed discussion of drought impacts and impact data.)

Unanswered questions include: What minimum set of standardized drought impact metrics should be tracked nationally and locally (e.g., crop losses, well failures, service interruptions, ecosystem threshold exceedances) to enable impact-based modeling? What reporting standards and governance structures are needed to ensure consistency across agencies and over time? How should impact data be normalized (e.g., inflation-adjusted dollars, exposure-adjusted losses, vulnerability indices) so that nonstationary inference reflects changing hazard rather than changes in accounting or development patterns? How can impact datasets be integrated with drought indicators to support hybrid models that are both operationally feasible and decision relevant? What impact-focused decision support tools exist or are needed?

Addressing this gap will require intentional investment in impact data infrastructure, including harmonized definitions, sustained monitoring programs, open data pipelines, and co-developed protocols with sectoral agencies (e.g., USDA for agriculture; USGS, USBR, and state water agencies for hydrologic impacts; utilities for service reliability; and resource agencies for ecological outcomes). Without such investment, the field will remain constrained to hazard-centric proxies and will struggle to develop truly decision-centered nonstationary drought frameworks that quantify evolving risk in terms that directly matter to users.

SUMMARY

To make nonstationary drought science actionable, the committee recommends a decision-centered approach that aligns analytical choices with the decisions the analysis is meant to inform. The core strategy is a two-pronged framework that supports both near-term, operational needs and longer-term planning. For short-horizon, contract-like applications (e.g., parametric triggers, insurance payouts), the emphasis should be on an updated stationary approach using contemporary baselines (e.g., 30 years ± 10 years) with disciplined refresh rules and transparent versioning so triggers remain stable, auditable, and reproducible. For long-horizon planning (e.g., infrastructure design, restoration, ecosystem management), the emphasis should shift to explicitly nonstationary models that leverage the full available record (including the paleoclimatic record) and allow drought-relevant distributions to evolve with time and/or physically meaningful covariates (e.g., temperature, circulation indices, water demand, LULC). Because these choices are inherently application dependent, development and maintenance should occur through sustained co-development among researchers, operational agencies and practitioners, and standards and regulatory stakeholders to ensure technical rigor, operational feasibility, and institutional acceptance.

A functional operational framework for drought assessment that incorporates nonstationarity must accommodate critical considerations regarding decision-specific guidance, reference implementations, benchmarks and stress tests, governance and change management, and impact data infrastructure (see Box 8-1). This framework provides approaches to incorporating nonstationarity into drought assessment; it is intended to enhance existing and future drought assessment approaches, rather than replace them. To be useful and used, such a framework must be adapted by agencies and organizations assessing changes in drought products by selecting appropriate drought data, metrics, and baselines appropriate to their applications, to produce decision-driven drought assessments and products that are fit for purpose rather than one-size-fits-all.

9
Framework in Action

The goal of this final chapter is to illustrate the recommended two-pronged framework for drought assessment in a nonstationary world using tangible examples, and in doing so, to provide an informative conclusion to this report. It is important to recognize that a strong foundation for drought assessment in the United States already exists and that this foundation has many valuable attributes to build upon. The National Oceanic and Atmospheric Administration's (NOAA) National Integrated Drought Information System (NIDIS) program is designed to coordinate drought monitoring, forecasting, early warning, planning, and information sharing with a broad spectrum of federal, Tribal and Native, state, university, and local partners across the country. NIDIS and the partnerships it has built over time are a great foundation for a national drought assessment capability that more comprehensively and accurately reflects nonstationarity and can illuminate future drought's complex impacts and outcomes. Importantly, to help readers understand what an expanded drought assessment framework that incorporates nonstationarity can do using the recommended framework, this chapter presents two examples of real, operational drought situations and one example of the long-term planning perspective and discusses the implications of all three. To be clear, these examples are intended to be illustrative only. The committee recommends that NIDIS and their partners design and implement an improved drought assessment enterprise that takes nonstationarity into account (see recommendations 8-1, 8-2, and 8-3) and benefits from this report.

Each of the drought examples presented here, and indeed all U.S. droughts of the twenty-first century, illustrate the growing challenges of assessing future drought due to nonstationarity across different systems, from the behavior of the climate system to the societal influences that together help shape a growing number of droughts. In the discussion that follows, this chapter presents drought examples to illustrate both the goals and strategies of the recommended two-pronged framework for assessing droughts in this world of nonstationarity. This discussion does not represent a comprehensive drought assessment, nor does it imply similar outcomes and conclusions for drought assessment in different geographic regions, systems, and decision frameworks. The broader implications of this proposed framework transcend these examples, and implementation of this framework should be necessarily co-developed with regional practitioners and local drought experts who are best positioned to tailor the framework, and related methods, reference periods, and indicators to system-specific conditions and decision needs.

SHORT-TERM OPERATIONAL DROUGHT ASSESSMENT

The short-term, operational component of the proposed framework is intended to improve drought monitoring, early warning, and near-term post-event analysis under nonstationary conditions. Its primary purpose is to support decisions that depend on an accurate depiction of current drought severity and risk in the context of a contemporary climate and hydrologic conditions, with consideration of the specific sectors and/or systems being affected. These decisions include drought declarations, emergency relief, water restrictions, insurance, and disaster relief programs triggered by drought assessment. This component of the framework is intended to provide clear communication to affected sectors regarding the expected rarity of any given event in order to describe their contemporary risk profile accurately as part of a larger convergence-of-evidence approach to drought monitoring and assessment. For these applications, the central challenge is how to describe drought not with respect to conditions from the distant past, but rather how anomalous they are relative to the present climate. Flash droughts are one example of a short-term phenomenon for which timely prediction/detection is imperative to planning and management of water resources and food security.

In this framework, short-term operational drought assessment relies on multiple lines of evidence that include quantitative drought indicators, drought impact reports, and local knowledge and experience. The first of these, drought indicators, are derived using an updated stationary approach with contemporary reference periods (described in detail in Chapter 8), generally on the order of 30 years, with flexibility to support system-specific considerations. The purpose of this shorter, contemporary baseline is to keep the reference climatology aligned with present conditions and contemporary risk while acknowledging the challenges and nuances associated with using drought indicators within a convergence-of-evidence approach for operational assessment frameworks. The updated stationary approach welcomes use of traditional drought indicators and indices (discussed in Chapter 6), either tailored to specific sectors or used in a more general form, and simply requires periodic updates of the reference periods used. This differs from the use of a full period of record as the reference period, which may appear to improve statistical sampling and parameterization via an increase in sample size, but may do so by violating assumptions of stationarity, blending past and present climate regimes in ways that distort true contemporary recurrence, risk, and severity.

An example snapshot of drought assessment in the Mid-South region (Mid-Mississippi to Ohio Valley) of the United States illustrates this framework in a short-term operational drought assessment context. The Mid-South, similar to the Southeast United States in Case Study 3 (see Chapter 2), has experienced increasing winter and spring precipitation during the twentieth century and first quarter of the twenty-first century (Marvel et al., 2023). However, this region was affected by a multimonth period of well-below average precipitation that spanned most of meteorological winter (December–February) in 2025–2026. Figure 9-1 shows a single drought index in this region in mid-March 2026 using the 90-day Standardized Precipitation Index (SPI) as an indicator. To demonstrate the implications of the proposed drought assessment framework, the SPI maps represent drought severity using two different baselines: (1) the contemporary baseline using the most recent 30-year period, 1997–2026, and (2) the full record baseline using the entire period of record, 1979–2026. The 90-day SPI values are categorized to match the U.S. Drought Monitor (USDM) categories, and map colors match those of the USDM maps.

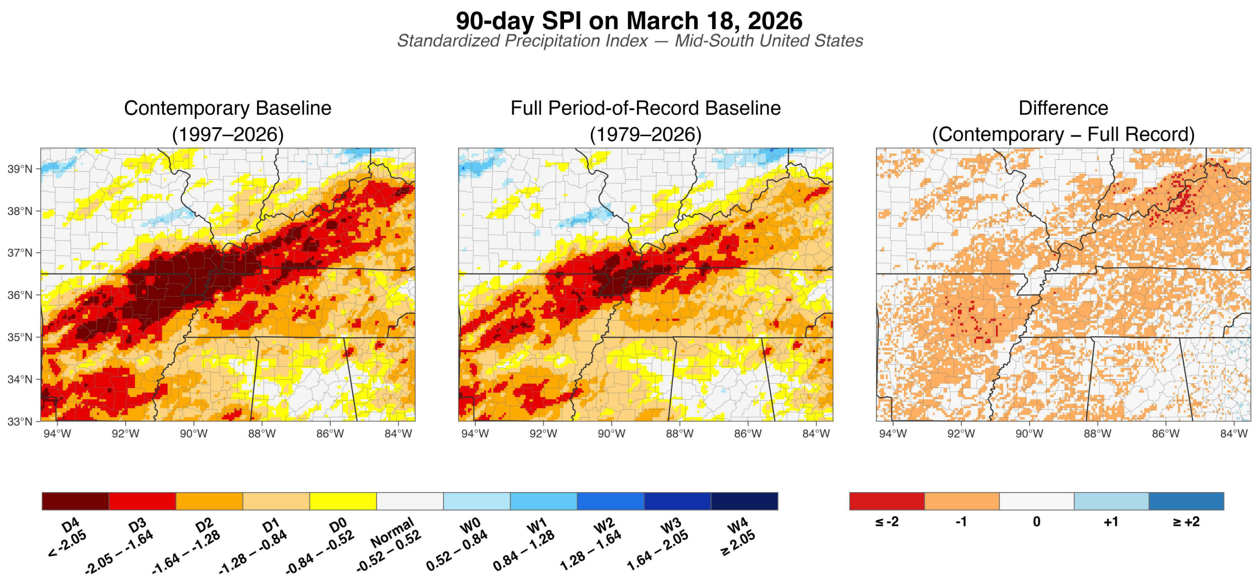


FIGURE 9-1 Maps of 90-day Standardized Precipitation Index (SPI) on March 18, 2026, showing SPI-based drought categories across the Mid-South United States.
NOTE: The left map shows 90-day SPI calculated using a contemporary baseline from 1997 to 2026. The center map shows 90-day SPI calculated using the full-record baseline from 1979 to 2026. The right map shows the difference between the two maps. SPI was calculated using precipitation from gridMet gridded meteorological fields.
SOURCE: Committee generated, using Montana Climate Office's https://d3drought.org data dashboard and https://data2.climate.umt.edu/gridmet/derived/conus_drought/ data archive.

Using the full period of record as a baseline (as is commonplace in many drought assessment systems) shows much of southeast Missouri, western Kentucky, northeast Arkansas, and western Tennessee as experiencing "severe" (D2) to "extreme" (D3) precipitation anomalies (representing meteorological drought, and in this discussion, "SPI/SPEI-based drought categories"), with only ~10 counties in the region showing significant areal extents of 90-day SPI values corresponding with "exceptional" (D4) drought categories. In comparison, using the contemporary reference period SPI values shows most of the region in extreme (D3) to exceptional (D4) drought categories, with >30 counties in the region showing 90-day SPI values corresponding with exceptional (D4) drought. The differences in drought severity between these maps are attributable to secular trend of increasing winter precipitation in this region. These changes in the regional hydroclimate of the Mid-South United States have decreased the probability of observing winter season precipitation deficits comparable to those occurring during the full period shown in Figure 9-1 and therefore decreased the overall risk of wintertime meteorological drought. Consequently, the statistical likelihood, and therefore risk, of the winter drought of 2025–2026 in this region is lower in today's climate (i.e., the last 30 years) than it is relative to the region's historical climate (i.e., the full historical record). This difference results in a more severe drought classification in the current (1997–2026) climate relative to the full 1979–2026 period of record.

The framework proposed in this report recommends the use of a contemporary baseline, such as the most recent 30-year period, to assess hydrometeorological drought indicators such as

90-day SPI for short-term operational applications and decisions. In the case of the Mid-South U.S. drought presented in Figure 9-1, and for most regions of the United States, decisions of drought declarations, state- and local-level coordination, emergency relief, water restrictions, and disaster relief programs risk being delayed if they are informed by drought indicators that use the full period of record. Such short-term decisions should be grounded in the most accurate and up-to-date assessment of drought risk (see Chapter 4). For example, the State of Missouri, according to its Drought Mitigation and Response Plan (Missouri DNR, 2023), could consider an “Alert Phase” or “Conservation Phase” for the southeast part of Missouri based on the full record 90-day SPI maps, but could consider a more severe “Drought Emergency Phase” for the region based on the contemporary baseline. These different phases correspond to different levels of state response, resource allocation, and agency prioritization for water conservation and drought mitigation in Missouri as well as in many other states with similar drought planning guidelines. Based on this example, this framework succeeds in describing drought with respect to its severity and risk relative to contemporary management systems (e.g., climate, economic/market, agronomic) and provides a robust tool for assessing drought in a region of the United States that has experienced change in drought severity and rarity. It should be noted that the proposed framework, in this case, is applied to one line of evidence for drought assessment: 90-day SPI. Operational drought assessment often uses a convergence-of-evidence approach for decision support, which melds multiple lines of evidence, including hydrometeorological indices like SPI, impact reports, and local knowledge. The proposed framework illustrated here with 90-day SPI is intended to augment the data used in the convergence-of-evidence approach for short-term drought assessment, not replace the approach itself.

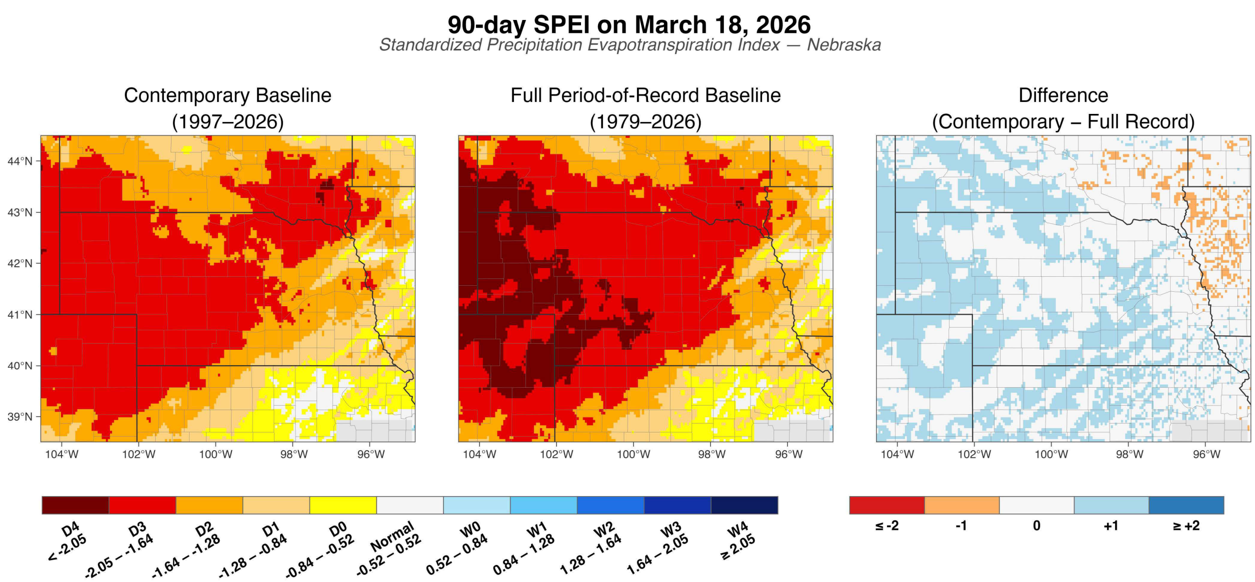


FIGURE 9-2 Maps of 90-day Standardized Precipitation Evapotranspiration Index (SPEI) on March 18, 2026, showing SPEI-based drought categories across Nebraska.
NOTE: The left map shows 90-day SPEI calculated using a contemporary baseline from 1997 to 2026. The center map shows 90-day SPEI calculated using the full-record baseline from 1979 to 2026. The right map shows the difference between the two maps. SPEI was calculated using precipitation and reference evapotranspiration (ET_o) from gridMet gridded meteorological fields.

SOURCE: Committee generated, using Montana Climate Office's https://d3drought.org data dashboard and https://data2.climate.umt.edu/gridmet/derived/conus_drought/ data archive.

Consider now the Standardized Precipitation Evapotranspiration Index (SPEI), which includes both reference evapotranspiration (ET_o) and precipitation (P) in its formulation, over Nebraska for the same period (see Figure 9-2). Here, the contemporary versus full period-of-record effect contrasts with the wetting trends shown in Figure 9-1. Over Nebraska, increasing temperatures have contributed to increases in atmospheric evaporative demand (as estimated via ET_o), representing a trend toward overall drier conditions. The result of the framework in this case is that the more contemporary 30-year record shows considerably less severe drought categories compared to using the full period of record, implying that what used to be exceptionally dry conditions now occur more often in the contemporary period. For example, the full period-of-record perspective suggests that more than 20 counties in Nebraska are experiencing a significant amount of D4 drought conditions as described by 90-day SPEI. In contrast, the contemporary 30-year reference period only shows a limited area of one county (in South Dakota) with D4 drought conditions. The lesser extent and severity of drought conditions in Nebraska based on the contemporary reference period reflects the warming trend the state has experienced in winter and spring (Bathke et al., 2025), and the associated increased frequency of negative water balance during this time of the year. In the case of Nebraska presented in Figure 9-2, decisions of drought declarations, state- and local-level coordination, emergency relief, water restrictions, and disaster relief programs risk being overprescribed or exhausted if they are informed by drought indicators that use the full period of record, which overestimate drought rarity (and therefore severity) in Nebraska's contemporary climate. For example, the State of Nebraska Drought Mitigation and Response Plan (State of Nebraska, 2000) calls for myriad state and local responses to drought, including the establishment of a hotline system for locating economical livestock feedstock sources. These actions require state- and local-level resources, often reallocated from other regulatory and/or scientific missions. Based on this example, this framework succeeds in describing drought, based on 90-day SPEI, with respect to its severity and risk relative to contemporary systems (e.g., climate, economic/market, agronomic), and can help state agencies and municipal managers and leaders allocate resources and financial support akin to the level of severity and rarity of a drought relative to current climate and experience. However, systems with longer memory or slower response times, such as many ecological systems or long-lived vegetation communities, may require longer reference periods to adequately represent drought-induced stress.

The framework proposed here applies to indicators with the objective of producing more accurate reflections of the statistical rarity and severity of a drought from the perspective of the indicator itself. However, a change in the reference period used to compute an indicator does not necessarily change the severity of the impacts that may result from drought. Using the example from Nebraska in Figure 9-2 and the current state of the Nebraska Drought Mitigation and Response Plan, the state of Nebraska may delay local response and resource allocation if they use a 90-day SPEI with a contemporary baseline because it shows less severe drought than the same indicator using a full period of record baseline. However, the baseline by which the indicator is computed has no effect on the tangible impacts of the drought. In this example, and without agricultural, ecological, and/or hydrological adaptation to changing climate and environmental conditions, stakeholders in Nebraska could experience an impact that is more severe than the drought severity depicted by the 90-day SPEI, and by extension, one that is more severe than the corresponding response by the state. This hypothetical situation exemplifies the need for drought adaptation practices to evolve alongside the rate of climate and environmental change driving drought nonstationarity. Critically, this is where the second prong of the proposed framework, long-term planning using explicitly nonstationary assessments, becomes important. While the short-term component is designed to characterize contemporary drought rarity and support operational response, the long-term component is intended to help stakeholders understand how drought risk, water availability, and associated impacts may evolve in the future, thereby informing adaptation, infrastructure planning, and long-term resilience strategies, as discussed in the "Long-term Drought Planning" section below.

The examples presented in Figures 9-1 and 9-2 provide contrasting examples of how the framework presented in this report can cause contemporary reflections of drought that are both more severe *or* less severe depending on the region, metric, season and timescale, despite reflecting the same exact on-the-ground hydrologic conditions. However, both achieve the same goal of more accurately portraying present-day drought risk for systems responding to ~30-year variations in climate, and both could be considered important contributions to the larger convergence-of-evidence approach for short-term operational drought assessment. Under this framework, drought classifications are based on how rare conditions are relative to a reference period, rather than on absolute values alone, consistent with current USDM-style approaches. As climate conditions change, values that were once rare may become more common and therefore be classified as less extreme, even if their real-world impacts remain serious or are getting worse. For example, a soil moisture condition that would previously have been classified as D4 (exceptional drought) may, over time, be classified as D3 as it becomes more frequent. This can create a disconnect, where stakeholders experience severe conditions but see a lower drought category. The intent is not to downplay impacts, but to distinguish between a shifting baseline climate and drought as an unusual departure from that baseline. Similarly, wildfire or water-supply impacts may worsen even as a drought category becomes less extreme relative to a contemporary baseline. For example, if low fuel moisture, high vapor pressure deficits, or reduced reservoir inflows become more common, a future D3 event may still correspond to fire danger or water-supply stress that previously would have been associated with D4 conditions. This does not necessarily mean the drought assessment is incorrect; rather, it reflects that many impacts, such as wildfire danger or water-supply shortages, are driven by absolute environmental thresholds and system vulnerabilities that may worsen even as the underlying conditions become more common relative to the contemporary climate. This further highlights the tension between drought as an anomalous condition and impacts that are triggered by absolute thresholds, meaning that drought categories and impact severity should not always be expected to align directly.

If historically extreme conditions become common, labeling them as "exceptional" droughts indefinitely would imply a constant state of emergency, which is not sustainable for assessment or response. In these cases, the issue extends beyond drought classification and disaster mitigation to broader structural change and the need for adaptation, making clear communication of this distinction critical. The next section demonstrates how the second prong of the framework focuses on, and supports, long-term planning applications.

LONG-TERM DROUGHT PLANNING

The long-term planning component of the proposed new drought assessment framework is explicitly aimed at accounting for nonstationarity in order to understand and communicate contemporary drought risk as it relates to expectations of future conditions. Decisions informed by long-term planning assessments include hazard mitigation planning, water supply planning, energy and water infrastructure development planning, and other forms of adaptation. These decisions play a critical role in a region's economic, environmental, and societal sustainability, and as such should properly incorporate drought nonstationarity information.

Analytical Approach

Droughts are a regular occurrence in the United States, yet the last 25 years have been exceptional in this country's history when it comes to drought, with the longest drought—officially a multidecadal megadrought—showing no signs of ending. The example of this Southwestern megadrought (see Box 2-2) illustrates a long-term planning application of the proposed drought assessment framework.

Figure 9-3 illustrates one component of drought conditions for June 2021 (as described using the 30-day SPEI) evaluated relative to both contemporary and future climates using explicit nonstationary methods. Importantly, this example is intended to serve as a methodological illustration showing how a single SPEI-based drought indicator may be re-evaluated within a nonstationary framework. It is not intended to represent a complete drought assessment or to replace an integrated, multi-indicator approach. In this figure, the observed 30-day deficit (P-ET_o) is held constant across all panels; only the probability distribution used to evaluate the event changes. Following Stagge et al. (2015), a generalized extreme value (GEV) distribution is fit in two ways to compute SPEI. First, a contemporary baseline is estimated using L-moments from the 1992–2021 gridMET dataset (Abatzoglou, 2013), analogous to how operational SPEI would typically be computed today. Second, an explicit nonstationary GEV is estimated using Generalized Additive Models for Location Scale and Shape (GAMLSS) maximum likelihood methods (Rigby and Stasinopoulos, 2005), with a linear trend in the location parameter, a log-linear trend in the scale parameter, and a constant shape parameter. This nonstationary model is computed on a continuous 1979–2100 time series formed by combining gridMET data (1979–2014) with bias-corrected NEX-GDDP-CMIP6 projections from the EC-Earth3 model under SSP3-7.0 (Thrasher et al., 2022). EC-Earth3 under SSP3-7.0 was selected as a plausible elevated-forcing scenario because EC-Earth3 is included in Mahony et al.'s (2022) 8-model CMIP6 subset for North America (constrained to the IPCC AR6 [IPCC, 2021] likely range of equilibrium climate sensitivity), exhibits lower precipitation bias than the ensemble mean, and is one of only four ensemble members with grid resolution sufficient to resolve Western Cordillera topography and elevation-dependent warming (Mahony et al., 2022). NEX-GDDP-CMIP6 ET_o is based on Hrozencik and others (2024).

The projected climate data is bias-corrected using cell-wise Quantile Delta Mapping (QDM; Cannon et al., 2015) relative to the gridMET reference period, applied separately to precipitation (using multiplicative correction) and reference evapotranspiration (using additive correction). The top row of Figure 9-3 shows the SPEI cast into U.S. Drought Monitor drought categories (see Table 6-1) for the same June 2021 event, evaluated relative to the contemporary GEV and the nonstationary GEV distributions projected for 2050 and 2100. Stippling indicates grid cells where likelihood-ratio testing rejects the stationary null hypothesis at $p < 0.05$. The bottom row expresses the climate-change signal more directly using the frequency multiplier, representing how many times more (or less) likely the same physical deficit becomes under future climate conditions. These results are shown both as a distribution across the Contiguous United States (CONUS) and as spatial maps for 2050 and 2100.

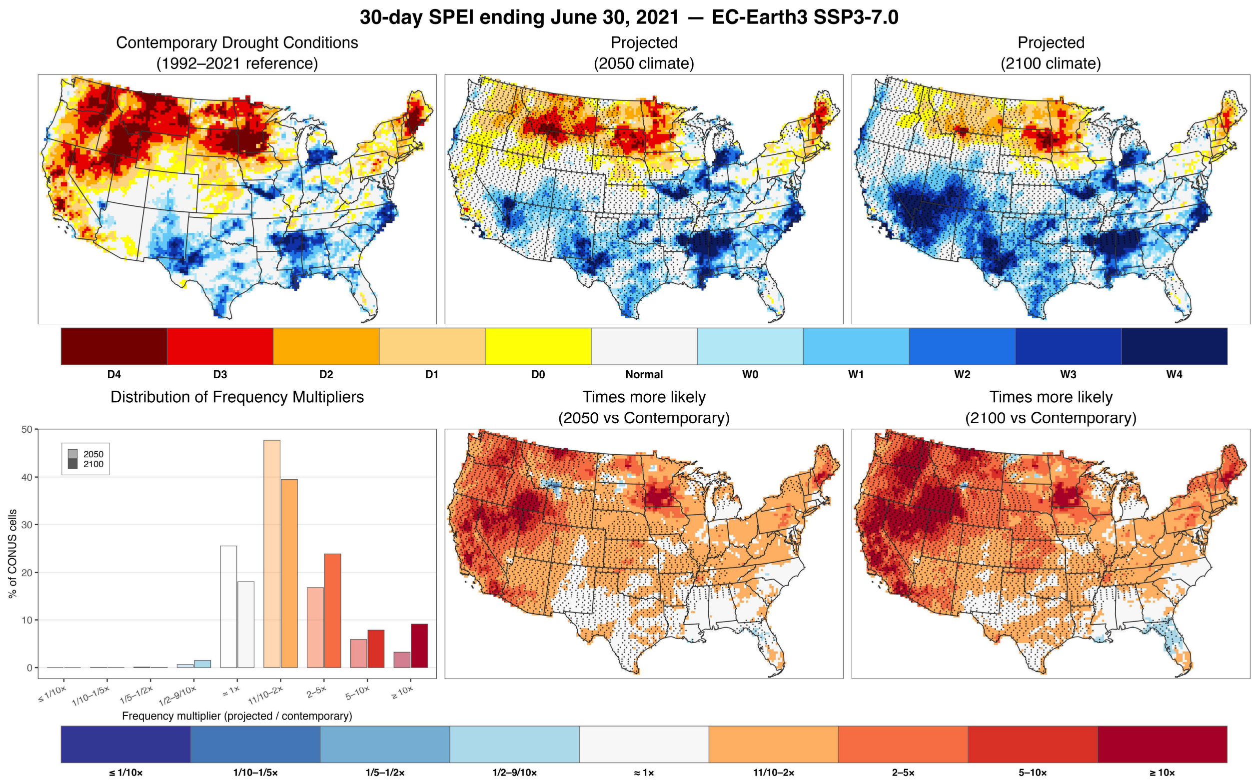


FIGURE 9-3 Thirty-day SPEI for the period ending June 30, 2021, evaluated against contemporary and future GEV distributions under SSP3-7.0 (EC-Earth3) using the GAMLSS approach.
NOTE: Top row: Left, U.S. Drought Monitor (USDM) categories for the observed June 2021 deficit ($P - ET_o$) evaluated against a contemporary GEV distribution (1992–2021); middle, the same event evaluated using a nonstationary GAMLSS GEV framework for 2050; and right, the same event evaluated for 2100 using the same GAMLSS framework. Stippling indicates grid cells with significant likelihood-ratio trends ($p < 0.05$). The same physical event becomes progressively less extreme as the underlying distributions shift toward drier conditions. Bottom row: Left, distribution across CONUS grid cells of the frequency multiplier, defined as the ratio of cumulative distribution function (CDF) values ($CDF_{future}/CDF_{contemporary}$) for 2050 (light shading) and 2100 (solid shading); middle and right, spatial distributions of the frequency multiplier for 2050 and 2100, respectively. Red shading indicates locations where this event is expected to become more likely under future climate conditions, while blue shading indicates locations where this event is expected to become less likely.

The framework proposed here recommends leveraging a longer period of record that incorporates both estimates of historical conditions as well as future projections of those conditions to assess how the rarity of current drought(s) is expected to change into the future; for example and due to climate warming, many droughts will become more severe and less rare. This exercise is intended to support long-term planning applications and decisions. In the case of drought conditions presented in Figure 9-3, classification of contemporary drought status under future projections using the GAMLSS approach indicates that moisture deficits of this severity are expected to become much more likely by mid-century. These results are consistent with projected increases in temperature and atmospheric evaporative demand under climate change. Ultimately, future droughts are likely to get worse, and plans and preparations need to be made for those future droughts, not for the droughts that are happening now. In contrast, the use of a longer baseline that incorporates historical and future periods, following the framework proposed in this report, permits assessment of drought and impact risk relative to contemporary systems (e.g., climate, economic/market, agronomic) in the context of recent past and potential future trends, among other forms of nonstationarity.

Water management agencies across the West routinely update drought mitigation and water resource plans that shape policy, regulation, infrastructure investment, and economic development over years to decades (e.g., the Southern Nevada Water Authority 2026 Water Resource Plan[1]). These planning activities depend on realistic estimates of future water supply, demand, and drought risk. As illustrated in Figure 9-3, drought assessments anchored only to the historical reference period may systematically underestimate the future likelihood and severity of drought conditions relevant to long-term planning decisions. The framework proposed here instead recommends that long-term planning assessments incorporate both historical and projected future climate information within an explicitly nonstationary framework, allowing drought risk estimates to better reflect evolving hydroclimatic conditions and the increasing likelihood of severe drought under climate change.

Scenario Planning

In some decision contexts, the best available modeled projections for long-term assessment may not be accepted as valid by the relevant decision-makers for any number of reasons. There may be significant scientific uncertainty around the projections for a particular location. Decision-makers and their constituents may lack trust in the models used to generate climate projections. Perhaps the costs of making changes in behavior or infrastructure—or the impacts of alternative courses of action—are sufficiently large that stakeholders are obliged to stress-test candidate strategies in "what if" exercises before taking action. For any of these reasons, long-term assessment may take place through some form of scenario planning and robust decision-making.

Scenario planning is a method for imagining possible futures, prompting decision-makers to consider strategies they might otherwise ignore (Schoemaker 1995). It is useful in situations where decision-makers do not agree on the possible states of the future, the likelihood each will occur, or how to value the impacts of different possible outcomes. While scenario planning may take different forms and purposes depending on the application, a standard objective is to identify robust strategies that perform reasonably well across a large range of plausible futures (Lempert et al. 2003).

Scenario planning could take the form of a water agency seeking to stress-test candidate strategies for action. In 2012, the United States Bureau of Reclamation started employing a form of scenario planning in the Colorado River Basin called Decision Making under Deep Uncertainty (DMDU). Their application of DMDU recognizes that uncertainty about future water conditions must be factored into their planning approaches. Rather than settling on a single set of long-term planning assumptions, their approach asks questions that recognize the importance of vulnerability, robustness, and adaptation. A sample question under a DMDU

[1] https://www.snwa.com/assets/pdf/water-resource-plan-2026.pdf, accessed June 11, 2026

approach would be to ask what actions should be taken now to allow for adaptation in the future, with current and future system vulnerabilities in mind (Smith et al. 2017). A DMDU approach requires simulating how the system behaves under many plausible futures. Information needs thus include simulated data from a suite of climate and hydrologic simulation models, sometimes augmented by paleoclimatic drought information, plus assumptions about water demand and institutional operating rules, and alternative management strategies and policies.

Scenario-based planning often takes the form of a short workshop in which stakeholders are invited to consider how they would react to alternative futures. Figure 9-4 illustrates two scenarios recently presented to rural communities in the Intermountain West: warmer and drier (Future Scenario 1) or warmer and wetter (Future Scenario 2) (Keller et al. 2025). Several important realities underpin this scenario planning example. First, temperatures over the past 100 years have increased significantly across the entire region. Second, future precipitation projections for the region exhibit significant variability across the region. And finally, stakeholders can envision and articulate strategies for adapting to a warmer future even in the absence of precise climate projections. Information needs for a scenario planning workshop may be more modest than for the DMDU approach, simply requiring temperature and precipitation projections along with qualitative estimates of the scientific confidence associated with both the temperature and precipitation projections.

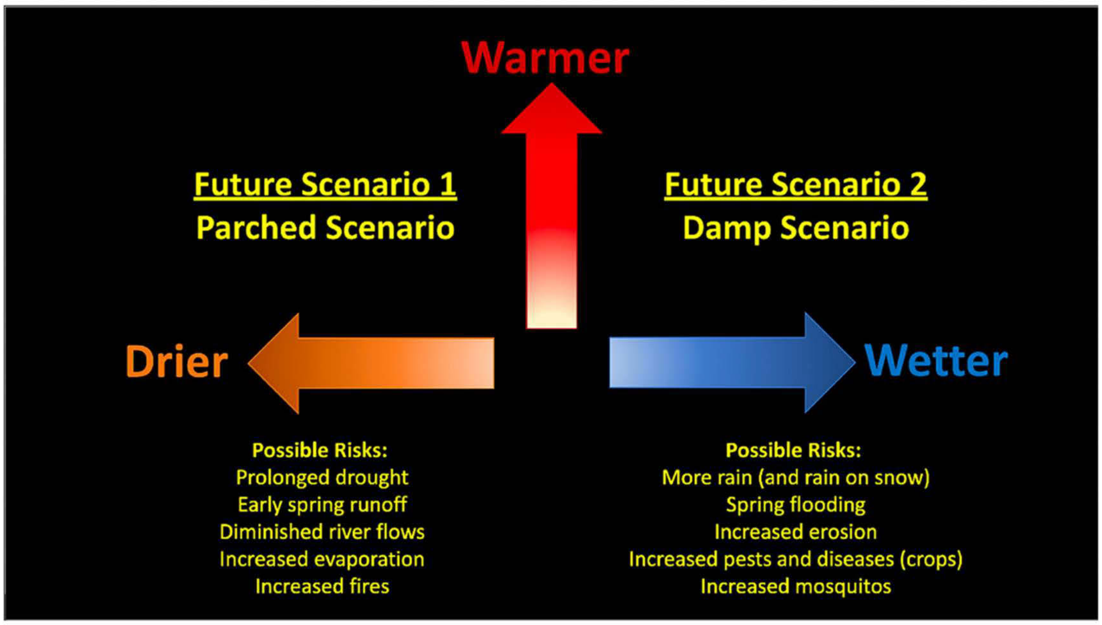


FIGURE 9-4 Scenario planning example from the Intermountain West.
NOTE: Parched scenario represents warmer-than-present temperatures and drier-than-present conditions. Damp scenario represents warmer-than-present temperatures and wetter-than-present conditions.
SOURCE: Keller et al. (2025). CC BY 4.0.

IMPLICATIONS OF THE FRAMEWORK FOR DROUGHT ASSESSMENT AND POLICY

Under the proposed approach, and consistent with USDM-style assessments, drought categories are tied to the contemporary rarity of an anomaly (e.g., D4 vs. D1, often interpreted as severity), rather than to the absolute value of an indicator alone. This distinction is important because if drought were defined solely by absolute thresholds, climatologically dry regions would be classified as being in drought most of the time, while wetter regions might rarely be classified as such, regardless of whether conditions were anomalous for that system.

As a result, if a condition that has historically caused drought impacts, such as a volumetric water content of 0.08 m^3/m^3, becomes more common over time, the framework is designed to reflect that shift by assigning this condition a less extreme drought category than it would have received under an older baseline. In this sense, a condition that was once classified as D4 may later be classified as D3, not necessarily because the absolute condition is less consequential in historical outcomes (e.g., historically observed crop yields and electricity generation) and historical management practices (e.g., irrigation routines, available forage for livestock), but because it is no longer as rare as it was relative to the contemporary climate. This raises a real and important practical implication: producers may reasonably experience similar impacts under a drought event if practices do not evolve alongside environmental change, even if the event is less anomalous statistically. This is where adaptation is needed to resolve impacts, rather than continued disaster relief.

The purpose for incorporating nonstationarity into drought assessment is not to diminish the importance of absolute conditions, but to distinguish between changes in background climate and drought as an anomalous departure from that background. If very low soil moisture becomes common, then continuing to classify it as exceptional drought would imply a perpetual drought emergency, which is not a workable basis for drought assessment or for decision-making. In that context, the issue extends beyond drought and disaster response to broader structural change, the need for adaptation, and reconsideration or updating of the policies and thresholds used to trigger drought response actions. As droughts occur, one important goal is to provide geographically specific assessments of what is ahead for each new and ongoing drought. In addition, no part of the United States is free of future drought risk, even though it is apparent that some regions are more drought prone than others, particularly given nonstationarity. For this reason, another important goal of the nation's long-term drought assessment capability needs to be a regular assessment of geographically specific future drought risks across the entire country (all 50 states and U.S. territories). Given nonstationarity, it is important to not wait for droughts to occur in the future, but rather to proactively understand what droughts may occur, and to support decisions that may need to be made, for example, in order to develop adaptation strategies. This is the intent of the second prong of the framework, to explicitly quantify future changes to drought dynamics and promote action to better prepare this nation for the future. No part of the United States should be assumed to be free of future drought risk.

CONCLUSION

This report recommends an improved framework for assessing drought under nonstationarity in the United States. The intent of this final chapter is to further motivate the need to take nonstationarity into account by sharing examples illustrating why nonstationarity matters. The recommended framework, components of which are summarized in Figure 9-5, and described in greater detail in Chapter 8, is designed to be driven by decision-makers in society and the decisions that they need to make regarding drought, on both short-term operational and long-term planning timescales. NIDIS and their partners are the ones who need to articulate the specific decision drivers and details of how the framework should be designed and implemented. Examples of decision drivers are given in Figure 9-5, with the overarching goal that an improved framework for drought assessment under uncertainty will lead to greater resilience to drought in the United States, both short-term and long-term.

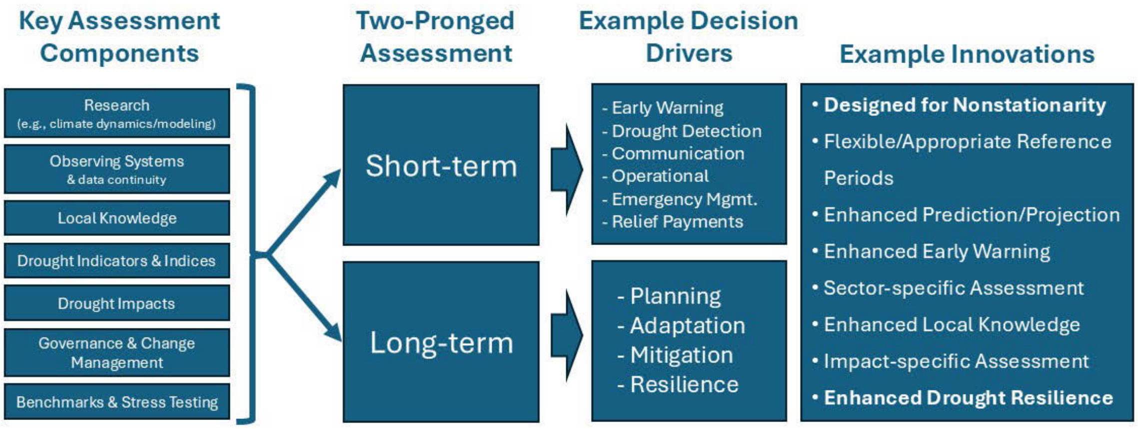


FIGURE 9-5 Elements of the proposed two-pronged assessment framework.
NOTE: This schematic highlights key components to be provided by the recommended assessment consortium, example decision drivers, and examples of the innovations that would yield improved drought assessments.

This report weaves together an understanding of how the drivers and nature of drought are changing in the United States, and how drought assessment needs to change to meet the challenge of nonstationarity, especially in the form of a changing climate. This challenge will require a range of research, including on how the climate varied in the past, how the climate system works, and how climate will change in the future, and also on how scientific information—drought assessments included—can best inform decision-making under uncertainty. Special attention must also focus on observing systems, in situ, paleoclimatic, and space-borne, that are essential to the drought assessment enterprise; continuity and completeness of these vital systems must be assured. Existing drought indicators and indices, many of which are invaluable and already widely used, depend on observing systems, and the creation of new innovative indicators and indices will no doubt require new observing capabilities. The use of local knowledge and drought impact data can be expanded to make drought assessments more useful and effective. With careful development, artificial intelligence/machine learning (AI/ML) approaches have the potential to advance drought assessment through assessment automation, state variable prediction, collection and synthesis of drought impact information, and modeling of drought parameters.

Key to improved drought assessment will be the successful participation of all the partners essential to effective decision-making, as well as a high level of transparency in terms of how all elements of drought assessment are implemented. This includes making assessment methodologies as transparent and reproducible as possible and also ensuring effective governance and change management as assessment protocols improve. Improvement requires benchmarks and stress-testing that are also structured and transparent to all users of drought assessments. Efforts to avoid potential biases associated with AI/ML approaches are warranted. Understanding assessment uncertainty is critical to making effective decisions, whether they relate to predictions or projections of future climate, connecting drought to impacts, or any other aspect of the assessment endeavor.

As stressed throughout this report, the NIDIS, National Drought Mitigation Center, and broader U.S. drought community have established an excellent foundation on which to build an improved operational drought assessment framework that takes nonstationarity into account. The nature of drought is changing in the United States, and so too must the ability of the U.S. to thrive in the face of increasingly complex and severe drought risks.

References

Abatzoglou, John T., Solomon Z. Dobrowski, Sean A. Parks, and Katherine C. Hegewisch. 2018. "TerraClimate, a High-Resolution Global Dataset of Monthly Climate and Climatic Water Balance from 1958–2015." *Scientific Data* 5 (1): 170191. https://doi.org/10.1038/sdata.2017.191.

Abatzoglou, John T., and A. Park Williams. 2016. "Impact of Anthropogenic Climate Change on Wildfire across Western US Forests." *Proceedings of the National Academy of Sciences* 113 (42): 11770–75. https://doi.org/10.1073/pnas.1607171113.

Abbaszadeh, Peyman, Hamid Moradkhani, and Xiwu Zhan. 2019. "Downscaling SMAP Radiometer Soil Moisture Over the CONUS Using an Ensemble Learning Method." *Water Resources Research* 55 (1): 324–44. https://doi.org/10.1029/2018WR023354.

Adeyeri, Oluwafemi E., Wen Zhou, Patrick Laux, et al. 2023. "Multivariate Drought Monitoring, Propagation, and Projection Using Bias-Corrected General Circulation Models." *Earth's Future* 11 (4): e2022EF003303. https://doi.org/10.1029/2022EF003303.

Adhikari, Pramod, Bart Geerts, Stefan Rahimi, Bryan Shuman, Kaitlin Smith, and Kinsale Day. 2025. "Global Warming Induced Changes in Extreme Precipitation in the Western United States: Projections From Dynamically Downscaled CMIP6 GCMs." *Geophysical Research Letters* 52 (17): e2025GL116113. https://doi.org/10.1029/2025GL116113.

AghaKouchak, A., A. Farahmand, F. S. Melton, et al. 2015. "Remote Sensing of Drought: Progress, Challenges and Opportunities." *Reviews of Geophysics* 53 (2): 452–80. https://doi.org/10.1002/2014RG000456.AghaKouchak, Amir, Linyin Cheng, Omid Mazdiyasni, and Alireza Farahmand. 2014. "Global Warming and Changes in Risk of Concurrent Climate Extremes: Insights from the 2014 California Drought." *Geophysical Research Letters* 41 (24): 8847–52. https://doi.org/10.1002/2014GL062308.

AghaKouchak, Amir, Ali Mirchi, Kaveh Madani, et al. 2021. "Anthropogenic Drought: Definition, Challenges, and Opportunities." *Reviews of Geophysics* 59 (2): e2019RG000683. https://doi.org/10.1029/2019RG000683.

AghaKouchak, Amir, Laurie S. Huning, Mojtaba Sadegh, et al. 2023. "Toward Impact-Based Monitoring of Drought and Its Cascading Hazards." *Nature Reviews Earth & Environment* 4 (8): 582–95. https://doi.org/10.1038/s43017-023-00457-2.

AghaKouchak, A., B. Pan, O. Mazdiyasni, M. Sadegh, S. Jiwa, W. Zhang, C. A. Love, S. Madadgar, S. M. Papalexiou, S. J. Davis, and K. Hsu. 2022. "Status and Prospects for Drought Forecasting: Opportunities in Artificial Intelligence and Hybrid Physical–Statistical Forecasting. *Philosophical Transactions of the Royal Society A* 380 (2238): 20210288.

Alessi, Marc J., and Maria Rugenstein. 2024. "Potential Near-Term Wetting of the Southwestern United States If the Eastern and Central Pacific Cooling Trend Reverses." *Geophysical Research Letters* 51 (13): e2024GL108292. https://doi.org/10.1029/2024GL108292.

Allen, Richard G., ed. 2000. *Crop Evapotranspiration: Guidelines for Computing Crop Water Requirements*. Repr. FAO Irrigation and Drainage Paper 56. Food and Agriculture Organization of the United Nations.

Allen, R. G., L. S. Pereira, D. Raes, and M. Smith. 1998. *Crop Evapotranspiration-Guidelines for Computing Crop Water Requirements-FAO Irrigation and Drainage Paper 56*. FAO Rome.

Allen, Simon K., Vicente Barros, Ian Burton, et al. 2012. *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change*. Preprint, unpublished. https://doi.org/10.13140/2.1.3117.9529.

Almazroui, Mansour, M. Nazrul Islam, Fahad Saeed, et al. 2021. "Projected Changes in Temperature and Precipitation Over the United States, Central America, and the Caribbean in CMIP6 GCMs." *Earth Systems and Environment* 5 (1): 1–24. https://doi.org/10.1007/s41748-021-00199-5.

AMS (American Meteorological Society). n.d. "Drought - Glossary of Meteorology." Accessed October 20, 2025. https://glossary .ametsoc.org/wiki/Drought.

AMS. 1997. "Policy Statement." *Bulletin of the American Meteorological Society*.

American Meteorological Society, May 1, 847–52. https://doi.org/10.1175/1520-0477-78.5.847. [It looks like these two references are the same source. As found, it would be styled as follows: AMS. 1997. Policy statement. *Bulletin of the American Meteorological Society* 78 (5): 847–52. [URL as above.]

AMS. 2002. "The Drought Monitor." *Bulletin of the American Meteorological Society* 83 (8): 1181–90. https://doi.org/10.1175/1520-0477(2002)083%253C1181:TDM%253E2.3.CO;2.

AMS. 2012. "Aridity." Glossary of Meteorology. https://glossary .ametsoc.org/wiki/Aridity.

Apurv, Tushar, and Ximing Cai. 2020. "Impact of Droughts on Water Supply in U.S. Watersheds: The Role of Renewable Surface and Groundwater Resources." *Earth's Future* 8 (10): e2020EF001648. https://doi.org/10.1029/2020EF001648.

Arsenault, Richard, Jean-Luc Martel, Frédéric Brunet, François Brissette, and Juliane Mai. 2023. "Continuous Streamflow Prediction in Ungauged Basins: Long Short-Term Memory Neural Networks Clearly Outperform Traditional Hydrological Models." *Hydrology and Earth System Sciences* 27 (1):139–57. https://doi.org/10.5194/hess-27-139-2023.

Ashraf, S., A. Nazemi, and A. AghaKouchak. 2021. "Anthropogenic Drought Dominates Groundwater Depletion in Iran." *Scientific Reports* 11 (1): 9135. https://doi.org/10.1038/s41598-021-88522-y.

Aubry, Keith B., Kevin S. Mckelvey, and Jeffrey P. Copeland. 2007. "Distribution and Broadscale Habitat Relations of the Wolverine in the Contiguous United States." *The Journal of Wildlife Management* 71(7): 2147–58. https://doi.org/10.2193/2006-548.

Avery, C. B., L. A. Jacobs, V. C. Salgado, et al. 2025. *Ch 2. Cultural Preservation and Revitalization in the Face of Climate Change , Status of Tribes Against Climate Change*. Institute for Tribal Environmental Professionals, Northern Arizona University.

Bachmair, S., I. Kohn, and K. Stahl. 2015. "Exploring the Link between Drought Indicators and Impacts." *Natural Hazards and Earth System Sciences* 15 (6): 1381–97. https://doi.org/10.5194/nhess-15-1381-2015.

Baez-Villanueva, Oscar M., Mauricio Zambrano-Bigiarini, Diego G. Miralles, et al. 2024. "On the Timescale of Drought Indices for Monitoring Streamflow Drought Considering Catchment Hydrological Regimes." *Hydrology and Earth System Sciences* 28 (6): 1415–39. https://doi.org/10.5194/hess-28-1415-2024.

Balting, Daniel F., Amir AghaKouchak, Gerrit Lohmann, and Monica Ionita. 2021. "Northern Hemisphere Drought Risk in a Warming Climate." *Npj Climate and Atmospheric Science* 4 (1): 61. https://doi.org/10.1038/s41612-021-00218-2.

Bamford, E., B. Parker, M. Shiple, E. Weight, and M. Woloszyn. 2020. NIDIS Tribal Drought Engagement Strategy For the Missouri River Basin and Midwest Drought Early Warning Systems (DEWS). NOAA NIDIS.

Barnett, T. P., et al. 2005. "Potential Impacts of a Warming Climate on Water Availability in Snow-Dominated Regions." *Nature* 438(7066, Nov.): 303–09. https://doi.org/10.1038/nature04141.

Barrow, C. J. 1992. *World Atlas of Desertification* (United Nations Environment Programme), edited by N. Middleton and D. S. G. Thomas. Edward Arnold. https://doi.org/10.1002/ldr.3400030407.

Basara, Jeffrey B., Jordan I. Christian, Ryann A. Wakefield, Jason A. Otkin, Eric H. Hunt, and David P. Brown. 2019. "The Evolution, Propagation, and Spread of Flash Drought in the Central United States during 2012." *Environmental Research Letters* 14 (8): 084025. https://doi.org/10.1088/1748-9326/ab2cc0.

Bathke, D. J., E. Hunt, H. Akin, A. D. Basche, J. E. Bell, D. R. DiLeo, R. Dixon, M. Durr, T. Haigh, and Hay. 2025. *Understanding and Assessing Climate Change: Preparing for Nebraska's Future.* University of Nebraska–Lincoln.

Bathke, Deborah J., Holly R. Prendeville, Aaron Jacobs, Richard Heim, Rick Thoman, and Brian Fuchs. 2019. "Defining Drought in a Temperate Rainforest." *Bulletin of the American Meteorological Society* 100 (12): 2665–68. https://doi.org/10.1175/BAMS-D-19-0223.1.

Bazrafshan, Javad, Majid Cheraghalizadeh, and Kokab Shahgholian. 2022. "Development of a Non-Stationary Standardized Precipitation Evapotranspiration Index (NSPEI) for Drought Monitoring in a Changing Climate." *Water Resources Management* 36 (10): 3523–43. https://doi.org/10.1007/s11269-022-03209-x.

Beck, Hylke E., Ming Pan, Diego G. Miralles, et al. 2021. "Evaluation of 18 Satellite- and Model-Based Soil Moisture Products Using In Situ Measurements from 826 Sensors." *Hydrology and Earth System Sciences* 25 (1): 17–40. https://doi.org/10.5194/hess-25-17-2021.

Beguería, Santiago, Sergio M. Vicente-Serrano, Fergus Reig, and Borja Latorre. 2014. "Standardized Precipitation Evapotranspiration Index (SPEI) Revisited: Parameter Fitting, Evapotranspiration Models, Tools, Datasets and Drought Monitoring." *International Journal of Climatology* 34 (10): 3001–23. https://doi.org/10.1002/joc.3887.

Bellew, Grace, and Melanie R. Boudreau. 2025. "Understanding the Breadth and Depth of Long-Term Ecological Data Collection in Canada and the United States." *FACETS* 10 (January): 1–9. https://doi.org/10.1139/facets-2025-0056.

Bennett, T. M. B., N. G. Maynard, P. Cochran, et al. 2014. *Ch. 12: Indigenous Peoples, Lands, and Resources. Climate Change Impacts in the United States: The Third National Climate Assessment*. U.S. Global Change Research Program. https://doi.org/10.7930/J09G5JR1.

Benson, M. H., and A. S. Garmestani. 2011. "Can We Manage for Resilience? The Integration of Resilience Thinking into Natural Resource Management in the United States." *Environmental Management* 48 (3): 392–99. https://doi.org/10.1007/s00267-011-9693-5.

Berg, Alexis, and Justin Sheffield. 2018. "Soil Moisture–Evapotranspiration Coupling in CMIP5 Models: Relationship with Simulated Climate and Projections." *Journal of Climate* 31 (12): 4865–78. https://doi.org/10.1175/JCLI-D-17-0757.1.

Berghuijs, W. R., R. A. Woods, and M. Hrachowitz. 2014. "A Precipitation Shift from Snow towards Rain Leads to a Decrease in Streamflow." *Nature Climate Change* 4 (7): 583–86. https://doi.org/10.1038/nclimate2246.

Bernknopf, Richard, David Brookshire, Yusuke Kuwayama, et al. 2018. "The Value of Remotely Sensed Information: The Case of a GRACE-Enhanced Drought Severity Index." *Weather, Climate, and Society* 10 (1): 187–203. https://doi.org/10.1175/WCAS-D-16-0044.1.

Bikhchandani, Sushil, Jack Hirshleifer, and John G. Riley. 2013. *The Analytics of Uncertainty and Information*. Second edition. Cambridge Surveys of Economic Literature. Cambridge University Press.

Boergens, Eva, Andreas Güntner, Henryk Dobslaw, and Christoph Dahle. 2020. "Quantifying the Central European Droughts in 2018 and 2019 With GRACE Follow-On." *Geophysical Research Letters* 47 (14): e2020GL087285. https://doi.org/10.1029/2020GL087285.

Bowling, Laura C., Pascal Storck, and Dennis P. Lettenmaier. 2000. "Hydrologic Effects of Logging in Western Washington, United States." *Water Resources Research* 36 (11): 3223–40. https://doi.org/10.1029/2000WR900138.

Brázdil, Rudolf, Andrea Kiss, Jürg Luterbacher, David J. Nash, and Ladislava Řezníčková. 2018. "Documentary Data and the Study of Past Droughts: A Global State of the Art." *Climate of the Past* 14(12): 1915–60. https://doi.org/10.5194/cp-14-1915-2018.

Brooks, Paul D., Andrew Gelderloos, Margaret A. Wolf, et al. 2021. "Groundwater-Mediated Memory of Past Climate Controls Water Yield in Snowmelt-Dominated Catchments." *Water Resources Research* 57 (10): e2021WR030605. https://doi.org/10.1029/2021WR030605.

Brown, Eleanor D., and Byron K. Williams. 2019. "The Potential for Citizen Science to Produce Reliable and Useful Information in Ecology." *Conservation Biology* 33 (3): 561–69. https://doi.org/10.1111/cobi.13223.

Brubaker, Kaye L., and Dara Entekhabi. 1996. "Analysis of Feedback Mechanisms in Land-Atmosphere Interaction." *Water Resources Research* 32 (5): 1343–57. https://doi.org/10.1029/96WR00005.

Brubaker, Kaye L., Dara Entekhabi, and P. S. Eagleson. 1993. "Estimation of Continental Precipitation Recycling." *Journal of Climate* 6 (6): 1077–89. https://doi.org/10.1175/1520-0442(1993)006%253C1077:EOCPR%253E2.0.CO;2.

Bruins, H. J. 2000: Drought Hazards in Israel and Jordan. Chapter 42 in *Drought: A Global Assessment, Volume II*, D. A. Wilhite, ed. Routledge: London.

Brunner, Lukas, Angeline G. Pendergrass, Flavio Lehner, Anna L. Merrifield, Ruth Lorenz, and Reto Knutti. 2020. "Reduced Global Warming from CMIP6 Projections When Weighting Models by Performance and Independence." *Earth System Dynamics* 11 (4): 995–1012. https://doi.org/10.5194/esd-11-995-2020.

Brust, Colin, John S. Kimball, Marco P. Maneta, Kelsey Jencso, and Rolf H. Reichle. 2021. "DroughtCast: A Machine Learning Forecast of the United States Drought Monitor." *Frontiers in Big Data* 4 (December): 773478. https://doi.org/10.3389/fdata.2021.773478.

Bryson, Reid A., and Thomas J. Murray. 1977. *Climates of Hunger: Mankind and the World's Changing Weather*. Madison : University of Wisconsin Press. http://archive.org/details/climatesofhunger0000brys_w0a6.

Budyko, M. I. 1961. "The Heat Balance of the Earth's Surface." *Soviet Geography* 2 (4): 3–13. https://doi.org/10.1080/00385417.1961.10770761.

Bureau of Land Management. 2024. National Drought and Water Availability. Instruction Memorandum No. 2024-034. U.S. Department of the Interior, Bureau of Land Management. https://www.blm.gov/policy/im2024-034.

Cabrini, Silvina, Gary Schnitkey, and Scott Irwin. n.d. *The Use of Climate Information in Midwest Agriculture: Results from a Farmer Survey – Part I*. https://doi.org/10.22004/AG.ECON.342720.

CA DWR (State of California Department of Water Resources). 2024. *State Water Project Long-Term Drought Plan*. State of California - California Natural Resources.

Cammalleri, Carmelo, Jonathan Spinoni, Paulo Barbosa, Andrea Toreti, and Jürgen V. Vogt. 2022. "The Effects of Non-stationarity on SPI for Operational Drought Monitoring in Europe." *International Journal of Climatology* 42 (6): 3418–30. https://doi.org/10.1002/joc.7424.

Cammalleri, Carmelo, and Jürgen V. Vogt. 2019. "Non-Stationarity in MODIS fAPAR Time-Series and Its Impact on Operational Drought Detection." *International Journal of Remote Sensing* 40 (4): 1428–44. https://doi.org/10.1080/01431161.2018.1524603.

Cancelliere, Antonino. 2017. "Non Stationary Analysis of Extreme Events." *Water Resources Management*31 (10): 3097–110. https://doi.org/10.1007/s11269-017-1724-4.

Cannon, Alex J., Stephen R. Sobie, and Trevor Q. Murdock. 2015. "Bias Correction of GCM Precipitation by Quantile Mapping: How Well Do Methods Preserve Changes in Quantiles and Extremes?" *Journal of Climate* 28 (17): 6938–59. https://doi.org/10.1175/JCLI-D-14-00754.1.

Carrão, Hugo, Gustavo Naumann, and Paulo Barbosa. 2016. "Mapping Global Patterns of Drought Risk: An Empirical Framework Based on Sub-National Estimates of Hazard, Exposure and Vulnerability." *Global Environmental Change* 39 (July): 108–24. https://doi.org/10.1016/j.gloenvcha.2016.04.012.

Carter, Nicole, M. Lynne Corn, Amy Abel, et al. 2008. *CRS Report for Congress: Apalachicola-Chattahoochee-Flint (ACF) Drought: Federal Water Management Issues*. No. RL34326.

Cartwright, Jennifer M., Caitlin E. Littlefield, Julia L. Michalak, Joshua J. Lawler, and Solomon Z. Dobrowski. 2020. "Topographic, Soil, and Climate Drivers of Drought Sensitivity in Forests and Shrublands of the Pacific Northwest, USA." *Scientific Reports* 10 (1): 18486. https://doi.org/10.1038/s41598-020-75273-5.

Chang, Ping, Dan Fu, Xue Liu, et al. 2025. "Future Extreme Precipitation Amplified by Intensified Mesoscale Moisture Convergence." *Nature Geoscience*, ahead of print, November 18. https://doi.org/10.1038/s41561-025-01859-1.

Changnon, Stanley Alcide. 1987. "Detecting Drought Conditions in Illinois." *Circular No. 169*. https://hdl.handle.net/2142/94485.

Charney, J. G. 1975. "Dynamics of Deserts and Drought in the Sahel." *Quarterly Journal of the Royal Meteorological Society* 101 (428): 193–202. https://doi.org/10.1002/qj.49710142802.

Chen, Liangzhi, Philipp Brun, Pascal Buri, et al. 2025. "Global Increase in the Occurrence and Impact of Multiyear Droughts." *Science* 387 (6731): 278–84. https://doi.org/10.1126/science.ado4245.

Cheng, Linyin, Amir AghaKouchak, Eric Gilleland, and Richard W. Katz. 2014. "Non-Stationary Extreme Value Analysis in a Changing Climate." *Climatic Change* 127 (2): 353–69. https://doi.org/10.1007/s10584-014-1254-5.

Chiang, Felicia, Omid Mazdiyasni, and Amir AghaKouchak. 2021. "Evidence of Anthropogenic Impacts on Global Drought Frequency, Duration, and Intensity." *Nature Communications* 12 (1): 2754. https://doi.org/10.1038/s41467-021-22314-w.

Christian, Jordan I., Jeffrey B. Basara, Eric D. Hunt, et al. 2021. "Global Distribution, Trends, and Drivers of Flash Drought Occurrence." *Nature Communications* 12 (1): 6330. https://doi.org/10.1038/s41467-021-26692-z.

Christian, Jordan I., Mike Hobbins, Andrew Hoell, et al. 2024. "Flash Drought: A State of the Science Review." *WIREs Water* 11 (3): e1714. https://doi.org/10.1002/wat2.1714.

Coble, Keith H., Mary Frances Miller, Roderick M. Rejesus, Ryan Boyles, Thomas O. Knight, and Barry K. Goodwin. 2011. *Methodology Analysis for Weighting Historical Experience – Implementation Report*.

Coder, L., A. Musolff, P. M. Kronsbein, K. Knöller, O. Büttner, K. Rinke, and J. TittelJ. 2025. "How Anthropogenic Modification of Riverscapes Reduces the Resilience of Floodplain Water Bodies to Drought." *Ecological Engineering* 219: 107686. https://doi.org/10.1016/j.ecoleng.2025.107686.

Coles, Stuart. 2001. "Extremes of Non-Stationary Sequences." In *An Introduction to Statistical Modeling of Extreme Values*, by Stuart Coles. Springer London. https://doi.org/10.1007/978-1-4471-3675-0_6.

Committee on Anthropogenic Greenhouse Gases and U.S. Climate: Evidence and Impacts, Climate Crossroads, Board on Atmospheric Sciences and Climate, et al. 2025. *Effects of Human-Caused Greenhouse Gas Emissions on U.S. Climate, Health, and Welfare*. National Academies Press. https://doi.org/10.17226/29239.

Commodity Credit Corporation. 2025. "Supplemental Agricultural Assistance Programs." *Federal Register*, January 17. https://www.federalregister.gov/documents/2025/01/17/2025-01104/supplemental-agricultural-assistance-programs.

Cook, Benjamin I., Kevin J. Anchukaitis, Ramzi Touchan, David M. Meko, and Edward R. Cook. 2016. "Spatiotemporal Drought Variability in the Mediterranean over the Last 900 Years." *Journal of Geophysical Research: Atmospheres* 121 (5): 2060–74. https://doi.org/10.1002/2015JD023929.

Cook, Benjamin I., Justin S. Mankin, and Kevin J. Anchukaitis. 2018. "Climate Change and Drought: From Past to Future." *Current Climate Change Reports* 4 (2): 164–79. https://doi.org/10.1007/s40641-018-0093-2.

Cook, B. I., J. S. Mankin, K. Marvel, A. P. Williams, J. E. Smerdon, and K. J. Anchukaitis. 2020. "Twenty-First Century Drought Projections in the CMIP6 Forcing Scenarios." *Earth's Future* 8 (6): e2019EF001461. https://doi.org/10.1029/2019EF001461.

Cook, Benjamin I., Ron L. Miller, and Richard Seager. 2009. "Amplification of the North American 'Dust Bowl' Drought through Human-Induced Land Degradation." *Proceedings of the National Academy of Sciences* 106 (13): 4997–5001. https://doi.org/10.1073/pnas.0810200106.

Cook, B. I., Seager, R., Williams, A. P., Puma, M. J., McDermid, S., Kelley, M., & Nazarenko, L. 2019. Climate Change Amplification of Natural Drought Variability: The Historic Mid-Twentieth-Century North American Drought in a Warmer World. *Journal of Climate*, *32*(17), 5417–5436. https://doi.org/10.1175/JCLI-D-18-0832.1

Cook, Benjamin I., Jason E. Smerdon, Edward R. Cook, et al. 2022. "Megadroughts in the Common Era and the Anthropocene." *Nature Reviews Earth & Environment* 3 (11): 741–57. https://doi.org/10.1038/s43017-022-00329-1.

Cook, Edward R., Richard Seager, Mark A. Cane, and David W. Stahle. 2007. "North American Drought: Reconstructions, Causes, and Consequences." *Earth-Science Reviews* 81 (1–2): 93–134. https://doi.org/10.1016/j.earscirev.2006.12.002.

Cook, Edward R., Connie A. Woodhouse, C. Mark Eakin, David M. Meko, and David W. Stahle. 2004. "Long-Term Aridity Changes in the Western United States." *Science* 306 (5698): 1015–18. https://doi.org/10.1126/science.1102586.

Cooley, Daniel. 2013. "Return Periods and Return Levels Under Climate Change." In *Extremes in a Changing Climate*, edited by Amir AghaKouchak, David Easterling, Kuolin Hsu, Siegfried Schubert, and Soroosh Sorooshian, vol. 65. Springer Netherlands. https://doi.org/10.1007/978-94-007-4479-0_4.

Corn, M. Lynne, et al. 2008. "Apalachicola-Chattahoochee-Flint (ACF) Drought: Federal Water Management Issues." *Policy* 7: 9529.

Crausbay, Shelley D., Aaron R. Ramirez, Shawn L. Carter, et al. 2017. "Defining Ecological Drought for the Twenty-First Century." *Bulletin of the American Meteorological Society*. American Meteorological Society, December 1, 2543–50. https://doi.org/10.1175/BAMS-D-16-0292.1.

Crausbay, Shelley D., Helen R. Sofaer, Amanda E. Cravens, et al. 2022. "A Science Agenda to Inform Natural Resource Management Decisions in an Era of Ecological Transformation." *BioScience* 72 (1):71–90. https://doi.org/10.1093/biosci/biab102.

Cravens, Amanda E., Jen Henderson, Jack Friedman, et al. 2021. "A Typology of Drought Decision Making: Synthesizing across Cases to Understand Drought Preparedness and Response Actions." *Weather and Climate Extremes* 33 (September): 100362. https://doi.org/10.1016/j.wace.2021.100362.

Critchfield, Howard J. 1974. *General Climatology*. 3d ed. Prentice-Hall.

CRS. 2023. *Drought in the United States: Science, Policy, and Selected Federal Authorities*. No. R46911.

Cuesta, Jose. 2026. "Gender Bias in Artificial Intelligence." *Journal of Economic Policy Reform* 29 (1):1–25. https://doi.org/10.1080/17487870.2025.2579039.

Daghagh Yazd, Sahar, Sarah Ann Wheeler, and Alec Zuo. 2019. "Key Risk Factors Affecting Farmers' Mental Health: A Systematic Review." *International Journal of Environmental Research and Public Health* 16 (23): 4849. https://doi.org/10.3390/ijerph16234849.

Dai, Meng, Ping Feng, Shengzhi Huang, et al. 2024. "Propagation from Meteorological to Hydrological Drought Considering Nonstationarity in the Luanhe River Basin: Spatiotemporal Pattern and Driving Factors." *Journal of Hydrometeorology* 25 (10): 1443–59. https://doi.org/10.1175/JHM-D-23-0179.1.

De Michele, C., A. Montanari, and R. Rosso. 1998. "The Effects of Non-Stationarity on the Evaluation of Critical Design Storms." *Water Science and Technology* 37 (11): 187–93. https://doi.org/10.2166/wst.1998.0465.

Delaney, Chris J., Robert K. Hartman, John Mendoza, et al. 2020. "Forecast Informed Reservoir Operations Using Ensemble Streamflow Predictions for a Multipurpose Reservoir in Northern California." *Water Resources Research* 56 (9): e2019WR026604. https://doi.org/10.1029/2019WR026604.

Department of the Interior, Bureau of Reclamation. 2025. WaterSMART Drought Response Program Framework. United States Bureau of Reclamation.

Deser, C. 2020. "Certain Uncertainty: The Role of Internal Climate Variability in Projections of Regional Climate Change and Risk Management." *Earth's Future* 8. doi:10.1029/2020EF001854.

Devasthale, Abhay, and Karl-Göran Karlsson. 2023. "Decadal Stability and Trends in the Global Cloud Amount and Cloud Top Temperature in the Satellite-Based Climate Data Records." *Remote Sensing* 15(15): 3819. https://doi.org/10.3390/rs15153819.

Dierauer, Jennifer R., Diana M. Allen, and Paul H. Whitfield. 2019. "Snow Drought Risk and Susceptibility in the Western United States and Southwestern Canada." *Water Resources Research* 55 (4): 3076–91. https://doi.org/10.1029/2018WR023229.

Dieter, Cheryl, Molly Maupin, Rodney Caldwell, et al. 2018. *Estimated Use of Water in the United States in 2015*. Circular 1441. USGS. https://doi.org/10.3133/cir1441.

Diffenbaugh, Noah S., Daniel L. Swain, and Danielle Touma. 2015. "Anthropogenic Warming Has Increased Drought Risk in California." *Proceedings of the National Academy of Sciences* 112 (13): 3931–36. https://doi.org/10.1073/pnas.1422385112.

Donaldson, Emily, Hailey Wilmer, Corrie Knapp, and Justin D. Derner. 2025. "Understanding How Ranchers Adaptively Manage for Drought in Northeastern Colorado." *Rangeland Ecology & Management* 98 (January): 83–93. https://doi.org/10.1016/j.rama.2024.08.026.

Dregne, H. E., and Donald A. Wilhite. n.d. "Drought and Desertification: Exploring the Linkages." In *Droughts: A Global Assessment*, 1st ed. Routledge.

Druckenmiller, M. L., R. L. Thoman, and T. A. Moon. 2025. "NOAA Arctic Report Card 2025: Executive Summary." *NOAA Technical Report OAR ARC; 25-01 (Arctic Report Card)*, ahead of print. https://doi.org/10.25923/NRZF-J897.

Dubrovsky, M., M. D. Svoboda, M. Trnka, et al. 2009. "Application of Relative Drought Indices in Assessing Climate-Change Impacts on Drought Conditions in Czechia." *Theoretical and Applied Climatology* 96 (1–2): 155–71. https://doi.org/10.1007/s00704-008-0020-x.

Easterling, D. R., J. R. Arnold, T. Knutson, et al. 2017. Ch. 7: "Precipitation Change in the United States." *Climate Science Special Report: Fourth National Climate Assessment, Volume I*. U.S. Global Change Research Program. https://doi.org/10.7930/J0H993CC.

Ehret, U., H. V. Gupta, M. Sivapalan, et al. 2014. "Advancing Catchment Hydrology to Deal with Predictions under Change." *Hydrology and Earth System Sciences* 18 (2): 649–71. https://doi.org/10.5194/hess-18-649-2014.

Elliott, Katherine J., Peter V. Caldwell, Steven T. Brantley, Chelcy F. Miniat, James M. Vose, and Wayne T. Swank. 2017. "Water Yield Following Forest–Grass–Forest Transitions." *Hydrology and Earth System Sciences* 21 (2): 981–97. https://doi.org/10.5194/hess-21-981-2017.

Enenkel, M., M. E. Brown, J. V. Vogt, et al. 2020. "Why Predict Climate Hazards If We Need to Understand Impacts? Putting Humans Back into the Drought Equation." *Climatic Change* 162 (3): 1161–76. https://doi.org/10.1007/s10584-020-02878-0.

Entekhabi, Dara. 2023. "Propagation in the Drought Cascade: Observational Analysis Over the Continental US." *Water Resources Research* 59 (9): e2022WR032608. https://doi.org/10.1029/2022WR032608.

Entekhabi, Dara, Eni G. Njoku, Peggy E. O'Neill, et al. 2010. "The Soil Moisture Active Passive (SMAP) Mission." *Proceedings of the IEEE* 98 (5): 704–16. https://doi.org/10.1109/JPROC.2010.2043918.

Erazo, Diana, Luke Grant, Guillaume Ghisbain, et al. 2024. "Contribution of Climate Change to the Spatial Expansion of West Nile Virus in Europe." *Nature Communications* 15 (1): 1196. https://doi.org/10.1038/s41467-024-45290-3.

Fang, Bin, Venkataraman Lakshmi, Christopher Hain, and Vikalp Mishra. 2025 (under review). "A Global 400-m High-Resolution Soil Moisture Dataset Derived from Multi-Sensor Remote Sensing Observations." *Scientific Data* 13 (1): 65. https://doi.org/10.1038/s41597-025-06356-z.

Fang, Bin, Venkataraman Lakshmi, and Runze Zhang. 2024. "Validation of Downscaled 1-km SMOS and SMAP Soil Moisture Data in 2010–2021." *Vadose Zone Journal* 23 (2): e20305. https://doi.org/10.1002/vzj2.20305.

Farm Service Agency. 2018. Livestock Disaster Assistance Programs for 2011 and Subsequent Years. United States Department of Agriculture.

Fergus, C. Emi, J. Renée Brooks, Philip R. Kaufmann, et al. 2022. "Natural and Anthropogenic Controls on Lake Water-level Decline and Evaporation-to-inflow Ratio in the Conterminous United States." *Limnology and Oceanography* 67 (7): 1484–501. https://doi.org/10.1002/lno.12097.

Ferrara, Emilio. 2024. "The Butterfly Effect in Artificial Intelligence Systems: Implications for AI Bias and Fairness." *Machine Learning with Applications* 15 (March): 100525. https://doi.org/10.1016/j.mlwa.2024.100525.

Findell, Kirsten L., and Elfatih A. B. Eltahir. 1997. "An Analysis of the Soil Moisture-rainfall Feedback, Based on Direct Observations from Illinois." *Water Resources Research* 33 (4): 725–35. https://doi.org/10.1029/96WR03756.

Findell, Kirsten L., and Elfatih A. B. Eltahir. 2003. "Atmospheric Controls on Soil Moisture–Boundary Layer Interactions. Part II: Feedbacks within the Continental United States." *Journal of Hydrometeorology* 4 (3): 570–83. https://doi.org/10.1175/15257541(2003)004%253C0570:ACOSML%253E2.0.CO;2.

Finlayson, Clive. 2014. The Improbable Primate: How Water Shaped Human Evolution. 1st ed. Oxford University Press.

Forbis, Joe, and Cuong Ly. 2024. "Application of Forecast-informed Reservoir Operations at US Army Corps of Engineers Dams in California." *Journal of Flood Risk Management* 18 (1): e13051. https://doi.org/10.1111/jfr3.13051.

Ford, Trent W., and Christopher F. Labosier. 2017. "Meteorological Conditions Associated with the Onset of Flash Drought in the Eastern United States." *Agricultural and Forest Meteorology* 247 (December): 414–23. https://doi.org/10.1016/j.agrformet.2017.08.031.

Frisvold, George B., Ning Zhang, Michael A. Crimmins, Daniel Ferguson, and Charles Maxwell. 2024. "Demand for Information for Wildland Fire Management." *Atmosphere* 15 (11): 1364. https://doi.org/10.3390/atmos15111364.

Fuentes, Ignacio, José Padarian, and R. Willem Vervoort. 2022. "Spatial and Temporal Global Patterns of Drought Propagation." *Frontiers in Environmental Science* 10 (March): 788248. https://doi.org/10.3389/fenvs.2022.788248.

Füssel, Hans-Martin. 2007b. "Vulnerability: A Generally Applicable Conceptual Framework for Climate Change Research." *Global Environmental Change* 17 (2): 155–67. https://doi.org/10.1016/j.gloenvcha.2006.05.002.

Gaffney, Owen, Amy Luers, Franklin Carrero-Martinez, et al. 2025. "The Earth Alignment Principle for Artificial Intelligence." *Nature Sustainability* 8 (5): 467–69. https://doi.org/10.1038/s41893-025-01536-6.

Gaines, Mollie D., Mirela G. Tulbure, and Vinicius Perin. 2022. "Effects of Climate and Anthropogenic Drivers on Surface Water Area in the Southeastern United States." *Water Resources Research* 58 (3):e2021WR031484. https://doi.org/10.1029/2021WR031484.

Galloway, Devin L., and Thomas J. Burbey. 2011. "Review: Regional Land Subsidence Accompanying Groundwater Extraction." *Hydrogeology Journal* 19 (8): 1459–86. https://doi.org/10.1007/s10040-0110775-5.

Gangopadhyay, Subhrendu, Connie A. Woodhouse, Gregory J. McCabe, Cody C. Routson, and David M. Meko. 2022. "Tree Rings Reveal Unmatched 2nd Century Drought in the Colorado River Basin." *Geophysical Research Letters* 49 (11): e2022GL098781. https://doi.org/10.1029/2022GL098781.

Gayman, D. 2022. "Over Nearly 30 Years, National Drought Mitigation Center Has Made Global Impact." IANR (Institute of Agriculture and Natural Resources) *News*, May 9, 2022, University of Nebraska–Lincoln. https://ianrnews.unl.edu/over-nearly-30-years-national-drought-mitigation-center-has-made-global-impact.

Gebrechorkos, Solomon H., Justin Sheffield, Sergio M. Vicente-Serrano, et al. 2025. "Warming Accelerates Global Drought Severity." *Nature* 642 (8068): 628–35. https://doi.org/10.1038/s41586-025-09047-2.

Gelfand, Alan, Montse Fuentes, Jennifer A. Hoeting, and Richard L. Smith. 2019. *Handbook of Environmental and Ecological Statistics*. 1st ed. Edited by Alan E. Gelfand, Montserrat Fuentes, Jennifer A. Hoeting, and Richard Lyttleton Smith. Chapman and Hall/CRC. https://doi.org/10.1201/9781315152509.

Gevaert, Anouk I., Ted I. E. Veldkamp, and Philip J. Ward. 2018. "The Effect of Climate Type on Timescales of Drought Propagation in an Ensemble of Global Hydrological Models." *Hydrology and Earth System Sciences* 22 (9): 4649–65. https://doi.org/10.5194/hess-22-4649-2018.

Giannini, Alessandra, Michela Biasutti, and Michel M. Verstraete. 2008. "A Climate Model-Based Review of Drought in the Sahel: Desertification, the Re-Greening and Climate Change." *Global and Planetary Change* 64 (3–4): 119–28. https://doi.org/10.1016/j.gloplacha.2008.05.004.

Gibbons, Kindrea, Michaela Gooch, Casey Mills, and Quinton Deppert. 2023. *Southeast U.S. Agriculture: Evaluating the Spatial and Temporal Distribution of Flash Droughts within Agricultural Areas and Regional Crop Calendars in the Southeast Using Earth Observations*. May 30. https://ntrs.nasa.gov/citations/20230006899.

Glotter, Michael, and Joshua Elliott. 2016. "Simulating US Agriculture in a Modern Dust Bowl Drought." *Nature Plants* 3 (1): 16193. https://doi.org/10.1038/nplants.2016.193.

González-Sendino, Rubén, Emilio Serrano, and Javier Bajo. 2024. "Mitigating Bias in Artificial Intelligence: Fair Data Generation via Causal Models for Transparent and Explainable Decision-Making." *Future Generation Computer Systems* 155 (June): 384–401. https://doi.org/10.1016/j.future.2024.02.023.

Gottlieb, Alexander R., and Justin S. Mankin. 2022. "Observing, Measuring, and Assessing the Consequences of Snow Drought." *Bulletin of the American Meteorological Society* 103 (4): E1041–60. https://doi.org/10.1175/BAMS-D-20-0243.1.

Gottlieb, Alexander R., and Justin S. Mankin. 2025. "Subseasonal Temperature Variability Drives Nonlinear Snow Loss With Warming." *Water Resources Research* 61 (8): e2024WR039724. https://doi.org/10.1029/2024WR039724.

Graveline, Marie-Hélène, and Daniel Germain. 2022b. "Disaster Risk Resilience: Conceptual Evolution, Key Issues, and Opportunities." *International Journal of Disaster Risk Science* 13 (3): 330–41. https://doi.org/10.1007/s13753-022-00419-0.

Green, Joshua, Julia Maturano, Emma Myrick, Kyle Pecsok, and Victor Schultz. 2021. *Illinois Disasters: Utilizing NASA Earth Observations to Enhance Drought Monitoring in Illinois*. August 12. https://ntrs.nasa.gov/citations/20210021355.

Greve, Peter, Boris Orlowsky, Brigitte Mueller, Justin Sheffield, Markus Reichstein, and Sonia I. Seneviratne. 2014. "Global Assessment of Trends in Wetting and Drying over Land." *Nature Geoscience* 7 (10):716–21. https://doi.org/10.1038/ngeo2247.Grise, Kevin M., and Sean M. Davis. 2020. "Hadley Cell Expansion in CMIP6 Models." *Atmospheric Chemistry and Physics* 20 (9): 5249–68. https://doi.org/10.5194/acp-20-5249-2020.

Gruber, Alexander, Tracy Scanlon, Robin Van Der Schalie, Wolfgang Wagner, and Wouter Dorigo. 2019. "Evolution of the ESA CCI Soil Moisture Climate Data Records and Their Underlying Merging Methodology." *Earth System Science Data* 11 (2): 717–39. https://doi.org/10.5194/essd-11-717-2019.

Gu, Lianhong, and Bo Gao. 2025. "The Ecological Impacts of Dry and Hot Shocks in the Land of Midnight Sun." *Global Change Biology* 31 (8): e70391. https://doi.org/10.1111/gcb.70391.

Guttman, Nathaniel B. 1994. "On the Sensitivity of Sample L Moments to Sample Size." *Journal of Climate* 7 (6): 1026–29. https://doi.org/10.1175/1520-0442(1994)007%253C1026:OTSOSL%253E2.0.CO;2.

Guttman, Nathaniel B. 1999. "Accepting the Standardized Precipitation Index: A Calculation Algorithm 1." *JAWRA Journal of the American Water Resources Association* 35 (2): 311–22. https://doi.org/10.1111/j.1752-1688.1999.tb03592.x.

GVSUD (Green Valley Special Utility District). 2023. *Water Conservation and Drought Contingency Plan*. Green Valley Special Utility District.

Haasnoot, Marjolijn, Maaike Van Aalst, Julie Rozenberg, et al. 2020. "Investments under Non-Stationarity: Economic Evaluation of Adaptation Pathways." *Climatic Change* 161 (3): 451–63. https://doi.org/10.1007/s10584-019-02409-6.

Haddeland, I., T. Skaugen, and D. P. Lettenmaier. 2007. "Hydrologic Effects of Land and Water Management in North America and Asia: 1700–1992." *Hydrology and Earth System Sciences* 11 (2): 1035–45. https://doi.org/10.5194/hess-11-1035-2007.

Haddeland, Ingjerd, Jens Heinke, Hester Biemans, et al. 2014. "Global Water Resources Affected by Human Interventions and Climate Change." *Proceedings of the National Academy of Sciences* 111 (9): 3251–56. https://doi.org/10.1073/pnas.1222475110.

Hadley, D. R., D. B. Abrams, D. H. Mannix, and C. Cullen. 2021. "Using Production Well Behavior to Evaluate Risk in the Depleted Cambrian-Ordovician Sandstone Aquifer System, Midwestern USA." *Water Resources Research* 57 (5): e2020WR028844. https://doi.org/10.1029/2020WR028844.

Hale, Katherine E., et al. 2023. "Recent Decreases in Snow Water Storage in Western North America." *Communications Earth & Environment* 4 (1, May): 170. https://doi.org/10.1038/s43247-023-00751-3.

Hallegatte, Stéphane. 2009. "Strategies to Adapt to an Uncertain Climate Change." *Global Environmental Change* 19 (2): 240–47. https://doi.org/10.1016/j.gloenvcha.2008.12.003.

Halofsky, Jessica E., et al. 2019. "Managing Effects of Drought and Other Water Resource Challenges in Alaska and the Pacific Northwest." In James M. Vose, David L. Peterson, Charles H. Luce, and Toral Patel-Weynand, eds., *Effects of Drought on Forests and Rangelands in the United States: Translating Science into Management Responses.* Gen. Tech. Rep. WO-98. Washington, DC: U.S. Department of Agriculture, Forest Service, Washington Office. Chapter 3, pp. 41–69.

Hamilton, S. K., M. Z. Hussain, A. K. Bhardwaj, B. Basso, and G. P. Robertson. 2015. "Comparative Water Use by Maize, Perennial Crops, Restored Prairie, and Poplar Trees in the US Midwest." *Environmental Research Letters* 10 (6): 064015. https://doi.org/10.1088/1748-9326/10/6/064015.

Hammond, John, Phillip Goodling, Jeremy Diaz, et al. 2026. "Machine Learning Generated Streamflow Drought Forecasts for the Conterminous United States (CONUS): Developing and Evaluating an Operational Tool to Enhance Sub-Seasonal to Seasonal Streamflow Drought Early Warning for Gaged Locations." *Frontiers in Water* 7 (January): 1709138. https://doi.org/10.3389/frwa.2025.1709138.

Hankin, Lacey E., Sarah A. Crumrine, and Chad T. Anderson. 2024. "Impacts of Mega Drought in Fire-Prone Montane Forests and Implications for Forest Management." *Forest Ecology and Management* 564 (July): 122010. https://doi.org/10.1016/j.foreco.2024.122010.

Hao, Zengchao, and Amir AghaKouchak. 2013. "Multivariate Standardized Drought Index: A Parametric Multi-Index Model." *Advances in Water Resources* 57 (July): 12–18. https://doi.org/10.1016/j.advwatres.2013.03.009.

Hao, Zengchao, and Vijay P. Singh. 2015. "Drought Characterization from a Multivariate Perspective: A Review." *Journal of Hydrology* 527 (August): 668–78. https://doi.org/10.1016/j.jhydrol.2015.05.031.

Harpold, Adrian, Michael Dettinger, and Seshadri Rajagopal. 2017. "Defining Snow Drought and Why It Matters." *Eos*, ahead of print, February 28. https://doi.org/10.1029/2017EO068775.

Hasan, Mohammad M., Steven J. Burian, and Michael E. Barber. 2020. "Determining the Impacts of Wildfires on Peak Flood Flows in High Mountain Watersheds." *International Journal of Environmental Impacts: Management, Mitigation and Recovery* 3 (4): 339–51. https://doi.org/10.2495/EI-V3-N4-339-351.

Hatami Bahman Beiglou, Pouyan, Lifeng Luo, Pang-Ning Tan, and Lisi Pei. 2021. "Automated Analysis of the US Drought Monitor Maps with Machine Learning and Multiple Drought Indicators." *Frontiers in Big Data* 4 (October): 750536. https://doi.org/10.3389/fdata.2021.750536.

Hayes, Michael, Mark Svoboda, Nicole Wall, and Melissa Widhalm. 2011. "The Lincoln Declaration on Drought Indices: Universal Meteorological Drought Index Recommended." *Bulletin of the American Meteorological Society*. April 1. https://doi.org/10.1175/2010BAMS3103.1.

HCUWCD (Hill Country Underground Water Conservation District). 2020. "Local Drought Index." October 15. https://hcuwcd.org/?page_id=283.

Heede, Ulla K., Nathan Lenssen, Kristopher B. Karnauskas, and Clara Deser. 2025. "Tropical Pacific Warming Patterns Influence Future Hydroclimate Shifts and Extremes in the Americas." *Earth's Future* 13 (9): e2025EF006014. https://doi.org/10.1029/2025EF006014.

Heim, Jr., Richard R. 2002. "A Review of Twentieth-Century Drought Indices Used in the United States." *Bulletin of the American Meteorological Society*. August 1. https://doi.org/10.1175/1520-0477-83.8.1149.

Heim, Jr., Richard R., Deborah Bathke, Barrie Bonsal, et al. 2023. "A Review of User Perceptions of Drought Indices and Indicators Used in the Diverse Climates of North America." *Atmosphere* 14 (12): 1794. https://doi.org/10.3390/atmos14121794.

Hewlett, John D., and J. D. Helvey. 1970. "Effects of Forest Clear-Felling on the Storm Hydrograph." *Water Resources Research* 6 (3): 768–82. https://doi.org/10.1029/WR006i003p00768.

Hirshleifer, J., and John G. Riley. 1979. "The Analytics of Uncertainty and Information-An Expository Survey." *Journal of Economic Literature* 17 (4): 1375–421. https://www.jstor.org/stable/2723720.

Hobbins, Michael T., Andrew Wood, Daniel J. McEvoy, et al. 2016. "The Evaporative Demand Drought Index. Part I: Linking Drought Evolution to Variations in Evaporative Demand." *Journal of Hydrometeorology* 17 (6): 1745–61. https://doi.org/10.1175/JHM-D-15-0121.1.

Hoell, A., J. Perlwitz, and J. Eischeid. 2019. *Assessment Report: The Causes, Predictability, and Historical Context of the 2017 US Northern Great Plains Drought*. NOAA/NIDIS/CIRES.

Hoell, A., R. Thoman, H. R. McFarland, and B. Parker. 2022. *Southeast Alaska Drought*. International Arctic Research Center, University of Alaska Fairbanks.

Hoell, Andrew, Britt-Anne Parker, Michael Downey, et al. 2020. "Lessons Learned from the 2017 Flash Drought across the U.S. Northern Great Plains and Canadian Prairies." *Bulletin of the American Meteorological Society* 101 (12): E2171–85. https://doi.org/10.1175/BAMS-D-19-0272.1.

Hoerling, Martin, and Arun Kumar. 2003. "The Perfect Ocean for Drought." *Science* 299 (5607): 691–94. https://doi.org/10.1126/science.1079053.

Hoffmann, David, Ailie J. E. Gallant, and Julie M. Arblaster. 2020. "Uncertainties in Drought From Index and Data Selection." *Journal of Geophysical Research: Atmospheres* 125 (18): e2019JD031946. https://doi.org/10.1029/2019JD031946.

Holden, Zachary A., Alan Swanson, Charles H. Luce, et al. 2018. "Decreasing Fire Season Precipitation Increased Recent Western US Forest Wildfire Activity." *Proceedings of the National Academy of Sciences* 115 (36): E8349–57. https://doi.org/10.1073/pnas.1802316115.

Hornbeck, Richard, and Pinar Keskin. 2014b. "The Historically Evolving Impact of the Ogallala Aquifer: Agricultural Adaptation to Groundwater and Drought." *American Economic Journal: Applied Economics* 6 (1): 190–219. https://doi.org/10.1257/app.6.1.190.

Howard, Ronald. 1966. "Information Value Theory." *IEEE Transactions on Systems Science and Cybernetics* 2 (1): 22–26. https://doi.org/10.1109/TSSC.1966.300074.

Howard, R. A. 2007. Information value theory. *IEEE Transactions on Systems Science and Cybernetics,* 2(1), 22-26. DOI: 10.1109/TSSC.1966.300074.

Hoylman, Zachary H., R. Kyle Bocinsky, and Kelsey G. Jencso. 2022. "Drought Assessment Has Been Outpaced by Climate Change: Empirical Arguments for a Paradigm Shift." *Nature Communications* 13 (1): 2715. https://doi.org/10.1038/s41467-022-30316-5.

Hoylman, Zachary H., Zachary Holden, R. Kyle Bocinsky, David Ketchum, Alan Swanson, and Kelsey Jencso. 2024. "Optimizing Drought Assessment for Soil Moisture Deficits." *Water Resources Research* 60 (6): e2023WR036087. https://doi.org/10.1029/2023WR036087.

HTGCD (Hays Trinity Groundwater Conservation District). 2023. *Hays Trinity Groundwater Conservation District: Drought Contingency Plan*. Hays Trinity Groundwater Conservation District.

Hrozencik, R. Aaron, Gabriela Perez-Quesada, and Kyle Bocinsky. 2024. *The Stocking Impact and Financial-Climate Risk of the Livestock Forage Disaster Program*. Unknown. https://doi.org/10.22004/AG.ECON.340568.

Hrozencik, R. Aaron, Gabriela Perez-Quesada, Kyle Bocinsky, and United States Department of Agriculture Economic Research Service. 2024. Stocking Impact and Financial-Climate Risk of the Livestock Forage Disaster Program. Economic Research Service, U.S. Department of Agriculture. https://doi.org/10.32747/2024.8254668.ers.

Hu, Yi-Ming, Zhong-Min Liang, Yong-Wei Liu, Jun Wang, Lei Yao, and Yawei Ning. 2015. "Uncertainty Analysis of SPI Calculation and Drought Assessment Based on the Application of Bootstrap." *International Journal of Climatology* 35 (8): 1847–57. https://doi.org/10.1002/joc.4091.

Hulme, M. 1989. "Is Environmental Degradation Causing Drought in the Sahel? An Assessment from Recent Empirical Research." *Geography* 74 (1): 38–46. https://www.jstor.org/stable/40571564.

Humphrey, Vincent, and Lukas Gudmundsson. 2019. "GRACE-REC: A Reconstruction of Climate-Driven Water Storage Changes over the Last Century." *Earth System Science Data* 11 (3): 1153–70. https://doi.org/10.5194/essd-11-1153-2019.

Hundecha, Y., A. St-Hilaire, T. B. M. J. Ouarda, S. El Adlouni, and P. Gachon. 2008. "A Nonstationary Extreme Value Analysis for the Assessment of Changes in Extreme Annual Wind Speed over the Gulf of St. Lawrence, Canada." *Journal of Applied Meteorology and Climatology* 47 (11): 2745–59. https://doi.org/10.1175/2008JAMC1665.1.

Huning, Laurie S., and Amir AghaKouchak. 2020. "Global Snow Drought Hot Spots and Characteristics." *Proceedings of the National Academy of Sciences* 117 (33): 19753–59. https://doi.org/10.1073/pnas.1915921117.

IPCC (Intergovernmental Panel On Climate Change). *Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. 1st ed. Cambridge University Press. https://doi.org/10.1017/9781009157896.

IPCC. 2012. *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change*. V. Barros, T. F. Stocker, D. Qin, D. J. Dokken, K. L. Ebi, M. D. Mastrandrea, K. J. Mach, G.-K. Plattner, S. K. Allen, M. Tignor, and P. M. Midgley, eds. Cambridge University Press, Cambridge, United Kingdom, and New York, United States, 582 pp.

Jackson, Stephen T. 2021. "Transformational Ecology and Climate Change." *Science* 373 (6559): 1085–86. https://doi.org/10.1126/science.abj6777.

Jarrahi, M. H., A. Karami, P. Conway, A. Memariani, C. Lutz. 2026. "Navigating the muddy waters of bias in artificial intelligence research: Understanding divergent meanings and conceptions. *Technology in Society* 84. https://doi.org/10.1016/j.techsoc.2025.103127.

Jantarasami, Lesley, Rachael Novak, Roberto Delgado, et al. 2018. Ch. 15: "Tribal and Indigenous Communities." *Impacts, Risks, and Adaptation in the United States: The Fourth National Climate Assessment, Volume II*. U.S. Global Change Research Program. https://doi.org/10.7930/NCA4.2018.CH15.

Jasperse, J., F. M. Ralph, M. Anderson, et al. 2020. *Lake Mendocino Forecast Informed Reservoir Operations Final Viability Assessment*. December 28. https://escholarship.org/uc/item/3b63q04n.

Jeong, M., S. Y. Park, H. W. Jang, and J. H. Lee. 2020. "Study on Derivation of Drought Severity-Duration-Frequency Curve through a Non-Stationary Frequency Analysis." *Journal of Korea Water Resources Association* 53: 107–19.

Jiang, Linghuo, Litong Wang, Tianshu Fang, and Vassilios Papadopoulos. 2018. "Disruption of Ergosterol and Tryptophan Biosynthesis, as Well as Cell Wall Integrity Pathway and the Intracellular pH Homeostasis, Lead to Mono-(2-Ethylhexyl)-Phthalate Toxicity in Budding Yeast." *Chemosphere* 206 (September): 643–54. https://doi.org/10.1016/j.chemosphere.2018.05.069.

Kageyama, Yuya, and Yohei Sawada. 2022. "Global Assessment of Subnational Drought Impact Based on the Geocoded Disasters Dataset and Land Reanalysis." *Hydrology and Earth System Sciences* 26 (18): 4707–20. https://doi.org/10.5194/hess-26-4707-2022.

Kasperson, Roger E., Ortwin Renn, Paul Slovic, et al. 1988. "The Social Amplification of Risk: A Conceptual Framework." *Risk Analysis* 8 (2): 177–87. https://doi.org/10.1111/j.1539-6924.1988.tb01168.x.

Katz, Richard W. 2013. "Statistical Methods for Nonstationary Extremes." In *Extremes in a Changing Climate*, edited by Amir AghaKouchak, David Easterling, Kuolin Hsu, Siegfried Schubert, and Soroosh Sorooshian, vol. 65. Springer Netherlands. https://doi.org/10.1007/978-94-007-4479-0_2.

Kchouk, Sarra, Lieke A. Melsen, David W. Walker, and Pieter R. Van Oel. 2022. "A Geography of Drought Indices: Mismatch between Indicators of Drought and Its Impacts on Water and Food Securities." *Natural Hazards and Earth System Sciences* 22 (2): 323–44. https://doi.org/10.5194/nhess-22-323-2022.

Keller, Mary L., Kristiana Hansen, J. J. Shinker, et al. 2025b. "Unwinding the Spiral of Silence in Rural America: Looking Backward with Stories to Plan Forward." *Frontiers in Climate* 7 (August): 1398452. https://doi.org/10.3389/fclim.2025.1398452.

Khan, Nasrullah, Hung T. T. Nguyen, Stefano Galelli, and Paolo Cherubini. 2022. "Increasing Drought Risks Over the Past Four Centuries Amidst Projected Flood Intensification in the Kabul River Basin (Afghanistan and Pakistan)—Evidence From Tree Rings." *Geophysical Research Letters* 49 (24): e2022GL100703. https://doi.org/10.1029/2022GL100703.

Kikon, A., and P. C. Deka. 2022. "Artificial Intelligence Application in Drought Assessment, Monitoring and Forecasting: A Review." *Stochastic Environmental Research and Risk Assessment* 36 (5): 1197–1214.

King, Karen E., Edward R. Cook, Kevin J. Anchukaitis, et al. 2024. "Increasing Prevalence of Hot Drought across Western North America since the 16th Century." *Science Advances* 10 (4): eadj4289. https://doi.org/10.1126/sciadv.adj4289.

KISS Continuity Study Team. 2024. "Toward a US Framework for Continuity of Satellite Observations of Earth's Climate and for Supporting Societal Resilience." *Earth's Future* 12 (2): e2023EF003757. https://doi.org/10.1029/2023EF003757.

Klavans, Jeremy M., Pedro N. DiNezio, Amy C. Clement, Clara Deser, Timothy M. Shanahan, and Mark A. Cane. 2025. "Human Emissions Drive Recent Trends in North Pacific Climate Variations." *Nature* 644 (8077): 684–92. https://doi.org/10.1038/s41586-025-09368-2.

Konikow, Leonard F. 2015. "Long-Term Groundwater Depletion in the United States." *Groundwater* 53 (1): 2–9. https://doi.org/10.1111/gwat.12306.

Krabbenhoft, C. A., G. H. Allen, P. Lin, S. E. Godsey, D. C. Allen, R. M. Burrows, A. G. DelVecchia, K. M. Fritz, M. Shanafield, A. J. Burgin, M. A. Zimmer, T. Datry, W. K. Dodds, C. N. Jones, M. C. Mims, C. Franklin, J. C. Hammond, S. Zipper, A. S. Ward, K. H. Costigan, … J. D. Olden. 2022. "Assessing Placement Bias of the Global River Gauge Network." *Nature Sustainability* 5: 586–92. https://doi.org/10.1038/s41893-022-00873-0.

Krueger, Erik S., Tyson E. Ochsner, and B. Wade Brorsen. 2024. "Soil Moisture Information Improves Drought Risk Protection Provided by the USDA Livestock Forage Disaster Program." *Bulletin of the American Meteorological Society* 105 (7): E1153–69. https://doi.org/10.1175/BAMS-D-23-0087.1.

Kuhn, Eric, and John Fleck. 2021. *Science Be Dammed How Ignoring Inconvenient Science Drained the Colorado River*. University of Arizona Press

Kuo, Yan-Ning, Flavio Lehner, Isla R. Simpson, et al. 2025. "Recent Southwestern US Drought Exacerbated by Anthropogenic Aerosols and Tropical Ocean Warming." *Nature Geoscience* 18 (7): 578–85. https://doi.org/10.1038/s41561-025-01728-x.

Kuwayama, Yusuke, Alexandra Thompson, Richard Bernknopf, Benjamin Zaitchik, and Peter Vail. 2019. "Estimating the Impact of Drought on Agriculture Using the U.S. Drought Monitor." *American Journal of Agricultural Economics* 101 (1): 193–210. https://doi.org/10.1093/ajae/aay037.

Kwon, Hyun-Han, and Upmanu Lall. 2016. "A Copula-based Nonstationary Frequency Analysis for the 2012–2015 Drought in California." *Water Resources Research* 52 (7): 5662–75. https://doi.org/10.1002/2016WR018959.

Lackstrom, Kirsten, Amanda Brennan, Daniel Ferguson, et al. 2013. *The Missing Piece: Drought Impacts Monitoring*. Report from a Workshop in Tucson, AZ. Carolinas Integrated Sciences & Assessments program and the Climate Assessment for the Southwest.

Lackstrom, Kirsten, Amanda Farris, David Eckhardt, et al. 2017. "CoCoRaHS Observers Contribute to 'Condition Monitoring' in the Carolinas: A New Initiative Addresses Needs for Drought Impacts Information." *Bulletin of the American Meteorological Society* 98 (12): 2527–31. https://doi.org/10.1175/BAMS-D-16-0306.1.

Lackstrom, Kirsten, Benjamin Haywood, Amanda Brennan, Janae Davis, and Kirstin Dow. 2014. *Drought and Coastal Ecosystems: Identifying Impacts and Opportunities to Inform Management*. Proceedings of the 2014 South Carolina Water Resources Conference.

Laimighofer, Johannes, and Gregor Laaha. 2022. "How Standard Are Standardized Drought Indices? Uncertainty Components for the SPI & SPEI Case." *Journal of Hydrology* 613 (October): 128385. https://doi.org/10.1016/j.jhydrol.2022.128385.

Lamjiri, Maryam A., F. Martin Ralph, and Michael D. Dettinger. 2020. "Recent Changes in United States Extreme 3-Day Precipitation Using the R-CAT Scale." *Journal of Hydrometeorology* 21 (6): 1207–21. https://doi.org/10.1175/JHM-D-19-0171.1.

Lapides, Dana A., W. Jesse Hahm, Daniella M. Rempe, John Whiting, and David N. Dralle. 2022. "Causes of Missing Snowmelt Following Drought." *Geophysical Research Letters* 49 (19): e2022GL100505. https://doi.org/10.1029/2022GL100505.

Lathrop, Alyssa. 2009. "A Tale of Three States: Equitable Apportionment of the Apalachicola-Chattahoochee-Flint River Basin." *Florida State University Law Review* 36 (4). https://ir.law.fsu.edu/lr/vol36/iss4/6.

Lawrimore, J., R. R. Heim, M. Svoboda, V. Swail, and P. J. Englehart. 2002. "Beginning a New Era of Drought Monitoring across North America." *Bulletin of the American Meteorological Society* 83: 1191–92. https://doi.org/10.1175/1520-0477-83.8.1191.

Le Roy Ladurie, Emmanuel. 1971. *Times of Feast, Times of Famine: A History of Climate since the Year 1000*. With Internet Archive. Garden City, NY., Doubleday. http://archive.org/details/timesoffeasttime0000lero.

Leeper, Ronald D., Rocky Bilotta, Bryan Petersen, et al. 2022. "Characterizing U.S. Drought over the Past 20 Years Using the U.S. Drought Monitor." *International Journal of Climatology* 42 (12): 6616–30. https://doi.org/10.1002/joc.7653.

Lehner, Flavio, Clara Deser, Isla R. Simpson, and Laurent Terray. 2018. "Attributing the U.S. Southwest's Recent Shift Into Drier Conditions." *Geophysical Research Letters* 45 (12): 6251–61. https://doi.org/10.1029/2018GL078312.

Lempert, Robert J. 2003. *Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis*. RAND Corporation.

L'Heureux, Michelle L., Dan C. Collins, and Zeng-Zhen Hu. 2013. "Linear Trends in Sea Surface Temperature of the Tropical Pacific Ocean and Implications for the El Niño-Southern Oscillation." *Climate Dynamics* 40 (5–6): 1223–36. https://doi.org/10.1007/s00382-012-1331-2.

Li, Chao, Francis Zwiers, Xuebin Zhang, Guilong Li, Ying Sun, and Michael Wehner. 2021. *Changes in Annual Extremes of Daily Temperature and Precipitation in CMIP6 Models*. *Journal of Climate*. May 1. https://doi.org/10.1175/JCLI-D-19-1013.1.

Li, Chuanhua, Cui Liu, Atsushi Tsunekawa, et al. 2024. "Climate Change Is Leading to a Convergence of Global Climate Distribution." *Geophysical Research Letters* 51 (11): e2023GL106658. https://doi.org/10.1029/2023GL106658.

Li, Fupeng, Jürgen Kusche, Roelof Rietbroek, et al. 2020. "Comparison of Data-Driven Techniques to Reconstruct (1992–2002) and Predict (2017–2018) GRACE-Like Gridded Total Water Storage Changes Using Climate Inputs." *Water Resources Research* 56 (5): e2019WR026551. https://doi.org/10.1029/2019WR026551.

Li, J. Z., Y. X. Wang, S. F. Li, and R. Hu. 2015. "A Nonstationary Standardized Precipitation Index Incorporating Climate Indices as Covariates." *Journal of Geophysical Research: Atmospheres* 120 (23). https://doi.org/10.1002/2015JD023920.

Li, Min, Zilong Feng, Mingfeng Zhang, Lijie Shi, and Yuhang Yao. 2026. "Dynamic Analysis of Drought Propagation in the Context of Climate Change and Watershed Characterization: A Quantitative Study Based on GAMLSS and Copula Models." *Natural Hazards and Earth System Sciences* 26 (1): 1–20. https://doi.org/10.5194/nhess-26-1-2026.

Li, Zhe, and Qinghua Ding. 2024. "A Global Poleward Shift of Atmospheric Rivers." *Science Advances* 10 (41): eadq0604. https://doi.org/10.1126/sciadv.adq0604.

Li, Zhiying, Jason E. Smerdon, Richard Seager, Noel Siegert, and Justin S. Mankin. 2024. "Emergent Trends Complicate the Interpretation of the United States Drought Monitor (USDM)." *AGU Advances* 5 (2): e2023AV001070. https://doi.org/10.1029/2023AV001070.

Lian, Xu, Shilong Piao, Anping Chen, et al. 2021. "Multifaceted Characteristics of Dryland Aridity Changes in a Warming World." *Nature Reviews Earth & Environment* 2 (4): 232–50. https://doi.org/10.1038/s43017-021-00144-0.

Lindell, Michael K. 2013. "Disaster Studies." *Current Sociology* 61 (5–6): 797–825. https://doi.org/10.1177/0011392113484456.

Linder, Julia, Douglas Jackson-Smith, Shoshanah Inwood, and Tiffany Woods. 2025. "Impacts of Extreme Weather on Farmer Mental Health." *Rural Sociology* 90 (4): e70027. https://doi.org/10.1111/ruso.70027.

Lisonbee, Joel, John Nielsen-Gammon, Blair Trewin, Gretel Follingstad, and Britt Parker. 2024. "Drought Assessment in a Changing Climate: A Review of Climate Normals for Drought Indices." *Journal of Applied and Service Climatology* 2024 (001): 1–17. https://doi.org/10.46275/JOASC.2024.05.001.

Lisonbee, Joel, Britt Parker, Erica Fleishman, et al. 2025. "Prioritization of Research on Drought Assessment in a Changing Climate." *Earth's Future* 13 (3): e2024EF005276. https://doi.org/10.1029/2024EF005276.

Lisonbee, Joel, Molly Woloszyn, and Marina Skumanich. 2021. "Making Sense of Flash Drought: Definitions, Indicators, and Where We Go from Here." *Journal of Applied and Service Climatology* 2021 (1): 1–19. https://doi.org/10.46275/JOASC.2021.02.001.

Littell, J. S., D. L. Peterson, K. L. Riley, Y. Liu, and C. H. Luce. 2016. "A Review of the Relationships between Drought and Forest fire in the United States." *Global Change Biology* 22: 2353-69. http://dx.doi.org/10.1111/gcb.13275.

Liu, Changhong, Cuiping Yang, Qi Yang, and Jiao Wang. 2021. "Spatiotemporal Drought Analysis by the Standardized Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI) in Sichuan Province, China." *Scientific Reports* 11 (1): 1280. https://doi.org/10.1038/s41598-020-80527-3.

Liu, Ying, Fuzhen Shan, Hui Yue, Xu Wang, and Yahui Fan. 2023. "Global Analysis of the Correlation and Propagation among Meteorological, Agricultural, Surface Water, and Groundwater Droughts." *Journal of Environmental Management* 333 (May): 117460. https://doi.org/10.1016/j.jenvman.2023.117460.

Loiola, Claudia, et al. "Hydrological Performance of Modular-Tray Green Roof Systems for Increasing the Resilience of Mega-Cities to Climate Change." 2019. *Journal of Hydrology*, vol. 573, pp. 1057–66, https://doi.org/10.1016/j.jhydrol.2018.01.004.

Lowe, Rachel, Sophie A. Lee, Kathleen M. O'Reilly, et al. 2021. "Combined Effects of Hydrometeorological Hazards and Urbanisation on Dengue Risk in Brazil: A Spatiotemporal Modelling Study." *The Lancet Planetary Health* 5 (4): e209–19. https://doi.org/10.1016/S2542-5196(20)30292-8.

Luke, A., J. A. Vrugt, A. AghaKouchak, R. Matthew, and B. F. Sanders. 2017. "Predicting Nonstationary Flood Frequencies: Evidence Supports an Updated Stationarity Thesis in the United States." *Water Resources Research* 53 (7): 5469–94. https://doi.org/10.1002/2016WR019676.

Lv, Shaoning, Bernd Schalge, Pablo Saavedra Garfias, and Clemens Simmer. 2020. "Required Sampling Density of Ground-Based Soil Moisture and Brightness Temperature Observations for Calibration and Validation of L-Band Satellite Observations Based on a Virtual Reality." *Hydrology and Earth System Sciences* 24 (4): 1957–73. https://doi.org/10.5194/hess-24-1957-2020.

Macauley, Molly K. 2006. "The Value of Information: Measuring the Contribution of Space-Derived Earth Science Data to Resource Management." *Space Policy* 22 (4): 274–82. https://doi.org/10.1016/j.spacepol.2006.08.003.

Madadgar, Shahrbanou, and Hamid Moradkhani. 2013. "Drought Analysis under Climate Change Using Copula." *Journal of Hydrologic Engineering* 18 (7): 746–59. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000532.

Mahony, Colin R., Tongli Wang, Andreas Hamann, and Alex J. Cannon. 2022. "A Global Climate Model Ensemble for Downscaled Monthly Climate Normals over North America." *International Journal of Climatology* 42 (11): 5871–91. https://doi.org/10.1002/joc.7566.

Makar, A. B., K. E. McMartin, M. Palese, and T. R. Tephly. 1975. "Formate Assay in Body Fluids: Application in Methanol Poisoning." *Biochemical Medicine* 13 (2): 117–26. https://doi.org/10.1016/0006-2944(75)90147-7.

Maliva, Robert, and Thomas Missimer. 2012. *Arid Lands Water Evaluation and Management*. Environmental Science and Engineering. Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-29104-3.

Mankin, J., I. Simpson, A. Hoell, J. Lisonbee, A. Sheffield, and D. Barrie. 2021. *NOAA Drought Task Force Report on the 2020–2021 Southwestern U.S. Drought*. NOAA Drought Task Force, MAPP, and NIDIS.

Mardian, Jacob. 2022. "The Role of Spatial Scale in Drought Monitoring and Early Warning Systems: A Review." *Environmental Reviews* 30 (3): 438–59. https://doi.org/10.1139/er-2021-0102.

Marshall, Sebastian R.O., Thanh-Nhan-Duc Tran, and Venkataraman Lakshmi. 2026 (under review). Flash vs. Seasonal Drought: Identifying the Characteristic Timescale of Soil Moisture Stress for Predicting Crop-Specific Yield Anomalies).

Marvel, Kate, Wenying Su, Roberto Delgado, et al. 2023. *Chapter 2: Climate Trends. Fifth National Climate Assessment*. Edited by Allison R. Crimmins, Christopher W. Avery, David R. Easterling, Kenneth E. Kunkel, Brooke C. Stewart, and Thomas K. Maycock. U.S. Global Change Research Program. https://doi.org/10.7930/NCA5.2023.CH2.

Mase, Amber Saylor, and Linda Stalker Prokopy. 2014. "Unrealized Potential: A Review of Perceptions and Use of Weather and Climate Information in Agricultural Decision Making." *Weather, Climate, and Society* 6 (1): 47–61. https://doi.org/10.1175/WCAS-D-12-00062.1.

Matteson, C. 2020. "NDMC's Directors Look Back at What Led to Center's Founding 25 Years Ago." *NDMC News*, August 6. University of Nebraska–Lincoln. https://drought.unl.edu/Publications/News.aspx?id=366.

McCabe, Gregory J., Michael A. Palecki, and Julio L. Betancourt. 2004. *Pacific and Atlantic Ocean Influences on Multidecadal Drought Frequency in the United States*. University of California. [Searched by title/authors for UC campus/city, but all results were *PNAS*.]

McGregor, Kent M. 2015. "Comparison of the Recent Drought in Texas to the Drought of Record Using Reanalysis Modeling." *Papers in Applied Geography* 1 (1): 34–42. https://doi.org/10.1080/23754931.2015.1009295.

Mckee, T. B., N. J. Doesken, and J. Kleist. 1993. *The Relationship of Drought Frequency and Duration to Time Scales. 8th Conference on Applied Climatology*. Anaheim, CA. American Meteorological Society. https://www.scirp.org/reference/ReferencesPapers?ReferenceID=2099290.

McKee, T. B., Doesken, N. J., and Kleist, J. 1995. "Drought Monitoring with Multiple Time Scales." In *Proceedings of the Ninth Conference on Applied Climatology* (pp. 233-236). Dallas, TX: American Meteorological Society.

McKinnon, Karen A., Andrew Poppick, and Isla R. Simpson. 2021. "Hot Extremes Have Become Drier in the United States Southwest." *Nature Climate Change* 11 (7): 598–604. https://doi.org/10.1038/s41558-021-01076-9.

Meko, David M., Connie A. Woodhouse, Christopher A. Baisan, et al. 2007. "Medieval Drought in the Upper Colorado River Basin." *Geophysical Research Letters* 34 (10): 2007GL029988. https://doi.org/10.1029/2007GL029988.

Mentaschi, Lorenzo, Michalis Vousdoukas, Evangelos Voukouvalas, et al. 2016. "Non-Stationary Extreme Value Analysis: A Simplified Approach for Earth Science Applications." Preprint, February 25. https://doi.org/10.5194/hess-2016-65.

Migała, Krzysztof, Ewa Łupikasza, Marzena Osuch, Magdalena Opała-Owczarek, and Piotr Owczarek. 2024. "Linking Drought Indices to Atmospheric Circulation in Svalbard, in the Atlantic Sector of the High Arctic." *Scientific Reports* 14 (1): 2160. https://doi.org/10.1038/s41598-024-51869-z.

Miller, Eric A., Hiroki Iwata, Masahito Ueyama, et al. 2023. "Evaluating the Drought Code for Lowland Taiga of Interior Alaska Using Eddy Covariance Measurements." *International Journal of Wildland Fire* 32 (8): 1226–43. https://doi.org/10.1071/WF22165.

Milly, P. C. D., Julio Betancourt, Malin Falkenmark, et al. 2008. "Stationarity Is Dead: Whither Water Management?" *Science* 319 (5863): 573–74. https://doi.org/10.1126/science.1151915.

Milly, P. C. D., and K. A. Dunne. 2020. "Colorado River Flow Dwindles as Warming-Driven Loss of Reflective Snow Energizes Evaporation." *Science* 367 (6483): 1252–55. https://doi.org/10.1126/science.aay9187.

Miralles, D. G., T. R. H. Holmes, R. A. M. De Jeu, J. H. Gash, A. G. C. A. Meesters, and A. J. Dolman. 2011. "Global Land-Surface Evaporation Estimated from Satellite-Based Observations." *Hydrology and Earth System Sciences* 15 (2): 453–69. https://doi.org/10.5194/hess-15-453-2011.

Miralles, Diego G., Pierre Gentine, Sonia I. Seneviratne, and Adriaan J. Teuling. 2019. "Land–Atmospheric Feedbacks during Droughts and Heatwaves: State of the Science and Current Challenges." *Annals of the New York Academy of Sciences* 1436 (1): 19–35. https://doi.org/10.1111/nyas.13912.

Mishra, A. K., and Vijay P. Singh. 2009. "Analysis of Drought Severity-area-frequency Curves Using a General Circulation Model and Scenario Uncertainty." *Journal of Geophysical Research: Atmospheres* 114 (D6): 2008JD010986. https://doi.org/10.1029/2008JD010986.

Mishra, Ashok K., and Vijay P. Singh. 2010. "A Review of Drought Concepts." *Journal of Hydrology* 391 (1–2): 202–16. https://doi.org/10.1016/j.jhydrol.2010.07.012.

Missouri DNR. 2023. "Missouri Drought Mitigation and Response Plan 2023." May 1. https://dnr.mo.gov/document-search/missouri-drought-mitigation-response-plan-2023.

Montana Administrative Rule 12.5.507. n.d. Title 12, Chapter 5, Subchapter 507: Angling Restriction and Fishing Closure Criteria. Administrative Rules of Montana. Montana Secretary of State.

Montana Drought Management. n.d. "Response Actions." Accessed March 13, 2026. https://drought.mt.gov/response-actions.

Morsy, Mona, Ruhollah Taghizadeh-Mehrjardi, Silas Michaelides, Thomas Scholten, Peter Dietrich, and Karsten Schmidt. 2021. "Optimization of Rain Gauge Networks for Arid Regions Based on Remote Sensing Data." *Remote Sensing* 13 (21): 4243. https://doi.org/10.3390/rs13214243.

Mosley, Luke M. 2015. "Drought Impacts on the Water Quality of Freshwater Systems; Review and Integration." *Earth-Science Reviews* 140 (January): 203–14. https://doi.org/10.1016/j.earscirev.2014.11.010.

Mote, Philip W., Alan F. Hamlet, Martyn P. Clark, and Dennis P. Lettenmaier. 2005. “Declining Mountain Snowpack in Western North America*.” *Bulletin of the American Meteorological Society* 86 (1): 39–50. https://doi.org/10.1175/BAMS-86-1-39

Mote, Philip W., Sihan Li, Dennis P. Lettenmaier, Mu Xiao, and Ruth Engel. 2018. “Dramatic Declines in Snowpack in the Western US.” *Npj Climate and Atmospheric Science* 1 (1): 2. https://doi.org/10.1038/s41612-018-0012-1.

Müller, Lena M., and Michael Bahn. (2022) “Drought Legacies and Ecosystem Responses to Subsequent Drought.” *Global Change Biology* 28, no. 17: 5086–103. https://doi.org/10.1111/gcb.16270.

Mueller, Nathaniel D., Ethan E. Butler, Karen A. McKinnon, et al. 2016. “Cooling of US Midwest Summer Temperature Extremes from Cropland Intensification.” *Nature Climate Change* 6 (3): 317–22. https://doi.org/10.1038/nclimate2825.

Mukherjee, Sourav, Ashok Mishra, and Kevin E. Trenberth. 2018. “Climate Change and Drought: A Perspective on Drought Indices.” *Current Climate Change Reports* 4 (2): 145–63. https://doi.org/10.1007/s40641-018-0098-x.

Muller, Lotte C. F. E., Marije Schaafsma, Maurizio Mazzoleni, and Anne F. Van Loon. 2024. “Responding to Climate Services in the Context of Drought: A Systematic Review.” *Climate Services* 35 (August): 100493. https://doi.org/10.1016/j.cliser.2024.100493.

Muñoz-Sabater, Joaquín, Emanuel Dutra, Anna Agustí-Panareda, et al. 2021. “ERA5-Land: A State-of-the-Art Global Reanalysis Dataset for Land Applications.” *Earth System Science Data* 13 (9): 4349–83. https://doi.org/10.5194/essd-13-4349-2021.

Najibi, Nasser, Alejandro J. Perez, Wyatt Arnold, Andrew Schwarz, Romain Maendly, and Scott Steinschneider. 2024. “A Statewide, Weather-Regime Based Stochastic Weather Generator for Process-Based Bottom-up Climate Risk Assessments in California – Part II: Thermodynamic and Dynamic Climate Change Scenarios.” *Climate Services* 34 (April): 100485. https://doi.org/10.1016/j.cliser.2024.100485.

Nandi, Subimal, and Sujata Biswas. 2024. “Spatiotemporal Distribution of Groundwater Drought Using GRACE-Based Satellite Estimates: A Case Study of Lower Gangetic Basin, India.” *Environmental Monitoring and Assessment* 196 (2): 151. https://doi.org/10.1007/s10661-024-12309-7.

NASEM (National Academies of Sciences, Engineering and Medicine). 2025. *Effects of Human-Caused Greenhouse Gas Emissions on U.S. Climate, Health, and Welfare*. The National Academies Press. https://doi.org/10.17226/29239.

National Drought Policy Commission. 2000. *Preparing for Drought in the 21st Century*. https://govinfo.library.unt.edu/drought/finalreport/fullreport/pdf/reportfull.pdf.

Naumann, Gustavo, Carmelo Cammalleri, Lorenzo Mentaschi, and Luc Feyen. 2021. “Increased Economic Drought Impacts in Europe with Anthropogenic Warming.” *Nature Climate Change* 11 (6): 485–91. https://doi.org/10.1038/s41558-021-01044-3.

Nearing, G., Cohen, D., Dube, V. *et al.* 2024. Global prediction of extreme floods in ungauged watersheds. *Nature* 627, 559–563. https://doi.org/10.1038/s41586-024-07145-1.

Nearing, Grey S., Frederik Kratzert, Alden Keefe Sampson, et al. 2021. “What Role Does Hydrological Science Play in the Age of Machine Learning?” *Water Resources Research* 57 (3): e2020WR028091. https://doi.org/10.1029/2020WR028091.

NIDIS (National Integrated Drought Information System). n.d.-a. “Northeast | Drought.Gov.” Drought.Gov, NIDIS, NOAA. Accessed March 13, 2026. https://www.drought.gov/dews/northeast.

NIDIS. n.d.-b. “What Is NIDIS? | Drought.Gov.” Accessed October 20, 2025. https://www.drought.gov/about.

NIDIS. 2025. “What Is Drought: Drought Basics.” Drought.Gov. https://www.drought.gov/what-is-drought/drought-basics.

Nie, Wanshu, Sujay V. Kumar, Augusto Getirana, et al. 2024. “Nonstationarity in the Global Terrestrial Water Cycle and Its Interlinkages in the Anthropocene.” *Proceedings of the National Academy of Sciences* 121 (45): e2403707121. https://doi.org/10.1073/pnas.2403707121.

Nie, Wanshu, Sujay V. Kumar, and Long Zhao. 2025. "Anthropogenic Influences on the Water Cycle Amplify Uncertainty in Drought Assessments." *One Earth* 8 (2): 101196. https://doi.org/10.1016/j.oneear.2025.101196.

Nikoo, Mohammad Reza, Erfan Zarei, and Malik Al-Wardy. 2025. "Non-Stationary Drought Patterns in Hyper-Arid Regions: Spatiotemporal and Multi-Timescale Drought Analysis." *Science of The Total Environment* 1000 (October): 180401. https://doi.org/10.1016/j.scitotenv.2025.180401.

OBrien, L. V., H. L. Berry, C. Coleman, and I. C. Hanigan. 2014. "Drought as a Mental Health Exposure." *Environmental Research* 131 (May): 181–87. https://doi.org/10.1016/j.envres.2014.03.014.

Oliver, John E., ed. 2005. *Encyclopedia of World Climatology*. Encyclopedia of Earth Sciences Series. Springer.

Oliver, John E., and Rhodes W. Fairbridge, eds. 1987. *The Encyclopedia of Climatology*. Encyclopedia of Earth Sciences, v. 11. Van Nostrand Reinhold.

Ongley, Edwin D., Zhang Xiaolan, and Yu Tao. 2010. "Current Status of Agricultural and Rural Non-Point Source Pollution Assessment in China." *Environmental Pollution* 158 (5): 1159–68. https://doi.org/10.1016/j.envpol.2009.10.047.

Onyutha, Charles. 2017. "On Rigorous Drought Assessment Using Daily Time Scale: Non-Stationary Frequency Analyses, Revisited Concepts, and a New Method to Yield Non-Parametric Indices." *Hydrology* 4 (4): 48. https://doi.org/10.3390/hydrology4040048.

Osman, Mahmoud, Benjamin Zaitchik, Jason Otkin, and Martha Anderson. 2024. "A Global Flash Drought Inventory Based on Soil Moisture Volatility." *Scientific Data* 11 (1): 965. https://doi.org/10.1038/s41597-024-03809-9.

Otkin, Jason A., Mark Svoboda, Eric D. Hunt, et al. 2018. "Flash Droughts: A Review and Assessment of the Challenges Imposed by Rapid-Onset Droughts in the United States." *Bulletin of the American Meteorological Society*. May 1. https://doi.org/10.1175/BAMS-D-17-0149.1.

Otterman, Joseph. 1974. "Baring High-Albedo Soils by Overgrazing: A Hypothesized Desertification Mechanism." *Science* 186 (4163): 531–33. https://doi.org/10.1126/science.186.4163.531.

Overpeck, Jonathan T. 2013. "The Challenge of Hot Drought." *Nature* 503 (7476): 350–51. https://doi.org/10.1038/503350a.

Overpeck, Jonathan T., and Bradley Udall. 2020. "Climate Change and the Aridification of North America." *Proceedings of the National Academy of Sciences* 117 (22): 11856–58. https://doi.org/10.1073/pnas.2006323117.

Oyounalsoud, M. S., A. G. Yilmaz, M. Abdallah, and A. Abdeljaber. 2024. "Drought Prediction Using Artificial Intelligence Models Based on Climate Data and Soil Moisture." *Scientific Reports* 14 (1): 19700.

PG&E (Pacific Gas and Electric Company). 2022. *2022 Integrated Resource Plan*. Pacific Gas and Electric Company.

Palagiri, Hussain, and Manali Pal. 2024. "Parametric and Non-Parametric Indices for Agricultural Drought Assessment Using ESACCI Soil Moisture Data over the Southern Plateau and Hills, India." *International Journal of Applied Earth Observation and Geoinformation* 134 (November): 104175. https://doi.org/10.1016/j.jag.2024.104175.

Palmer, Wayne C. 1965. Meteorological Drought. Vol. 30. U.S. Department of Commerce, Weather Bureau.

Park, Chanyoung, and Brian J. Soden. 2025. "Negligible Contribution from Aerosols to Recent Trends in Earth's Energy Imbalance." Science Advances 11 (48): eadv9429. https://doi.org/10.1126/sciadv.adv9429.

Parker, B. A., J. Lisonbee, E. Ossowski, H. R. Prendeville, and D. Todey. 2023. "Drought Assessment in a Changing Climate: Priority Actions and Research Needs." https://doi.org/10.25923/5zm3-6x83.

Parkinson, Claire L. 2022. "The Earth-Observing Aqua Satellite Mission: 20 Years and Counting." *Earth and Space Science* 9 (9): e2022EA002481. https://doi.org/10.1029/2022EA002481.

Parry, W. H., F. Martorano, and E. K. Cotton. 1976. "Management of Life-Threatening Asthma with Intravenous Isoproterenol Infusions." *American Journal of Diseases of Children* (1960) 130 (1): 39–42. https://doi.org/10.1001/archpedi.1976.02120020041006.

Parsons, David J., Dolores Rey, Maliko Tanguy, and Ian P. Holman. 2019. "Regional Variations in the Link between Drought Indices and Reported Agricultural Impacts of Drought." *Agricultural Systems* 173 (July): 119–29. https://doi.org/10.1016/j.agsy .2019.02.015.

Pausata, Francesco S. R., Dominic Alain, Roberto Ingrosso, Katja Winger, Michelle S. M. Drapeau, and Ariane Burke. 2023. "Changes in Climate Extremes in Zambia during Green and Dry Sahara Periods and Their Potential Impacts on Hominid Dispersal." *Quaternary Science Reviews* 321 (December): 108367. https://doi.org/10.1016/j.quascirev.2023.108367.

Pendergrass, Angeline G., Gerald A. Meehl, Roger Pulwarty, et al. 2020. "Flash Droughts Present a New Challenge for Subseasonal-to-Seasonal Prediction." *Nature Climate Change* 10 (3): 191–99. https://doi.org/10.1038/s41558-020-0709-0.

Polasky, Stephen, Stephen R. Carpenter, Carl Folke, and Bonnie Keeler. 2011. "Decision-Making under Great Uncertainty: Environmental Management in an Era of Global Change." *Trends in Ecology & Evolution* 26 (8): 398–404. https://doi.org/10.1016/j.tree.2011.04.007.

Popp, Thomas, Michaela I. Hegglin, Rainer Hollmann, et al. 2020. "Consistency of Satellite Climate Data Records for Earth System Monitoring." *Bulletin of the American Meteorological Society* 101 (11): E1948–71. https://doi.org/10.1175/BAMS-D-19-0127.1.

Preece, Jonathon R., Thomas L. Mote, Judah Cohen, et al. 2023. "Summer Atmospheric Circulation over Greenland in Response to Arctic Amplification and Diminished Spring Snow Cover." *Nature Communications* 14 (1): 3759. https://doi.org/10.1038/s41467-023-39466-6.

Prein, Andreas F., Roy M. Rasmussen, Kyoko Ikeda, Changhai Liu, Martyn P. Clark, and Greg J. Holland. 2017. "The Future Intensification of Hourly Precipitation Extremes." *Nature Climate Change* 7 (1): 48–52. https://doi.org/10.1038/nclimate3168.

Ragno, Elisa, Amir AghaKouchak, Linyin Cheng, and Mojtaba Sadegh. 2019. "A Generalized Framework for Process-Informed Nonstationary Extreme Value Analysis." *Advances in Water Resources* 130 (August): 270–82. https://doi.org/10.1016/j.advwatres.2019.06.007.

Ragno, Elisa, Amir AghaKouchak, Charlotte A. Love, Linyin Cheng, Farshid Vahedifard, and Carlos H. R. Lima. 2018. "Quantifying Changes in Future Intensity-Duration-Frequency Curves Using Multimodel Ensemble Simulations." *Water Resources Research* 54 (3): 1751–64. https://doi.org/10.1002/2017WR021975.

Rashid, Md. Mamunur, and Simon Beecham. 2019. "Development of a Non-Stationary Standardized Precipitation Index and Its Application to a South Australian Climate." *Science of The Total Environment* 657 (March): 882–92. https://doi.org/10.1016/j.scitotenv.2018.12.052.

Rawls, W. J., D. L. Brakensiek, and K. E. Saxtonn. 1982. "Estimation of Soil Water Properties." *Transactions of the ASAE* 25 (5): 1316–20. https://doi.org/10.13031/2013.33720.

Redmond, Kelly T. 2002. "The Depiction of Drought: A Commentary." *Bulletin of the American Meteorological Society* 83 (8): 1143–48. https://doi.org/10.1175/1520-0477-83.8.1143.

Renard, B., M. Lang, and P. Bois. 2006. "Statistical Analysis of Extreme Events in a Non-Stationary Context via a Bayesian Framework: Case Study with Peak-Over-Threshold Data." *Stochastic Environmental Research and Risk Assessment* 21 (2): 97–112. https://doi.org/10.1007/s00477-006-0047-4.

Richardson, D., A. S. Black, D. Irving, et al. 2022. "Global Increase in Wildfire Potential from Compound Fire Weather and Drought." *npj Climate and Atmospheric Science* 5: 23 . https://doi.org/10.1038/s41612-022-00248-4.

Riebsame, W. E., S. A. Changnon, Jr., and T. R. Karl. 1991. *Drought and Natural Resources Management in the United States: Impacts and Implications of the 1987-89 Drought*. Westview Press: Boulder. 174 pp.

Rigby, R. A., and D. M. Stasinopoulos. 2005. "Generalized Additive Models for Location, Scale and Shape." *Journal of the Royal Statistical Society Series C: Applied Statistics* 54 (3): 507–54. https://doi.org/10.1111/j.1467-9876.2005.00510.x.

Rim, Chang-Soo. 2013. "The Implications of Geography and Climate on Drought Trend: Implications Of Geography and Climate on Drought Trend." *International Journal of Climatology* 33 (13): 2799–815. https://doi.org/10.1002/joc.3628.

Rocha-Ortega, Maya, Pilar Rodriguez, and Alex Córdoba-Aguilar. 2021. "Geographical, Temporal and Taxonomic Biases in Insect GBIF Data on Biodiversity and Extinction." *Ecological Entomology* 46 (4): 718–28. https://doi.org/10.1111/een.13027.

Roderick, Michael L., Peter Greve, and Graham D. Farquhar. 2015. "On the Assessment of Aridity with Changes in Atmospheric CO2." *Water Resources Research* 51 (7): 5450–63. https://doi.org/10.1002/2015WR017031.

Rodríguez-Flores, J. M., A. S. Fernandez-Bou, J. P. Ortiz-Partida, and J. Medellín-Azuara. 2023. "Drivers of Domestic Wells Vulnerability during Droughts in California's Central Valley." *Environmental Research Letters* 19 (1): 014003. https://doi.org/10.1088/1748-9326/ad0d39.

Routson, Cody C., Connie A. Woodhouse, and Jonathan T. Overpeck. 2011. "Second Century Megadrought in the Rio Grande Headwaters, Colorado: How Unusual Was Medieval Drought?: Second Century Megadrought." *Geophysical Research Letters* 38 (22): n/a-n/a. https://doi.org/10.1029/2011GL050015.

Russo, S., A. Dosio, A. Sterl, P. Barbosa, and J. Vogt. 2013. "Projection of Occurrence of Extreme Dry-wet Years and Seasons in Europe with Stationary and Nonstationary Standardized Precipitation Indices." *Journal of Geophysical Research: Atmospheres* 118 (14): 7628–39. https://doi.org/10.1002/jgrd.50571.

Ryu, Jihun, Shih-Yu Wang, Jee-Hoon Jeong, Hyungjun Kim, and Jin-Ho Yoon. 2025. "Time of Emergence (TOE) of Potential Aridification in the Western United States." *Journal of Hydrology* 656 (August): 133029. https://doi.org/10.1016/j.jhydrol.2025.133029.

Sahin, Sinan. 2012. "An Aridity Index Defined by Precipitation and Specific Humidity." *Journal of Hydrology* 444–445 (June): 199–208. https://doi.org/10.1016/j.jhydrol.2012.04.019.

Sakthivel, K. M., and V. Nandhini. 2024. "Modeling Extreme Values of Non-Stationary Precipitation Data with Effects of Covariates." *Indian Journal of Science and Technology* 17 (22): 2283–95. https://doi.org/10.17485/IJST/v17i22.655.

Samantaray, Alok Kumar, Meenu Ramadas, Meghna Babbar-Sebens, and Sudip Gautam. 2025. "Assessment of Nonstationary Drought Frequency under Climate Change Using Copula and Bayesian Hierarchical Models." *Journal of Hydrologic Engineering* 30 (2): 04025002. https://doi.org/10.1061/JHYEFF.HEENG-6319.

Sarhadi, Ali, María Concepción Ausín, Michael P. Wiper, Danielle Touma, and Noah S. Diffenbaugh. 2018. "Multidimensional Risk in a Nonstationary Climate: Joint Probability of Increasingly Severe Warm and Dry Conditions." *Science Advances* 4 (11): eaau3487. https://doi.org/10.1126/sciadv.aau3487.

Sarhadi, Ali, Donald H. Burn, María Concepción Ausín, and Michael P. Wiper. 2016. "Time-varying Nonstationary Multivariate Risk Analysis Using a Dynamic Bayesian Copula." *Water Resources Research* 52 (3): 2327–49. https://doi.org/10.1002/2015WR018525.

Saxton, K. E., and W. J. Rawls. 2006. "Soil Water Characteristic Estimates by Texture and Organic Matter for Hydrologic Solutions." *Soil Science Society of America Journal* 70 (5): 1569–78. https://doi.org/10.2136/sssaj2005.0117.

Schaberg, Paul G., David V. D'Amore, Paul E. Hennon, Joshua M. Halman, and Gary J. Hawley. 2011. "Do Limited Cold Tolerance and Shallow Depth of Roots Contribute to Yellow-Cedar Decline?" *Forest Ecology and Management* 262 (12): 2142–50. https://doi.org/10.1016/j.foreco.2011.08.004.

Scanlon, Bridget R., Claudia C. Faunt, Laurent Longuevergne, et al. 2012. "Groundwater Depletion and Sustainability of Irrigation in the US High Plains and Central Valley." *Proceedings of the National Academy of Sciences* 109 (24): 9320–25. https://doi.org/10.1073/pnas.1200311109.

Schmidt, Daniel F., and Kevin M. Grise. 2021. *Drivers of Twenty-First-Century U.S. Winter Precipitation Trends in CMIP6 Models: A Storyline-Based Approach*. Journal of Climate. August 1. https://doi.org/10.1175/JCLI-D-21-0080.1.

Schmidt, John C., Charles B. Yackulic, and Eric Kuhn. 2023. "The Colorado River Water Crisis: Its Origin and the Future." *WIREs Water* 10 (6): e1672. https://doi.org/10.1002/wat2.1672.

Schmidt, John C., Charles B. Yackulic, and Eric Kuhn. 2023. "The Colorado River Water Crisis: Its Origin and the Future." *WIREs Water* 10 (6): e1672. https://doi.org/10.1002/wat2.1672.

Schoemaker, Paul J. H. 1995. "Scenario Planning: A Tool for Strategic Thinking." *MIT Sloan Management Review*, January 15. https://sloanreview.mit.edu/article/scenario-planning-a-tool-for-strategic-thinking/.

Schuurman, Gregor, Hawkins-Hoffman Cat, David Cole, et al. 2020. *Resist-Accept-Direct (RAD)—a Framework for the 21st-Century Natural Resource Manager*. National Park Service. https://doi.org/10.36967/nrr-2283597.

Schwarz, Andrew, Z. Q. Richard Chen, Alejandro Perez, and Minxue He. 2025. "Evaluation and Adjustment of Historical Hydroclimate Data: Improving the Representation of Current Hydroclimatic Conditions in Key California Watersheds." *Hydrology* 12 (2): 22. https://doi.org/10.3390/hydrology12020022.

Seager, Richard, and Martin Hoerling. 2014. "Atmosphere and Ocean Origins of North American Droughts." *Journal of Climate* 27 (12): 4581–606. https://doi.org/10.1175/JCLI-D-13-00329.1.

Seager, Richard, Yochanan Kushnir, Celine Herweijer, Naomi Naik, and Jennifer Velez. 2005. *Modeling of Tropical Forcing of Persistent Droughts and Pluvials over Western North America: 1856–2000*. Lamont-Doherty Earth Observatory, Columbia University.

Seager, Richard, Mingfang Ting, Patrick Alexander, et al. 2023. "Ocean-Forcing of Cool Season Precipitation Drives Ongoing and Future Decadal Drought in Southwestern North America." *Npj Climate and Atmospheric Science* 6 (1): 141. https://doi.org/10.1038/s41612-023-00461-9.

Seneviratne, Sonia I., Thierry Corti, Edouard L. Davin, et al. 2010. "Investigating Soil Moisture–Climate Interactions in a Changing Climate: A Review." *Earth-Science Reviews* 99 (3): 125–61. https://doi.org/10.1016/j.earscirev.2010.02.004.

Seo, Jae Young, and Sang-Il Lee. 2019. "Spatio-Temporal Groundwater Drought Monitoring Using Multi-Satellite Data Based on an Artificial Neural Network." *Water* 11 (9): 1953. https://doi.org/10.3390/w11091953.

SFWMD (Southwest Florida Water Management District). 2026. *WSO Modified Phase II Water Shortage Restrictions*. February 8.

Shang, Lanyu, Bozhang Chen, Shiwei Liu, et al. 2025. "SIDE: Socially Informed Drought Estimation Toward Understanding Societal Impact Dynamics of Environmental Crisis." *Proceedings of the AAAI Conference on Artificial Intelligence* 39 (27): 28359–67. https://doi.org/10.1609/aaai.v39i27.35057.

Shang, Lanyu, Bozhang Chen, Anav Vora, Yang Zhang, Ximing Cai, and Dong Wang. 2024. "SocialDrought: A Social and News Media Driven Dataset and Analytical Platform towards Understanding Societal Impact of Drought." *Proceedings of the International AAAI Conference on Web and Social Media* 18 (May): 2051–62. https://doi.org/10.1609/icwsm.v18i1.31447.

Shao, Shuting, Hongbo Zhang, Vijay P. Singh, Hao Ding, Jingru Zhang, and Yanrui Wu. 2022. "Nonstationary Analysis of Hydrological Drought Index in a Coupled Human-Water System: Application of the GAMLSS with Meteorological and Anthropogenic Covariates in the Wuding River Basin, China." *Journal of Hydrology* 608 (May): 127692. https://doi.org/10.1016/j.jhydrol.2022.127692.

Sharp, J. 2010. *The Impacts of Urbanization on Groundwater Systems and Recharge*. https://doi.org/10.4409/Am-004-10-0008.

Shaw, T. A., J. M. Arblaster, T. Birner, et al. 2024. "Emerging Climate Change Signals in Atmospheric Circulation." *AGU Advances* 5 (6): e2024AV001297. https://doi.org/10.1029/2024AV001297.

Sheffield, Justin, and Eric F. Wood. 2012. *Drought: Past Problems and Future Scenarios*. Routledge. https://doi.org/10.4324/9781849775250.

Sheffield, Justin, Eric F. Wood, and Michael L. Roderick. 2012. "Little Change in Global Drought over the Past 60 Years." *Nature* 491 (7424): 435–38. https://doi.org/10.1038/nature11575.

Shulski, M., G. Wendler, S. Alden, and N. Larkin. 2005. "Alaska's Exceptional 2004 Fire Season: Paper 1.5." In *Sixth Symposium on Fire and Forest Meteorology*. University of Alaska Fairbanks.

Shulski, Martha, and Gerd Wendler. 2007. *The Climate of Alaska*. University of Alaska Press.

Siirila-Woodburn, Erica R., Alan M. Rhoades, Benjamin J. Hatchett, et al. 2021. "A Low-to-No Snow Future and Its Impacts on Water Resources in the Western United States." *Nature Reviews Earth & Environment* 2 (11): 800–819. https://doi.org/10.1038/s43017-021-00219-y.

Skiadaresis, Georgios, Bernhard Muigg, and Willy Tegel. 2021. "Historical Forest Management Practices Influence Tree-Ring Based Climate Reconstructions." *Frontiers in Ecology and Evolution* 9 (September): 727651. https://doi.org/10.3389/fevo.2021.727651.

Slater, Louise J., Bailey Anderson, Marcus Buechel, et al. 2021. "Nonstationary Weather and Water Extremes: A Review of Methods for Their Detection, Attribution, and Management." *Hydrology and Earth System Sciences* 25 (7): 3897–935. https://doi.org/10.5194/hess-25-3897-2021.

Smith, Kelly Helm, Mark E. Burbach, Michael J. Hayes, et al. 2021. "Whose Ground Truth Is It? Harvesting Lessons from Missouri's 2018 Bumper Crop of Drought Observations." *Weather, Climate, and Society* 13, no. 2: 227–44. https://doi.org/10.1175/WCAS-D-19-0140.1.

Smith, K. H., C. Knutson, and M. Svoboda. 2023. *The Cascading and Compounding Impacts of Drought*. School of Natural Resources: Faculty Publications. 1733. https://www.unccd.int/resources/brief/cascading-and-compounding-impacts-drought.

Smith, Kelly Helm, Mark Svoboda, Michael Hayes, et al. 2014. "Local Observers Fill In the Details on Drought Impact Reporter Maps." *Bulletin of the American Meteorological Society* 95 (11): 1659–62. https://doi.org/10.1175/1520-0477-95.11.1659.

Smith, Mark Stafford, Lisa Horrocks, Alex Harvey, and Clive Hamilton. 2011. "Rethinking Adaptation for a 4° C World." *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 369 (1934): 196–216. https://doi.org/10.1098/rsta.2010.0277.

Soares, Gabriel, Yosuke Yamazaki, Jürgen Matzka, et al. 2018. "Equatorial Counter Electrojet Longitudinal and Seasonal Variability in the American Sector." *Journal of Geophysical Research: Space Physics* 123 (11): 9906–20. https://doi.org/10.1029/2018JA025968.

Sofia, Giulia, Claudio Zaccone, and Paolo Tarolli. 2024. "Agricultural Drought Severity in NE Italy: Variability, Bias, and Future Scenarios." *International Soil and Water Conservation Research* 12 (2): 403–18. https://doi.org/10.1016/j.iswcr.2023.07.003.

Sohoulande Djebou, Dagbegnon Clement. 2017. "Bridging Drought and Climate Aridity." *Journal of Arid Environments* 144 (September): 170–80. https://doi.org/10.1016/j.jaridenv.2017.05.002.

Solomon, Levi E., Andrew F. Casper, Kristopher A. Maxson, et al. 2022. "A Case Study of Large Floodplain River Restoration: Two Decades of Monitoring the Merwin Preserve and Lessons Learned through Water Level Fluctuations and Uncontrolled Reconnection to a Large River." *Wetlands* 42, no. 6: 59. https://doi.org/10.1007/s13157-022-01581-3.

Souther, Sara, Sarah Colombo, and Nanebah N. Lyndon. 2023. "Integrating Traditional Ecological Knowledge into US Public Land Management: Knowledge Gaps and Research Priorities." *Frontiers in Ecology and Evolution* 11 (March): 988126. https://doi.org/10.3389/fevo.2023.988126.

Sreeparvathy, Vijay, Sengupta Debdut, and Ashok Mishra. 2025. "A Review of Advances in Flash Drought Research: Challenges and Future Directions." *Earth's Future* 13 (8): e2025EF006603. https://doi.org/10.1029/2025EF006603.

Stagge, James H., Irene Kohn, Lena M. Tallaksen, and Kerstin Stahl. 2015. "Modeling Drought Impact Occurrence Based on Meteorological Drought Indices in Europe." *Journal of Hydrology* 530 (November): 37–50. https://doi.org/10.1016/j.jhydrol.2015.09.039.

Stagge, James H., Lena M. Tallaksen, Lukas Gudmundsson, Anne F. Van Loon, and Kerstin Stahl. 2015. "Candidate Distributions for Climatological Drought Indices (SPI and SPEI)." *International Journal of Climatology* 35 (13): 4027–40. https://doi.org/10.1002/joc.4267.

Stahl, Kerstin, Irene Kohn, Veit Blauhut, et al. 2016. "Impacts of European Drought Events: Insights from an International Database of Text-Based Reports." *Natural Hazards and Earth System Sciences* 16 (3): 801–19. https://doi.org/10.5194/nhess-16-801-2016.

Stahle, David W. 2020. "Anthropogenic Megadrought." *Science* 368 (6488): 238–39. https://doi.org/10.1126/science.abb6902.

Stanke, Carla, Marko Kerac, Christel Prudhomme, Jolyon Medlock, and Virginia Murray. 2013. "Health Effects of Drought: A Systematic Review of the Evidence." *PLoS Currents*, ahead of print. https://doi.org/10.1371/currents.dis.7a2cee9e980f91ad7697b570bcc4b004.

State of Nebraska, Climate Assessment Response Committee. 2000. *Nebraska Drought Mitigation and Response Plan*. Lincoln, NE. https://carc.nebraska.gov/docs/NebraskaDrought.pdf.

Staten, Paul W., Kevin M. Grise, Sean M. Davis, et al. 2020. "Tropical Widening: From Global Variations to Regional Impacts." *Bulletin of the American Meteorological Society* 101 (6): E897–904. https://doi.org/10.1175/BAMS-D-19-0047.1.

Stern, M. A., L. E. Flint, A. L. Flint, and Boynton. 2022. "Selecting the Optimal Fine-Scale Historical Climate Data for Assessing Current and Future Hydrological Conditions." *Journal of Hydrometeorology*, ahead of print, January 14. https://doi.org/10.1175/JHM-D-21-0045.1.

Stevenson, Samantha, Sloan Coats, Danielle Touma, et al. 2022. "Twenty-First Century Hydroclimate: A Continually Changing Baseline, with More Frequent Extremes." *Proceedings of the National Academy of Sciences* 119 (12): e2108124119. https://doi.org/10.1073/pnas.2108124119.

Strohbach, Michael W., Anneke O. Döring, Malte Möck, et al. 2019. "The 'Hidden Urbanization': Trends of Impervious Surface in Low-Density Housing Developments and Resulting Impacts on the Water Balance." *Frontiers in Environmental Science* 7 (March): 29. https://doi.org/10.3389/fenvs.2019.00029.

Su, Chengjia, and Xiaohong Chen. 2019. "Covariates for Nonstationary Modeling of Extreme Precipitation in the Pearl River Basin, China." *Atmospheric Research* 229 (November): 224–39. https://doi.org/10.1016/j.atmosres.2019.06.017.

Sun, Fubao, Michael L. Roderick, and Graham D. Farquhar. 2018. "Rainfall Statistics, Stationarity, and Climate Change." *Proceedings of the National Academy of Sciences* 115 (10): 2305–10. https://doi.org/10.1073/pnas.1705349115.

Sun, Peng, Chenhao Ge, Rui Yao, et al. 2024. "Development of a Nonstationary Standardized Precipitation Evapotranspiration Index (NSPEI) and Its Application across China." *Atmospheric Research* 300 (April): 107256. https://doi.org/10.1016/j.atmosres.2024.107256.

Sung, Kyungmin, Max C. A. Torbenson, and James H. Stagge. 2024. "Assessing Decadal- to Centennial-Scale Nonstationary Variability in Meteorological Drought Trends." *Hydrology and Earth System Sciences* 28 (9): 2047–63. https://doi.org/10.5194/hess-28-2047-2024.

Svensson, Cecilia, Jamie Hannaford, and Ilaria Prosdocimi. 2017. "Statistical Distributions for Monthly Aggregations of Precipitation and Streamflow in Drought Indicator Applications." *Water Resources Research* 53 (2): 999–1018. https://doi.org/10.1002/2016WR019276.

Svoboda, Mark D., Brian A. Fuchs, and University of Nebraska–Lincoln. 2016. *Handbook of Drought Indicators and Indices.* With Integrated Drought Management Programme, World Meteorological Organization, and Global Water Partnership. WMO, no. 1173. World Meteorological Organization.

Svoboda, Mark, Doug LeComte, Mike Hayes, et al. 2002. "The Drought Monitor." *Bulletin of the American Meteorological Society* 83 (8): 1181–90. https://doi.org/10.1175/1520-0477-83.8.1181.

Swain, Daniel L., Andreas F. Prein, John T. Abatzoglou, et al. 2025. "Hydroclimate Volatility on a Warming Earth." *Nature Reviews Earth & Environment* 6 (1): 35–50. https://doi.org/10.1038/s43017-024-00624-z.

Tallaksen, Lena, and Henny van Lanen. 2004. "Hydrological Drought: Processes and Estimation Methods for Streamflow and Groundwater – 1st Edition." *European Drought Centre*. https://europeandroughtcentre.com/resources/hydrological-drought-1st-edition/.

Thoman, A., and H. R. McFarland. 2024. *Alaska's Changing Environment 2.0*. Alaska Center for Climate Assessment and Policy, International Arctic Research Center.

Thornthwaite, C. W. 1948. "An Approach toward a Rational Classification of Climate." *Geographical Review* 38 (1): 55. https://doi.org/10.2307/210739.

Thornwaite, Charles Warren, and John Russel Mather. 1955. *The Water Balance*. Drexel Institute of Technology, Laboratory of Climatology.

Thornwaite, Charles Warren, and John Russell Mather. 1957. *Instructions and Tables for Computing Potential Evapotranspiration and the Water Balance*. Laboratory of Climatology, Drexel Institute of Technology.

Thrasher, Bridget, Weile Wang, Andrew Michaelis, Forrest Melton, Tsengdar Lee, and Ramakrishna Nemani. 2022. "NASA Global Daily Downscaled Projections, CMIP6." *Scientific Data* 9 (1): 262. https://doi.org/10.1038/s41597-022-01393-4.

Tijdeman, E., L. J. Barker, M. D. Svoboda, and K. Stahl. 2018. "Natural and Human Influences on the Link Between Meteorological and Hydrological Drought Indices for a Large Set of Catchments in the Contiguous United States." *Water Resources Research* 54 (9): 6005–23. https://doi.org/10.1029/2017WR022412.

Ting, Mingfang, Richard Seager, Cuihua Li, Haibo Liu, and Naomi Henderson. 2018. "Mechanism of Future Spring Drying in the Southwestern United States in CMIP5 Models." *Journal of Climate*. June 1. https://doi.org/10.1175/JCLI-D-17-0574.1.

Todd, Victoria L., Timothy M. Shanahan, Pedro N. DiNezio, et al. 2025. "North Pacific Ocean–Atmosphere Responses to Holocene and Future Warming Drive Southwest US Drought." *Nature Geoscience* 18 (7): 646–52. https://doi.org/10.1038/s41561-025-01726-z.

Tomasella, Javier, Ana Paula M. A. Cunha, Paloma Angelina Simões, and Marcelo Zeri. 2023. "Assessment of Trends, Variability and Impacts of Droughts across Brazil over the Period 1980–2019." *Natural Hazards* 116 (2): 2173–90. https://doi.org/10.1007/s11069-022-05759-0.

Tran, T. N. D., SK Do, S.R.O. Marshall, et al. 2026 (in preparation). *Global Standardized Soil Moisture Index Dataset for Disaster Monitoring*.

TREAS (U.S. Department of Treasury). 2016. "Internal Revenue Bulletin: 2016-42 | Internal Revenue Service." https://www.irs.gov/irb/2016-42_IRB.

Trenberth, Kevin E., Aiguo Dai, Gerard Van Der Schrier, et al. 2014. "Global Warming and Changes in Drought." *Nature Climate Change* 4 (1): 17–22. https://doi.org/10.1038/nclimate2067.

Tuttle, Samuel, and Guido Salvucci. 2016. "Empirical Evidence of Contrasting Soil Moisture–Precipitation Feedbacks across the United States." *Science* 352 (6287): 825–28. https://doi.org/10.1126/science.aaa7185.

Tuttle, Samuel E., and Guido D. Salvucci. 2017. "Confounding Factors in Determining Causal Soil Moisture-Precipitation Feedback." *Water Resources Research* 53 (7): 5531–44. https://doi.org/10.1002/2016WR019869.

Udall, Bradley, and Jonathan Overpeck. 2017. "The Twenty-first Century Colorado River Hot Drought and Implications for the Future." *Water Resources Research* 53 (3): 2404–18. https://doi.org/10.1002/2016WR019638.

Um, Myoung-Jin, Yeonjoo Kim, Daeryong Park, and Jeongbin Kim. 2017. "Effects of Different Reference Periods on Drought Index (SPEI) Estimations from 1901 to 2014." *Hydrology and Earth System Sciences* 21 (10): 4989–5007. https://doi.org/10.5194/hess-21-4989-2017.

UNCCD (United Nations Convention to Combat Desertification). 2023.

USDA (U.S. Department of Agriculture). 2003. *Fact Sheet Sales of Surplus Non-Fat Dry Milk*. April.

USDA. 2020. Review of Information Used to Produce the United States Drought Monitor, Submitted by the Office of the Chief Economist as Partial Execution of Section 12512 (Improvements to the United States Drought Monitor) of The Agricultural Improvement Act of 2018.

USDA. 2024a. "Emergency Loan Program | Farm Service Agency." Farm Service Agency, U.S Department of Agriculture, October. https://www.fsa.usda.gov/tools/informational/fact-sheets/emergency-loan-program-2024pdf.

USDA. 2024b. *RAINFALL INDEX INSURANCE STANDARDS HANDBOOK*. August 28.

USDA. 2025a. "Farm & Commodity Policy - Title XI: Crop Insurance Program Provisions | Economic Research Service." February 18. https://www.ers.usda.gov/topics/farm-economy/farm-commodity-policy/title-xi-crop-insurance-program-provisions.

USDA. 2025b. "Emergency Livestock Relief Program (ELRP) - 2023/2024 | Farm Service Agency." May. https://www.fsa.usda.gov/tools/informational/fact-sheets/emergency-livestock-relief-program-elrp-20232024.

USDA. 2025c. "Livestock Forage Disaster Program (LFP) | Farm Service Agency." May. https://www.fsa.usda.gov/tools/informational/fact-sheets/livestock-forage-disaster-program-lfp.

USDA. 2025d. "Risk Management - Crop Insurance at a Glance | Economic Research Service." September 23. https://www.ers.usda.gov/topics/farm-practices-management/risk-management/crop-insurance-at-a-glance.

USDM (U.S. Drought Monitor). n.d. "Drought Classification | U.S. Drought Monitor." U.S. Drought Monitor. Accessed March 13, 2026. https://droughtmonitor.unl.edu/About/AbouttheData/DroughtClassification.aspx.

USGCRP (U.S. Global Change Research Program). 2023. *Fifth National Climate Assessment*. Edited by Allison R. Crimmins, Christopher W. Avery, David R. Easterling, Kenneth E. Kunkel, Brooke C. Stewart, and Thomas K. Maycock. https://doi.org/10.7930/NCA5.2023.

USGS (U.S. Geological Survey). 2018. *Estimated Use of Water in the United States in 2015*. Circular. https://doi.org/10.3133/cir1441.

van der Velde, Rogier, Andreas Colliander, Michiel Pezij, et al. 2021. "Validation of SMAP L2 Passive-Only Soil Moisture Products Using Upscaled In Situ Measurements Collected in Twente, the Netherlands." *Hydrology and Earth System Sciences* 25 (1): 473–95. https://doi.org/10.5194/hess-25-473-2021.

van Dijk, Albert I. J. M., Hylke E. Beck, Russell S. Crosbie, et al. 2013. "The Millennium Drought in Southeast Australia (2001–2009): Natural and Human Causes and Implications for Water Resources, Ecosystems, Economy, and Society." *Water Resources Research* 49 (2): 1040–57. https://doi.org/10.1002/wrcr.20123.

Van Loon, Anne F. 2015. "Hydrological Drought Explained." *WIREs Water* 2 (4): 359–92. https://doi.org/10.1002/wat2.1085.

Van Loon, Anne F., Sarra Kchouk, Alessia Matanó, et al. 2024. "Review Article: Drought as a Continuum – Memory Effects in Interlinked Hydrological, Ecological, and Social Systems." *Natural Hazards and Earth System Sciences* 24 (9): 3173–205. https://doi.org/10.5194/nhess-24-3173-2024.

Van Loon, Anne F., Kerstin Stahl, Giuliano Di Baldassarre, et al. 2016. "Drought in a Human-Modified World: Reframing Drought Definitions, Understanding, and Analysis Approaches." *Hydrology and Earth System Sciences* 20 (9): 3631–50. https://doi.org/10.5194/hess-20-3631-2016.

Vano, Julie A., et al. 2014 "Understanding Uncertainties in Future Colorado River Streamflow." *Bulletin of the American Meteorological Society* 95 (1): 59–78. https://doi.org/10.1175/BAMS-D-12-00228.1.

Vasiliades, L., P. Galiatsatou, and A. Loukas. 2015. "Nonstationary Frequency Analysis of Annual Maximum Rainfall Using Climate Covariates." *Water Resources Management* 29 (2): 339–58. https://doi.org/10.1007/s11269-014-0761-5.

Vélez-Nicolás, Mercedes, Santiago García-López, Verónica Ruiz-Ortiz, Santiago Zazo, and José Luis Molina. 2022. "Precipitation Variability and Drought Assessment Using the SPI: Application to Long-Term Series in the Strait of Gibraltar Area." *Water* 14 (6): 884. https://doi.org/10.3390/w14060884.

Vergni, L., F. Todisco, and F. Mannocchi. 2017. "Evaluating the Uncertainty and Reliability of Standardized Indices." *Hydrology Research* 48 (3): 701–13. https://doi.org/10.2166/nh.2016.076.

Vergopolan, Noemi, Justin Sheffield, Nathaniel W. Chaney, et al. 2022. "High-Resolution Soil Moisture Data Reveal Complex Multi-Scale Spatial Variability Across the United States." *Geophysical Research Letters* 49 (15): e2022GL098586. https://doi.org/10.1029/2022GL098586.

Vicente-Serrano, S. M., and S. Beguería. 2016. "Comment on 'Candidate Distributions for Climatological Drought Indices (SPI and SPEI)' by James H. Stagge et al." *International Journal of Climatology* 36 (4): 2120–31. https://doi.org/10.1002/joc.4474.

Vicente-Serrano, Sergio M., Santiago Beguería, and Juan I. López-Moreno. 2010. "A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index." *Journal of Climate* 23 (7): 1696–718. https://doi.org/10.1175/2009JCLI2909.1.

Vicente-Serrano, Sergio M., Fernando Domínguez-Castro, Santiago Beguería, et al. 2025. "Atmospheric Drought Indices in Future Projections." *Nature Water* 3 (4): 374–87. https://doi.org/10.1038/s44221-025-00416-9.

Vicente-Serrano, Sergio M., Fernando Domínguez-Castro, Fergus Reig, et al. 2023. "A Global Drought Monitoring System and Dataset Based on ERA5 Reanalysis: A Focus on Crop-growing Regions." *Geoscience Data Journal* 10 (4): 505–18. https://doi.org/10.1002/gdj3.178.

Vicente-Serrano, Sergio M., Juan I. López-Moreno, Santiago Beguería, Jorge Lorenzo-Lacruz, Cesar Azorin-Molina, and Enrique Morán-Tejeda. 2012. "Accurate Computation of a Streamflow Drought Index." *Journal of Hydrologic Engineering* 17 (2): 318–32. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000433.

Vicente-Serrano, Sergio M., Tim R. McVicar, Diego G. Miralles, Yuting Yang, and Miquel Tomas-Burguera. 2020. "Unraveling the Influence of Atmospheric Evaporative Demand on Drought and Its Response to Climate Change." *WIREs Climate Change* 11 (2): e632. https://doi.org/10.1002/wcc.632.

Vose, James M., David L. Peterson, Charles H. Luce, and Toral Patel-Weynand. 2019. *Effects of Drought on Forests and Rangelands in the United States: Translating Science into Management Responses*. WO-GTR-98. U.S. Department of Agriculture, Forest Service. https://doi.org/10.2737/WO-GTR-98.

Walker, David W., Juliana Lima Oliveira, Louise Cavalcante, et al. 2024. "It's Not All about Drought: What 'Drought Impacts' Monitoring Can Reveal." *International Journal of Disaster Risk Reduction* 103 (March): 104338. https://doi.org/10.1016/j.ijdrr.2024.104338.

Walker, David W., Noemi Vergopolan, Louise Cavalcante, et al. 2024. "Flash Drought Typologies and Societal Impacts: A Worldwide Review of Occurrence, Nomenclature, and Experiences of Local Populations." *Weather, Climate, and Society* 16 (1): 3–28. https://doi.org/10.1175/WCAS-D-23-0015.1.

Walsh, Brianne, Simon Constanzo, and Bill Dennison. 2015. *Ecological Drought in Alaska*. December 2.

Walston, Joshua M., Stephanie A. McAfee, and Daniel J. McEvoy. 2023. "Evaluating Drought Indices for Alaska." *Earth Interactions* 27 (1): e220025. https://doi.org/10.1175/EI-D-22-0025.1.

Wang, Jingxian, Andrea Castelletti, Mariana Madruga De Brito, and Barbara Pernici. 2025. "Drought Perceived Impacts via Text Mining of Social Media." *Environmental Research: Water* 1 (4): 045007. https://doi.org/10.1088/3033-4942/ae2e37.

Wang, Wen, Jingshu Wang, and Renata Romanowicz. 2021. "Uncertainty in SPI Calculation and Its Impact on Drought Assessment in Different Climate Regions over China." *Journal of Hydrometeorology*, ahead of print, March 23. https://doi.org/10.1175/JHM-D-20-0256.1.

Wang, Yixuan, Jianzhu Li, Ping Feng, and Rong Hu. 2015. "A Time-Dependent Drought Index for Non-Stationary Precipitation Series." *Water Resources Management* 29 (15): 5631–47. https://doi.org/10.1007/s11269-015-1138-0.

Wang, Zengyan, Tao Che, Tianjie Zhao, Liyun Dai, Xiaojun Li, and Jean-Pierre Wigneron. 2021. "Evaluation of SMAP, SMOS, and AMSR2 Soil Moisture Products Based on Distributed Ground Observation Network in Cold and Arid Regions of China." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 14: 8955–70. https://doi.org/10.1109/JSTARS.2021.3108432.

Western, Andrew W., Rodger B. Grayson, and Günter Blöschl. 2002. "Scaling of Soil Moisture: A Hydrologic Perspective." *Annual Review of Earth and Planetary Sciences* 30 (1): 149–80. https://doi.org/10.1146/annurev.earth.30.091201.140434.

White, Kristopher D., and Jonathan L. Case. 2014. "Assessing the Utility of 3-Km Land Information System Soil Moisture Data for Drought Monitoring and Hydrologic Applications." Paper presented at National Weather Association Annual Meeting. October 18. https://ntrs.nasa.gov/citations/20140016697.

Wilhite, Donald A. 2000. "Drought Preparedness and Response in the Context of Sub-Saharan Africa." *Journal of Contingencies and Crisis Management* 8 (2): 81–92. https://doi.org/10.1111/1468-5973.00127.

Wilhite, Donald A., and Margie Buchanan-Smith. 2005. "Drought as Hazard: Understanding the Natural and Social Context." *Drought and Water Crises: Science, Technology, and Management Issues* 3: 29.

Wilhite, D. A. 1997. "Western Drought Coordination Council: Frequently Asked Questions." *Drought Network News (1994–2001).* 106. https://digitalcommons.unl.edu/droughtnetnews/106

Wilhite, D. A. 2000. "Responding to Drought: Common Threads from the Past, Visions for the Future." Chapter 40 in *Drought: A Global Assessment*, Volume II, D. A. Wilhite, ed. Routledge: London. 304 pp.

Wilhite, Donald A., ed. 2016. *Droughts: A Global Assessment*. Routledge. https://doi.org/10.4324/9781315830896.

Wilhite, Donald A., and Michael H. Glantz. 1985. "Understanding: The Drought Phenomenon: The Role of Definitions." *Water International* 10 (3): 111–20. https://doi.org/10.1080/02508068508686328.

Wilhite, D. A., and M. Buchanan-Smith. 2005. "Drought as Hazard: Understanding the Natural and Social Context." *Drought and Water Crises: Science, Technology, and Management Issues* 3: 29.

Wilhite, Donald A., and Michael H. Glantz. 1985. "Understanding: The Drought Phenomenon: The Role of Definitions." *Water International* 10 (3): 111–20. https://doi.org/10.1080/02508068508686328.

Wilhite, Donald A., Mannava V. K. Sivakumar, and Roger Pulwarty. 2014. "Managing Drought Risk in a Changing Climate: The Role of National Drought Policy." *Weather and Climate Extremes* 3 (June): 4–13. https://doi.org/10.1016/j.wace.2014.01.002.

Wilks, Daniel S. 2011. *Statistical Methods in the Atmospheric Sciences*. 3rd ed. International Geophysics Series, v. 100. Academic Press.

Williams, A. Park, John T. Abatzoglou, Alexander Gershunov, et al. 2019. "Observed Impacts of Anthropogenic Climate Change on Wildfire in California." *Earth's Future* 7 (8): 892–910. https://doi.org/10.1029/2019EF001210.

Williams, A. Park, Edward R. Cook, Jason E. Smerdon, et al. 2020. "Large Contribution from Anthropogenic Warming to an Emerging North American Megadrought." *Science* 368 (6488): 314–18. https://doi.org/10.1126/science.aaz9600.

Williams, A. Park, Benjamin I. Cook, and Jason E. Smerdon. 2022a. "Rapid Intensification of the Emerging Southwestern North American Megadrought in 2020–2021." *Nature Climate Change* 12 (3): 232–34. https://doi.org/10.1038/s41558-022-01290-z.

Williams, A. Park, Ben Livneh, Karen A. McKinnon, et al. 2022b. "Growing Impact of Wildfire on Western US Water Supply." *Proceedings of the National Academy of Sciences* 119 (10): e2114069119. https://doi.org/10.1073/pnas.2114069119.

Williams, A. Park, Karen A. McKinnon, Kevin J. Anchukaitis, et al. 2024. "Anthropogenic Intensification of Cool-Season Precipitation Is Not Yet Detectable Across the Western United States." *Journal of Geophysical Research: Atmospheres* 129 (12): e2023JD040537. https://doi.org/10.1029/2023JD040537.

Wills, Robert C. J., Yue Dong, Cristian Proistosecu, Kyle C. Armour, and David S. Battisti. 2022. "Systematic Climate Model Biases in the Large-Scale Patterns of Recent Sea-Surface Temperature and Sea-Level Pressure Change." *Geophysical Research Letters* 49 (17): e2022GL100011. https://doi.org/10.1029/2022GL100011.

Wine, Michael L., Daniel Cadol, and Oleg Makhnin. 2018. "In Ecoregions across Western USA Streamflow Increases during Post-Wildfire Recovery." *Environmental Research Letters* 13 (1): 014010. https://doi.org/10.1088/1748-9326/aa9c5a.

Wisner, Ben, and Irasema Alcántara-Ayala. 2023. "Revisiting Frameworks: Have They Helped Us Reduce Disaster Risk?" *Jàmbá Journal of Disaster Risk Studies* 15 (1). https://doi.org/10.4102/jamba.v15i1.1491.

Wisner, Benjamin. 2016. "Vulnerability as Concept, Model, Metric, and Tool." In *Oxford Research Encyclopedia of Natural Hazard Science*, by Benjamin Wisner. Oxford University Press. https://doi.org/10.1093/acrefore/9780199389407.013.25.

WMO (World Meteorological Organization), ed. 1992. *International Meteorological Vocabulary =: Vocabulaire Météorologique International*. 2nd ed. WMO/OMM/VMO, no. 182. Secretariat of the World Meteorological Organization.

WMO. 2012. *Standardized Precipitation Index User Guide.* WMO, No. 1090. World Meteorological Organization.

WMO. 2022. "Drought." World Meteorological Organization, December 16. https://wmo.int/topics/drought.

Woodcock, Curtis, Tim Canty, Andrew Collard, et al. n.d. *2023 NASA Earth Science Senior Review*. National Aeronautics and Space Administration.

Woodhouse, Connie A., Stephen T. Gray, and David M. Meko. 2006. "Updated Streamflow Reconstructions for the Upper Colorado River Basin." *Water Resources Research* 42 (5): 2005WR004455. https://doi.org/10.1029/2005WR004455.

Woodhouse, Connie A., David M. Meko, Glen M. MacDonald, Dave W. Stahle, and Edward R. Cook. 2010. "A 1,200-Year Perspective of 21st Century Drought in Southwestern North America." *Proceedings of the National Academy of Sciences* 107 (50): 21283–88. https://doi.org/10.1073/pnas.0911197107.

Woodhouse, Connie A., and Jonathan T. Overpeck. 1998. "2000 Years of Drought Variability in the Central United States." *Bulletin of the American Meteorological Society* 79 (12): 2693–714. https://doi.org/10.1175/1520-0477(1998)079%253C2693:YODVIT%253E2.0.CO;2.

Worku, Gebrekidan, Ermias Teferi, Amare Bantider, and Yihun T. Dile. 2019. "Observed Changes in Extremes of Daily Rainfall and Temperature in Jemma Sub-Basin, Upper Blue Nile Basin, Ethiopia." *Theoretical and Applied Climatology* 135 (3–4): 839–54. https://doi.org/10.1007/s00704-018-2412-x.

Wu, Hong, Mark D. Svoboda, Michael J. Hayes, Donald A. Wilhite, and Fujiang Wen. 2007. "Appropriate Application of the Standardized Precipitation Index in Arid Locations and Dry Seasons." *International Journal of Climatology* 27 (1): 65–79. https://doi.org/10.1002/joc.1371.

Wu, Xiaotao, Guihua Lu, Zhiyong Wu, Hai He, Tracy Scanlon, and Wouter Dorigo. 2020. "Triple Collocation-Based Assessment of Satellite Soil Moisture Products with In Situ Measurements in China: Understanding the Error Sources." *Remote Sensing* 12 (14): 2275. https://doi.org/10.3390/rs12142275.

Xia, Yinfeng, Ming Zhang, Daniel C. W. Tsang, et al. 2020. "Recent Advances in Control Technologies for Non-Point Source Pollution with Nitrogen and Phosphorous from Agricultural Runoff: Current Practices and Future Prospects." *Applied Biological Chemistry* 63 (1): 8. https://doi.org/10.1186/s13765-020-0493-6.

Xu, Feng, Yanping Qu, Virgílio A. Bento, et al. 2024. "Understanding Climate Change Impacts on Drought in China over the 21st Century: A Multi-Model Assessment from CMIP6." *Npj Climate and Atmospheric Science* 7 (1): 32. https://doi.org/10.1038/s41612-024-00578-5.

Xu, Pengcheng, Dong Wang, Yuankun Wang, et al. 2023. "+Dynamic Identification and Risk Analysis of Compound Dry-Hot Events Considering Nonstationarity." *Journal of Hydrology* 616 (January): 128852. https://doi.org/10.1016/j.jhydrol.2022.128852.

Xu, Yang, Xuan Zhang, Xiao Wang, Zengchao Hao, Vijay P. Singh, and Fanghua Hao. 2019. "Propagation from Meteorological Drought to Hydrological Drought under the Impact of Human Activities: A Case Study in Northern China." *Journal of Hydrology* 579 (December): 124147. https://doi.org/10.1016/j.jhydrol.2019.124147.

Yuan, Xing, Yumiao Wang, Peng Ji, Peili Wu, Justin Sheffield, and Jason A. Otkin. 2023. "A Global Transition to Flash Droughts under Climate Change." *Science* 380 (6641): 187–91. https://doi.org/10.1126/science.abn6301.

Zargar, Amin, Rehan Sadiq, Bahman Naser, and Faisal I. Khan. 2011. "A Review of Drought Indices." *Environmental Reviews* 19 (NA): 333–49. https://doi.org/10.1139/a11-013.

Zaw, Zaw, Ze-Xin Fan, Achim Bräuning, et al. 2020. "Drought Reconstruction Over the Past Two Centuries in Southern Myanmar Using Teak Tree-Rings: Linkages to the Pacific and Indian Oceans." *Geophysical Research Letters* 47 (10): e2020GL087627. https://doi.org/10.1029/2020GL087627.

Zeng, Zhaoqi, Wenxiang Wu, Josep Peñuelas, et al. 2023. "Increased Risk of Flash Droughts with Raised Concurrent Hot and Dry Extremes under Global Warming." *Npj Climate and Atmospheric Science* 6 (1):134. https://doi.org/10.1038/s41612-023-00468-2.

Zhang, Baoqing, Amir AghaKouchak, Yuting Yang, Jiahua Wei, and Guangqian Wang. 2019. "A Water-Energy Balance Approach for Multi-Category Drought Assessment across Globally Diverse Hydrological Basins." *Agricultural and Forest Meteorology* 264 (January): 247–65. https://doi.org/10.1016/j.agrformet.2018.10.010.

Zhang, Fangyue, Joel A. Biederman, Matthew P. Dannenberg, Dong Yan, Sasha C. Reed, and William K. Smith. 2021. "Five Decades of Observed Daily Precipitation Reveal Longer and More Variable Drought Events Across Much of the Western United States." *Geophysical Research Letters* 48 (7): e2020GL092293. https://doi.org/10.1029/2020GL092293.

Zhang, Lijuan, Cuizhen Wang, Xiaxiang Li, Hongwen Zhang, Wenliang Li, and Lanqi Jiang. 2018. "Impacts of Agricultural Expansion (1910s–2010s) on the Water Cycle in the Songneng Plain, Northeast China." *Remote Sensing* 10 (7): 1108. https://doi.org/10.3390/rs10071108.

Zhang, Qiang, Danzhou Wang, Anlan Feng, et al. 2025. "Improved Non-Stationary SPEI and Its Application in Drought Monitoring in China." *Journal of Hydrology* 652 (May): 132706. https://doi.org/10.1016/j.jhydrol.2025.132706.

Zhang, Qin, Shujie Cheng, Lina Liu, et al. 2025. "Projections of Climate Change and Its Impacts Based on CMIP6 Models—Calling Attention to Quantifying and Constraining Uncertainty." *Environmental Research Letters* 20 (3): 031002. https://doi.org/10.1088/1748-9326/adb1f7.

Zhang, Sijia, Donghai Wang, Zhengkun Qin, Yaoyao Zheng, and Jianping Guo. 2018. "Assessment of the GPM and TRMM Precipitation Products Using the Rain Gauge Network over the Tibetan Plateau." *Journal of Meteorological Research* 32 (2): 324–36. https://doi.org/10.1007/s13351-018-7067-0.

Zhang, Xue-Yan, Jiming Jin, Xubin Zeng, Charles P. Hawkins, Antônio A. M. Neto, and Guo-Yue Niu. 2022. "The Compensatory CO2 Fertilization and Stomatal Closure Effects on Runoff Projection From 2016–2099 in the Western United States." *Water Resources Research* 58 (1): e2021WR030046. https://doi.org/10.1029/2021WR030046.

Zhang, Yunfan, Lei Cheng, Lu Zhang, et al. 2022. "Does Non-Stationarity Induced by Multiyear Drought Invalidate the Paired-Catchment Method?" *Hydrology and Earth System Sciences* 26 (24): 6379–97. https://doi.org/10.5194/hess-26-6379-2022.

Zhou, Sha, and Bofu Yu. 2025. "Reconciling the Discrepancy in Projected Global Dryland Expansion in a Warming World." *Global Change Biology* 31 (3): e70102. https://doi.org/10.1111/gcb.70102.

Zhuang, Yizhou, Rong Fu, Joel Lisonbee, Amanda M. Sheffield, Britt A. Parker, and Genoveva Deheza. 2024. "Anthropogenic Warming Has Ushered in an Era of Temperature-Dominated Droughts in the Western United States." *Science Advances* 10 (45): eadn9389. https://doi.org/10.1126/sciadv.adn9389.

PREPUBLICATION COPY—Uncorrected Proofs

Appendix A
Committee Member and Staff Biographical Sketches

Jonathan T. Overpeck (Chair) is the Samuel A. Graham Dean of the School for Environment and Sustainability (SEAS) at the University of Michigan. At Michigan, he is the William B. Stapp Collegiate Professor in SEAS, a professor of Earth and environmental science, and a professor of climate and space science and engineering. He was a postdoctoral fellow and research scientist at Columbia University and NASA Goddard Institute for Space Studies, before being appointed as the founding head of the National Oceanic and Atmospheric Administration (NOAA) Paleoclimatology Program. He served as the founding director of the World Data Center for Paleoclimatology, before moving to the University of Arizona where he was a professor of geosciences, the director of the Institute for the Study of Planet Earth, and a founding co-director of the Institute of the Environment. Overpeck is a fellow of the American Geophysical Union and the American Academy for the Advancement of Science and is a member of the U.S. National Academy of Sciences. Other awards include the U.S. Department of Commerce Gold Medal, a Guggenheim Fellowship, the Walter Orr Roberts award of the American Meteorological Society, and the Quivira Coalition's Radical Center Award. Overpeck earned his Ph.D. and M.Sc. from Brown University and B.A. (honors) from Hamilton College.

Overpeck is a founding member of the Colorado River Research Group which has produced white papers on the Colorado River, including on topics related to drought. Overpeck writes and gives talks on a wide variety of drought-related issues, including water management, monsoon dynamics, and climate.

Amir AghaKouchak is a professor of civil and environmental engineering and Earth system science at the University of California, Irvine. His research focuses on natural hazards and climate extremes and crosses the boundaries between hydrology, climatology, and remote sensing. One of his main research areas is studying and understanding the interactions between different types of climatic and non-climatic hazards including compound and cascading events. AghaKouchak has published over 260 journal articles in peer-reviewed journals. He has received several honors and awards including the American Geophysical Union's (AGU) James B. Macelwane Medal, a fellow of AGU, and the American Society of Civil Engineers (ASCE) Norman Medal, and Huber Research Prize. AghaKouchak has a Ph.D. in civil and environmental engineering from the University of Stuttgart.

Clara Deser is a senior scientist and former head of the Climate Analysis Section at the National Science Foundation-National Center for Atmospheric Research (NSF-NCAR). Prior to NCAR, Deser was a postdoc and then a research associate at the University of Colorado – CIRES. Deser has participated in numerous national and international committees and panels, including the President's Council of Advisors on Science and Technology (PCAST), U.S. and International CLIVAR, Intergovernmental Panel on Climate Change (IPCC) contributing author; and as co-lead of the IPCC Polar Amplification Model Intercomparison Project, Community Earth System Model (CESM) 1 and CESM2 Large Ensembles, and the U.S. CLIVAR Working Group on Large Ensembles. Deser is a member of the U.S. National Academy of Sciences, American Geophysical Union (AGU), and the American Meteorological Society (AMS), and has received the AMS Meisinger and Charney Medals, and the AGU Bjerknes and Revelle Medals. Deser received a B.S. from MIT in Earth and planetary sciences and a Ph.D. from the University of Washington in atmospheric sciences.

Trent W. Ford is the state climatologist for Illinois and is an associate research scientist with the Illinois State Water Survey and Prairie Research Institute at the University of Illinois. He is an expert in hydroclimate variability, extremes, and climate change impacts. His work spans fundamental to translational understanding of the climate system and its interactions with water, especially related to drought dynamics and impacts. As state climatologist, Trent leads climate and drought monitoring, research, and data collection for the state of Illinois. He has helped guide state-level climate resilience planning, including co-authoring the Illinois State Water Plan and All-Hazard Mitigation Plan. Trent currently serves on the Illinois Specialty Growers Association advisory board and the State of Illinois' Water Plan Task Force. He works with communities, state agencies, private sector, and special interest groups on issues related to weather, climate, and climate change in Illinois and the broader Midwest region. He regularly engages the public through dozens of online and in-person presentations each year, and works with K–12 educators on climate curriculum and science literacy. Ford earned a bachelors in geography from Illinois State University before completing his masters and Ph.D. in geography at Texas A&M University.

Kristiana M. Hansen is an agricultural economist and extension water resource economist in the Department of Agricultural and Applied Economics at the University of Wyoming. Hansen's research is in water resource economics and community resilience to weather and climate variability, especially within the agricultural sector. She conducts applied, interdisciplinary research on how agricultural, municipal, and recreational water users respond to changes in water availability in Wyoming and other water-scarce locations, with an emphasis on the impact of agricultural and water resource management on local rural economies. Current research includes analysis of the risks and impacts of different ways that Wyoming and other upper Colorado River Basin states could meet their obligations to downstream states under the Colorado River Compact. Her Extension program seeks to inform and improve regional decision-making in water management and allocation. Hansen holds a B.A. in economics from Reed College and a Ph.D. in agricultural and resource economics from the University of California, Davis.

Richard R. Heim, Jr., retired in 2024 after a 42-year career with NOAA. He joined NOAA through the NWS meteorologist intern program. Heim served as a meteorologist with the National Centers for Environmental Information (NCEI, formerly NCDC) from 1985 to 2024, working in user engagement and managing the 1961–1990 U.S. and Global Climate Normals project, Snow Climatology project, and Climate Reference Network, but he is best known for his work in the field of drought monitoring and research. He was an author of the weekly interagency U.S. Drought Monitor (2001–2024), monthly international North American Drought Monitor (2003–2024), and Global Drought Narrative (2022–2024), as well as author of the NCEI monthly online State of the Climate Drought reports (1999–2024) and Synoptic Discussion (2011–2019) and was the Product Area Leader responsible for NCEI's entire drought product portfolio (2019–2024). Heim authored over seven dozen articles published in scientific journals, 26 of which he was sole author or lead author. Awards include five Department of Commerce Bronze Medal Awards and the 2019 Department of Commerce Silver Medal Award for work in the field of drought monitoring. Heim holds a B.S. in mathematics with five minors and a masters in geography/meteorology/climatology from the University of Nebraska–Lincoln.

Heim retired in December 2024 from the NOAA National Centers for Environmental Information (NCEI). He was an author of the monthly *State of the Climate Drought* reports (1999–2024), the U.S. Drought Monitor (USDM) (2001–2024), the North American Drought Monitor (NADM) (2003–2024), and the Global Drought Narrative (2022–2024).

Jennifer J. Henderson is an assistant professor of geography in the Department of Geosciences at Texas Tech University where she directs the Risk and Education in Disasters (RED) Lab. Henderson is a social scientist whose research focuses on human-environment relationships in the context of weather and climate extremes. She studies risk communication and decision-making contexts for a variety of hazards, including drought, fire, flooding, tornadoes, and hurricanes. Over the past 10 years, Henderson has focused, in particular, on compound and cascading disasters and their impacts on varying populations, as well as the challenges experts face in communicating them. She frequently collaborates with colleagues from atmospheric sciences, engineering, public safety, and operational meteorology on projects that integrate a diverse range of methods and theoretical frameworks to address real-world problems. In addition to her research, Henderson is the incoming Planning Commissioner for the American Meteorological Society and is a member of the NOAA Science Advisory Board's Environmental Information Services Working Group. She holds a Ph.D. in science and technology studies from Virginia Tech.

Zachary H. Hoylman is a research assistant professor at the University of Montana and the assistant state climatologist for Montana at the Montana Climate Office. His interdisciplinary work integrates climate, hydrology, and ecosystems, with expertise in drought informatics, remote sensing, and geospatial data analysis. His academic studies focused on hydrologic processes and climate interactions that drive ecosystem vulnerability to climate change across the Western United States. More recently, Hoylman's research examines the limitations of traditional assumptions of climate stationarity in drought assessment, advocating for adaptive approaches that account for the realities of a rapidly changing climate. His current work leverages artificial intelligence and machine learning to improve total water assessments and drought prediction, supporting climate adaptation efforts across Montana and the broader United States. Hoylman has a Ph.D. from the University of Montana.

Yusuke Kuwayama is an associate professor in the School of Public Policy at the University of Maryland, Baltimore County, and a fellow at Resources for the Future (RFF) in Washington, D.C. He studies the economics of water resource and ecosystem management, with a focus on federal and state regulation of ambient water pollution, water management to protect aquatic species habitats, and sustainable water use in agriculture. He is an at-large appointee to the Chesapeake Bay Program's Scientific and Technical Advisory Committee (STAC) and serves on the Water Science and Technology Board at the National Academies. He previously served as director of the Consortium for the Valuation of Applications Benefits Linked with Earth Science (VALUABLES), a cooperative agreement between RFF and NASA. He received his Ph.D. in agricultural and applied economics and an M.S. in economics from the University of Illinois Urbana-Champaign and an A.B. in economics from Amherst College.

Venkataraman Lakshmi is the John L. Newcomb Professor of Engineering in the Department of Civil and Environmental Engineering at the University of Virginia. He has served as Cox Visiting Professor at Stanford University and program director for hydrologic sciences at the National Science Foundation. Lakshmi is a fellow of the American Society of Civil Engineers (ASCE), Geological Society of America (GSA), American Society of Agronomy (ASA), and American Association for the Advancement of Science (AAAS). He is currently serving as editor for *Vadose Zone Journal* and the founding editor-in-chief of *Remote Sensing in Earth System Science* (Springer Journals). He has served on the National Academies Panel for the Decadal Survey of Earth Observations from Space and as chair of the planning committee for Groundwater Recharge and Flow: Approaches and Challenges for Monitoring and Modeling Using Remotely Sensed Data. He is currently serving as a member of the Water Science and Technology Board, National Academy of Sciences, and vice chair of the Earth Science Advisory Committee for NASA. He is the president of the Hydrology Section of the American Geophysical Union. Lakshmi earned a Ph.D. in civil and environmental engineering from Princeton.

Justin S. Mankin is an associate professor of geography at Dartmouth. He holds courtesy appointments in Earth and planetary sciences and the Ecology, Evolution, Environment and Society (EEES) graduate program and is an adjunct associate research scientist at Lamont-Doherty Earth Observatory (LDEO). Mankin is principal investigator of Dartmouth's Climate Modeling and Impacts Group, studying the origins and impacts of climate variability and change, including on drought. Previously, he was co-lead of the NOAA Drought Task Force (2021–2024) and led the synthesis report on the 2020–2023 Western U.S. drought. He serves on the American Meteorological Society's Climate Variability and Change Committee, is a University Corporation for Atmospheric Research (UCAR) member representative, and a graphics lead author for NCA6. He is an editor at *Earth's Future* and an associate editor at *Journal of Climate*. He was named a 2025 MIT and WHOI H. Burr Steinbach Scholar, received the American Geophysical Union's 2024 Global Environmental Change Early Career Award, and delivered a keynote for the National Academies workshop on Climate Change and Migration. His previous career was as an intelligence officer working in South Asia and the Middle East. He holds degrees from Columbia (B.A., M.P.A.), London School of Economics (M.Sc.), and Stanford (Ph.D.), and completed his training at LDEO and NASA GISS as an Earth Institute postdoctoral fellow.

Karen A. McKinnon is an associate professor at UCLA where she is jointly appointed in the Department of Atmospheric and Oceanic Sciences, Department of Statistics and Data Science, and Institute of the Environment and Sustainability. Her research sits at the nexus of climate change and statistics and is aimed at improving our understanding and prediction of climate extremes, variability, and change, particularly over land. McKinnon currently serves as a co-lead of the NOAA Drought Task Force. McKinnon is a 2024 National Science Foundation CAREER awardee, a 2023 Kavli fellow, and a 2021 Packard fellow in science and engineering. She received her Ph.D. at Harvard University and was an advanced study postdoctoral fellow at the National Center for Atmospheric Research.

Staff

Charles Burgis is a program officer with the Earth Systems and Resources Program Area. He has a Ph.D. in civil and environmental engineering from the University of Virginia.

Dominique Jenkins is a senior program assistant with the Earth Systems and Resources Program Area. She received a bachelors degree from the University of Maryland, College Park.

Steven Stichter is a senior program officer with the Earth Systems and Resources Program Area. He has a master's degree in regional planning from the University of North Carolina, Chapel Hill.

Appendix B
Report Conclusions and Recommendations

1 Introduction

Conclusion 1-1: An enhanced framework for drought assessment under nonstationarity should consider and address the differing needs and components of drought assessment for both operational/emergency management and long-term planning applications.

2 Defining Drought Monitoring and Assessment

Conclusion 2-1: Drought definitions should encompass both reduced water supply and increased water demand.

3 Drivers of Drought in a Changing Climate

Conclusion 3-1: Drought assessment methodologies should incorporate both water supply and evaporative demand, as well as precipitation phase (snow versus rain).

Conclusion 3-2: Further research is needed to constrain regional projections of precipitation in the United States.

Conclusion 3-3: Drought assessment should aim to incorporate near-real-time information, as well as shorter timescale metrics, in order to better identify emerging flash droughts.

Conclusion 3-4: There is high confidence that climate warming, by itself, is likely to continue worsening trends in drought severity, frequency, duration, and possible onset speed, except where and/or when offset by sufficient increases in precipitation.

Conclusion 3-5: Further understanding of the physical and biological drivers of drought and how they may change as the climate warms, including assessing Earth System Model prediction and projection skill, is an urgent research need that underpins effective drought assessment.

4 Nonstationarity, Aridification, and Drought

Conclusion 4-1: Nonstationarity challenges drought classification and assessment because drought is conventionally defined using static thresholds relative to a baseline climate; if different baselines are used, or if the climate evolves relative to a fixed baseline (as with aridification), the same physical conditions can be classified differently or missed entirely.

Conclusion 4-2: Across parts of the United States, the climatological reference period used in operational drought classification no longer matches the observed hydroclimate, with consequences for the character, frequency, and severity of drought.

Conclusion 4-3: A stand-alone aridification product that tracks the local climatological water balance does not currently exist but is needed to help distinguish transient anomalies from secular climate trends in both the research and water planning communities.

Conclusion 4-4: Nonstationarity erodes the utility of drought classification for emergency management while simultaneously increasing the maladaptation costs of drought assessment regimes that encode static climate assumptions.

Conclusion 4-5: The decision costs of drought nonstationarity are large and an assessment framework resilient to nonstationarity must serve both operational needs (i.e., reflecting true current conditions) and planning needs (i.e., the drivers and timescales of baseline changes), or be transparent about which aim it is serving.

Recommendation 4-1: NOAA, NSF, NASA, and other science partners involved in the national drought assessment enterprise should prioritize scientific research into drought dynamics and aridification, including how climate variability and change influence the frequency, severity, duration, onset, intensification, and other aspects of drought needed to support relevant decision-making. The research should also prioritize improving approaches used to assess drought and aridification risks seasons to decades into the future.

Conclusion 4-6: Baseline selection is not a neutral methodological choice; instead, it is a design choice for drought-related decision-making and should be treated as such.

Conclusion 4-7: Because baseline choice materially affects drought classification and the decisions it informs, drought monitoring products and decision-support tools should communicate the baseline used, its limitations under nonstationarity, and the implications for interpretation.

Conclusion 4-8: Existing nonstationary drought indices represent an important methodological advance but also face limitations, including too narrow a focus on meteorological variables and limited engagement with the broader impacts of drought.

5 Drought Assessment Data Sources and Nonstationarity

Conclusion 5-1: Effective drought assessment under nonstationarity requires both long-term observational records and contemporary high-resolution datasets. In situ observations like precipitation and streamflow may span over a century whereas more recent Earth observations are available only for a few decades. To better leverage multiple data sources for drought assessment under anthropogenic climate change, dynamic reference periods can be used that are regularly updated while maintaining parallel long-term baselines that preserve historical context.

Recommendation 5-1: Federal agencies (such as USGS, NOAA/NWS, USDA, USCRN) operating in situ hydrological networks (streamflow, COOP, SCAN, SNOTEL, USCRN, and state-operated hydrological and mesonet networks) should prioritize continuity of long-term datasets with strategic placement across diverse soil types, crop covers, topographic settings, climatic zones, and ecosystem types to capture the heterogeneity of drought response and strengthen standardized data archiving, quality control protocols, and open-access frameworks to facilitate seamless integration with satellite and model-based products.

Conclusion 5-2: Many Earth-observing missions are approaching or have exceeded their designed operational lifespans (e.g., Aqua and SMAP) and several flagship missions are rapidly running out of energy. Gaps between missions (e.g., GRACE and GRACE Follow-On) create discontinuities in time series that undermine trend analysis, degrade baseline characterizations and assimilation in land models, and introduce inconsistencies in drought assessment and classification. Sustaining these critical Earth observations is essential for accurate and timely drought assessment.

Recommendation 5-2: To ensure continuity and support proactive planning, NASA and USGS, in coordination with NOAA, should develop explicit mission succession strategies with multidecadal funding commitments to preserve critical Earth observation records, thereby avoiding gaps in records essential for drought detection and assessment. This includes incorporating explicit prelaunch cross-calibration protocols with predecessor systems, overlapping periods enabling robust inter-sensor comparison, and prioritizing long-term homogeneity essential for detecting climate signals under nonstationarity.

Conclusion 5-3: Land models and reanalysis systems provide spatially continuous, temporally consistent estimates of drought-relevant variables, but inconsistencies in long-term trends and anomaly magnitudes across different models complicate their integration in operational monitoring and, more critically, undermine confidence in distinguishing climate-driven changes from model structural artifacts under nonstationarity.

Recommendation 5-3: To improve model-based drought product interoperability and compatibility, NOAA and NASA, in collaboration with the broader hydrological modeling community, should establish guidance on standardized modeling output specifications and model multiproduct integration and validation methods. Additionally, to strengthen attribution of observed drought changes to climatic drivers, NOAA and NASA should support intercomparison studies quantifying model-to-model uncertainty under diverse climatic and land surface conditions.

6 Drought Indicators, Indices, and Nonstationarity

Conclusion 6-1: Reference periods under the context of nonstationarity should be treated as adaptable parameters, updated or reevaluated as conditions change and/or flexible to apply to specific systems and decision framework, rather than fixed climatologies assumed to remain valid over time.

Recommendation 6-1: NOAA, USDA, USGS, affiliated regional climate centers, and national drought assessment partners such as the National Drought Mitigation Center (NDMC) should develop flexible methods to examine drought information with different reference periods in consultation with drought data providers, practitioners, and end users. This could include producing multiple datasets concurrently using different reference periods (e.g., the last 30 years, the most recent climate normal period, and the full period of record) or enabling dynamic generation of drought indices using user-defined reference periods. In doing so, methods should balance flexibility for system-specific applications with the need for consistent, transparent, reproducible, and comparable assessments of drought conditions across space and time.

Conclusion 6-2: Strengthening standardization around analytical methods, reference period design, and metadata transparency is a necessary step toward more consistent, reproducible, and risk-aligned drought assessment in a nonstationary climate.

Conclusion 6-3: Transparent documentation of analytical methods, reference periods, and uncertainty is essential for ensuring that drought metrics are interpretable, comparable, and appropriately applied as climate conditions evolve.

Recommendation 6-2: NOAA, USDA, USGS, and affiliated regional climate centers, in coordination with academic and practitioner communities, should develop and adopt shared standards for documenting and publishing metadata associated with drought metrics, including methods, reference periods, and uncertainty.

Conclusion 6-4: Efforts within the drought assessment community should continue to explore transparent and reproducible approaches to drought assessment while recognizing that expert judgment, local expertise, Indigenous and Traditional Ecological Knowledge, and other ways of knowing provide critical perspectives not fully captured by purely quantitative approaches.

Conclusion 6-5: Reference periods that align with risk profiles of specific systems are needed to inform shared drought assessment and decision-making. Such reference periods should be developed with engagement of all affected communities.

Recommendation 6-3: NOAA, USDA, and USGS, in collaboration with state and federal agencies (including the USDA Climate Hubs and NCEI's Regional Climate Centers), should convene key communities affected by drought to identify reference periods that align with risk profiles of specific systems, to better inform decision-making for each system.

7 Drought Impacts, Impact Data, and Nonstationarity

Conclusion 7-1: Impacts are complicated manifestations of drought, but they are nonetheless critical to the entire drought assessment process.

Conclusion 7-2: System exposure and adaptive capacity are important parts of the risk of drought impacts, and changes in either can affect the likelihood and/or severity of a drought impact. Therefore, along with drought impact data, drought assessment should regularly collect and report information on changes in a system's drought exposure and/or adaptive capacity.

Conclusion 7-3: Assessment of drought impacts requires information on drought conditions as well as the status and adaptive capacity of affected systems to inform operational drought response and long-term planning, but mechanisms for collecting and using such data do not exist consistently across the United States. State government agencies (e.g., natural resource, agriculture, and environmental protection agencies) in collaboration with local governments may be best positioned to undertake collection of data and planning that are relevant to drought exposure (e.g., water use, stream gauge, and low flow measurements) and adaptive capacity across systems (e.g., through water supply and hazard mitigation plans) and use of that information to reduce drought impact risk (e.g., tabletop exercises of existing drought plans).

Conclusion 7-4: The growing wealth of drought impact information presents an opportunity to improve drought assessment at national, state, and local levels, especially as innovations and AI and other technology and science continue to be developed.

Recommendation 7-1: NIDIS should work with decision-makers, scientists, and the broader drought community to develop a set of best practices by which drought impacts data can be consistently and effectively used for all aspects of drought assessment, especially for state drought plans and other policy and action plans.

Conclusion 7-5: The current infrastructure for collecting and communicating drought impacts is inadequate and impact data are not collected evenly across drought impact types (e.g., less actionable impact information for ecological drought), which has created uneven emphasis for drought assessment and response on some systems (e.g., agriculture) over other systems (e.g., wetlands) that are impacted by drought.

Recommendation 7-2: NIDIS should facilitate the development or improvement of systems for systematic collection, reporting, and integration of drought impacts consistently across sectors, regions, and interests, for multiple uses, including drought assessment, adaptation, and other decision-making. In this work, NIDIS should collaborate with the U.S. Department of Agriculture (agriculture and forest), Department of Interior (coastal, ecological, water resources), Department of Homeland Security (drought response/resilience, national security), Bureau of Land Management (fire, rangeland), Health and Human Services (public health), Environmental Protection Agency (water resources, air and water quality), and Tribal communities, as well as the broader drought community.

Conclusion 7-6: Current drought impact reporting systems do not capture consistent or comprehensive drought impact information across time, geography, or drought types, which limits the usefulness of impact data to drought assessment and decision-making.

Conclusion 7-7: Changes in human and nonhuman systems create nonstationarity in drought impacts and can change the impact-indicator relationship.

Conclusion 7-8: Drought impact collection and reporting systems need flexibility to respond to new or newly realized impacts and emerging threats.

8 Framework for Incorporating Nonstationarity into Drought Assessment

Conclusion 8-1: A framework for incorporating nonstationarity in drought assessment to inform decision-making should be designed around a two-pronged drought analysis framework that integrates (1) short-term operational/emergency management assessments and (2) long-term planning assessments, depending on the application.

Conclusion 8-2: For drought assessments used for short-term operational decision-making, an updated stationary approach based on contemporary baselines (e.g., 30 years ± 10 years, depending on the type of drought assessment, systems of interest, and decision frameworks) is appropriate, assuming it is implemented with clear rules for baseline refreshing, documentation, versioning, and reproducibility.

Conclusion 8-3: Drought assessments designed to support long-term planning (including post-event assessment, and projection) should be based on explicitly nonstationary models that use the full available observational record including paleoclimatic information (when available and relevant) and model-based predictions/projections. The assessment framework should allow statistical parameters to evolve with time and/or physically meaningful covariates (e.g., temperature, circulation indices, water demand, land use land cover). This framework for modeling evolving statistical parameters can be implemented using either traditional statistical approaches or emerging artificial intelligence and machine learning methods for representing nonstationarity.

Conclusion 8-4: Developing a shared approach to drought assessment under nonstationarity requires the engagement of a wide range of stakeholders, including from (1) the research community to advance methods, diagnostics, dynamical understanding, uncertainty quantification, and open reference implementations; (2) operational agencies and practitioners (e.g., water agencies, farmers, ranchers, forest and rangeland managers, wildfire managers, drought monitoring systems, and infrastructure owners) who can define decision requirements and operational constraints; and (3) standards and regulatory stakeholders (e.g., professional societies, guidance-setting bodies, and insurance regulators) to ensure transparency, stability, and acceptance for high-stakes applications.

Conclusion 8-5: An improved framework for drought assessment should include approaches that are increasingly tailored to specific conditions and decision contexts, as well as agency- and user-specific applications.

Recommendation 8-1: To support the development of a common drought assessment framework, NOAA/NIDIS should facilitate the establishment of a consortium that includes representatives from the research community, operational agencies and practitioners, and standards and regulatory stakeholders.

Recommendation 8-2: NOAA/NIDIS, in collaboration with other agencies such as USDA, should develop a common drought assessment framework that integrates approaches for both short-term operational and long-term planning applications. In this framework, short-term operational assessments should be based on contemporary baselines, with clear rules for baseline refreshing, documentation, versioning, and reproducibility; and long-term planning assessments should be based on nonstationary models that use the full available observational record (including the paleoclimatic record) together with model-based predictions and projections, and that allow distribution parameters to evolve over time and/or with physically meaningful covariates.

Recommendation 8-3: NOAA/NIDIS should facilitate development, with a consortium of key drought sector representatives, of a set of application-specific guidelines, specifying baseline lengths, update frequency, documentation standards, and reporting requirements for short-term and long-term drought analysis, with complementary guidelines tailored to specific applications or sectors.

Recommendation 8-4: The drought assessment community should invest in research and development to strengthen convergence-of-evidence approaches by introducing more transparent, structured, and reproducible frameworks for selecting the baseline period and integrating multiple indicators. These efforts should aim to formalize how the baseline period is selected and how indicators are combined, weighted, and interpreted, based on expert judgment and domain-specific knowledge.

Conclusion 8-6: The entire United States is at risk of drought and aridification in the future, and this risk should be assessed at regular intervals in recognition that the understanding of nonstationarity (both climatic and otherwise) and drought dynamics changes in time. This regular assessment should focus on providing stakeholders with the information they need to increase resilience to future drought and aridification.

Recommendation 8-5: NOAA and its partners should carry out regular national drought assessment that facilitates long-term (seasons to decades) planning for all regions in the United States, whether they are currently experiencing drought or not. These long-term assessments should take into both natural and human-driven forms of nonstationarity, including natural and human-forced climate change, and should be designed to enhance resilience to possible future drought.

Appendix C
Code used for Generating Selected Graphics

Public sharing of methods and code used for analysis and modeling enhances the transparency and reproducibility of such analysis, including for drought assessment. Consistent with calls in this report for such methodological transparency, the committee is sharing code used to produce selected data-driven, committee-generated graphics in this report.

This code is available through a public repository maintained by the National Academies for this study. The link to this repository is available on the National Academies Press page for this report.