Northern Australia Climate Program

Centre for Applied Climate Sciences

Drought Outlook Products Review

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MEAT & LIVESTOCK AUSTRALIA

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Overview

This report presents a review of currently available drought forecast tools and research into drought forecasting, with the goal of identifying a suitable approach for the development of a prototype drought outlook tool for northern Australia. Key findings include:

- Two operational drought forecast tools are currently available on-line; these are (i) the **US Drought Outlook** (available as monthly and seasonal/3-month drought forecasts) produced by the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center (CPC) and available through the National Integrated Drought Information System (NIDIS); and (ii) the **World Bank Global Forecast Drought Tool** developed by the International Research Institute for Climate and Society (IRI) at Columbia University, in collaboration with the CPC and University of Maine.
- The US Monthly and Seasonal Drought Outlooks, presented as forecast maps, are developed by merging data from a number of sources: CPC temperature and precipitation outlooks; long lead forecasts such as the National Centres for Environmental Prediction (NCEP) Climate Forecast System (CFS) and the North American Multi-Model Ensemble (NMME) system; short-term weather forecasts from NCEP and ECMWF; and current conditions from the US Drought Monitor.
- The World Bank Global Forecast Drought Tool, presented as global/regional forecast drought severity and drought risk maps, provides probabilistic forecasts of future Standardised Precipitation Index (SPI) as an indicator of drought for a range of accumulation periods (3, 6, 9 or 12 months) based on monthly precipitation predictions from multiple NMME models and initial observed SPI conditions.
- Considerable ongoing research is conducted into drought forecasting and published in the academic literature; approaches include statistical, dynamical and hybrid prediction methods. Three reviews of drought forecasting approaches have also been published, with discussion of the relative advantages and disadvantages of the different approaches, while the NOAA Drought Task Force has developed a Drought Capability Assessment Protocol in an attempt to better ensure the rigorous assessment of research in order to build capability.
- Ongoing gaps and challenges identified by the NOAA Drought Task Force in 2016 include improving the objectivity of inputs into drought monitoring tools; ensuring accurate data collection from gauge-based observation networks and real-time merging of in-situ observations and (bias-corrected) satellite data; improvements in prediction of the full drought cycle (onset, duration, severity, recovery); improved understanding of key governing processes in the coupled ocean-atmosphere-land system and their predictability; developing hydrological seasonal prediction systems; and development of a seamless ensemble-based drought monitoring and prediction system.
- Development of a prototype drought outlook tool for northern Australia might feasibly be based on the simplified drought forecasting approach of IRI's World Bank Global Forecast Drought Tool, using the Combined Drought Index (CDI) currently under development through NACP in conjunction with ACCESS-S model SCF/precipitation forecasts.

Northern Australia Climate Program

DROUGHT OUTLOOK PRODUCTS – REVIEW

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Introduction

Drought is an extreme climate event, characterized by below-normal precipitation over a period of months to years (Dai, 2010). It is often characterised as a slow onset natural hazard, but is one of the least understood, though potentially most damaging, especially to vulnerable populations in developing regions (Pozzi et al., 2013) where extreme drought can lead to famine. Globally, drought significantly impacts agricultural productivity, water availability and quality and economic activity (Figure 1). Monitoring and early warning systems, based on drought forecasting, are therefore critical to effective drought mitigation planning (Wilhite and Svoboda, 2000).

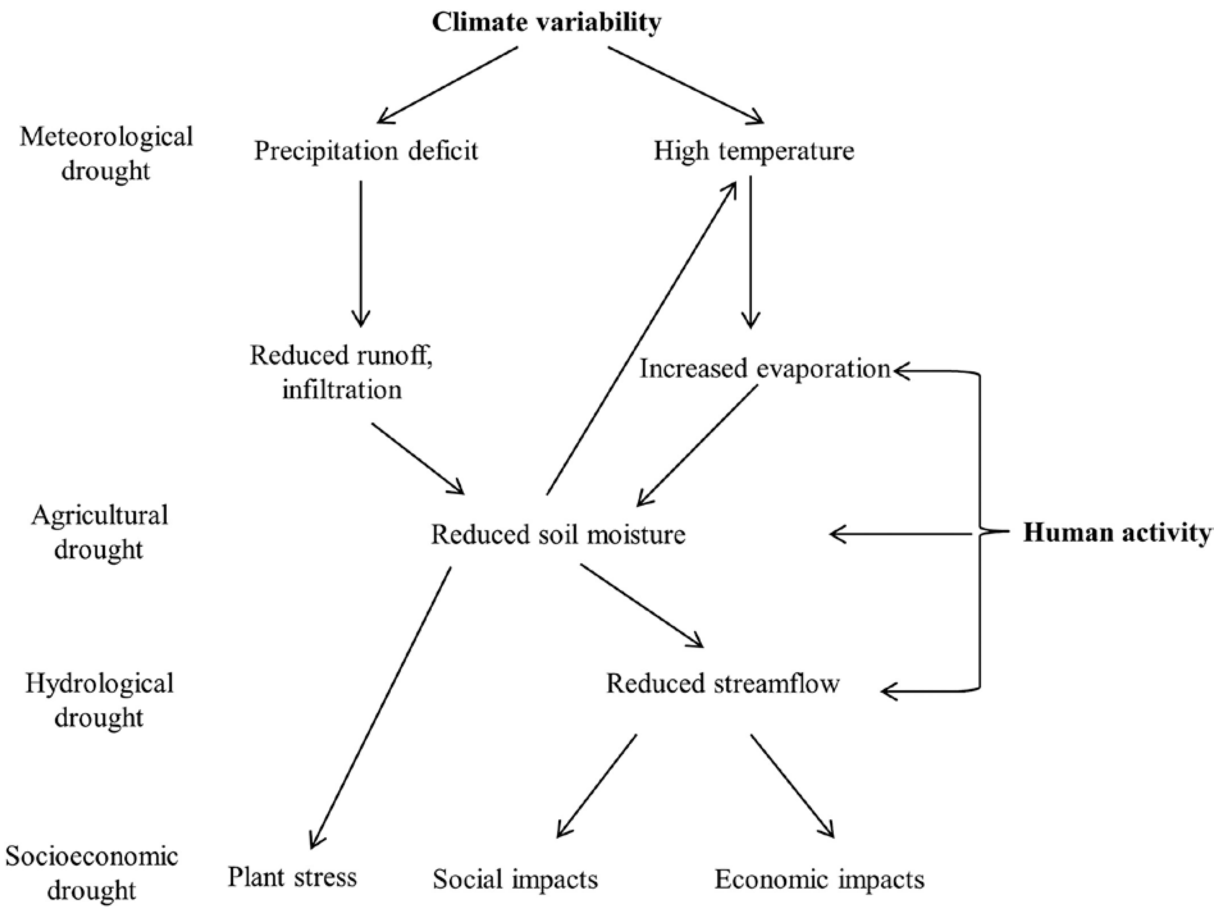

Figure 1 Interaction of different variables in the hydrological cycle during drought (Source Hao et al. 2018)

This review looks at currently available drought forecasting tools and the status of drought forecasting capability (in terms of leading edge research and challenges in drought modelling). It concludes by considering the value of such approaches in the Australian context, where—while Australian researchers significantly contribute to advancement of the science—no drought forecasting/outlook tool currently exists.

Literature Review

Drought forecasting is the focus of considerable ongoing research and the basis for a growing body of papers published in the academic literature. This intense interest, as well as the ongoing evolution of new data collection and analysis methods and tools (e.g. big data approaches and machine learning) and advancements in climate modelling overall, have led to significant and ongoing improvements in drought modelling skill over recent decades. In response to the intense research interest in the topic, the NOAA Drought Task Force has developed a Drought Capability Assessment Protocol—identifying assessment metrics; verification periods and datasets; and baseline and benchmarking standards—in an attempt to build forecasting capability through rigorous assessment of the research (NOAA Drought Task Force, 2016).

The NOAA Drought Task Force (2016) publication also describes the state of the science of drought forecasting and outlines how recent research has improved understanding of why drought occurs, as well as enhanced capabilities to (i) monitor the current state of drought, and (ii) predict its onset and evolution over periods of weeks to seasons. In addition, we have found three published reviews of drought forecasting approaches, which provide comparisons of forecasting approaches (Mishra & Singh, 2011; Hao et al., 2018; Fung et al., 2019). In each case, these papers discuss the advances, challenges, and future prospects of drought prediction and the relative advantages and disadvantages of the different forecasting approaches.

Figures 2 and 3 capture the general elements of drought forecasting approaches; these can then categorise into three main types: statistical, dynamical and hybrid prediction methods. These are briefly described below and examples are provided in Appendix A.

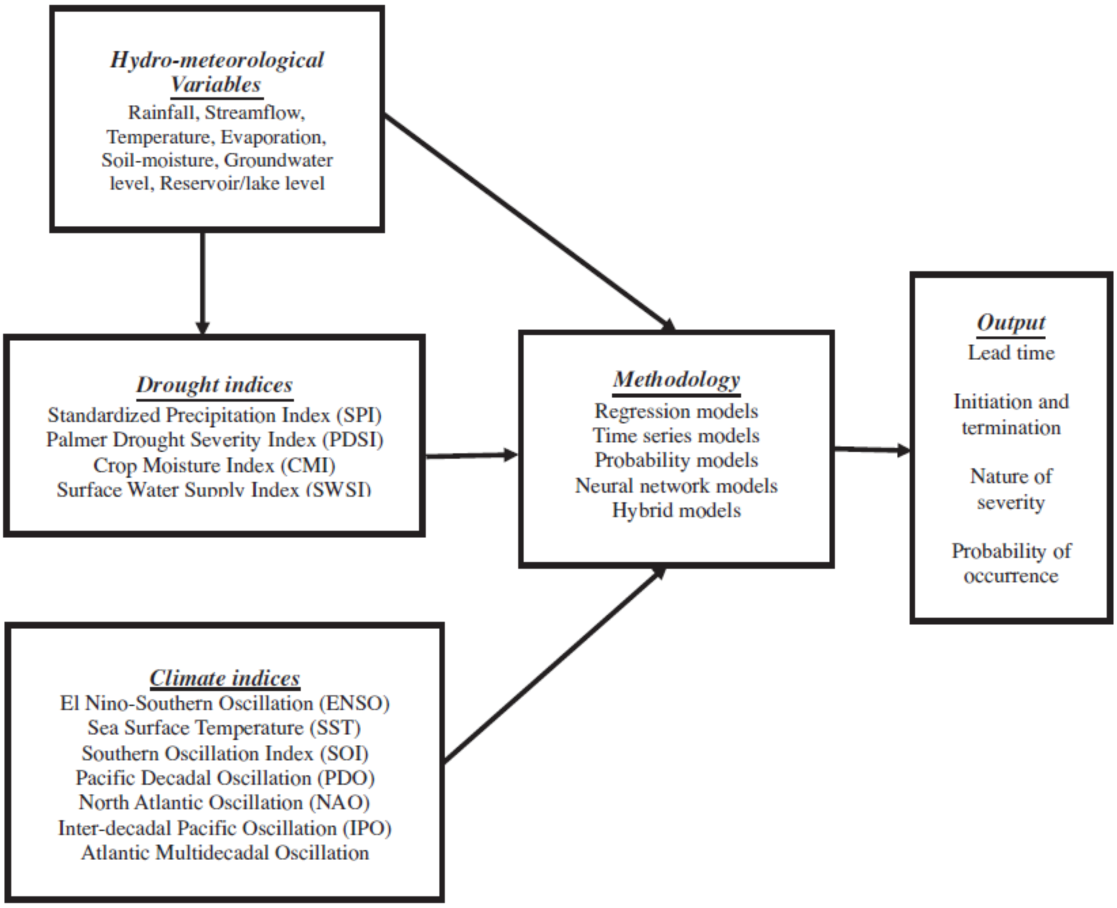

Figure 2 Elements involved in drought forecasting (Source Mishra & Singh, 2011)

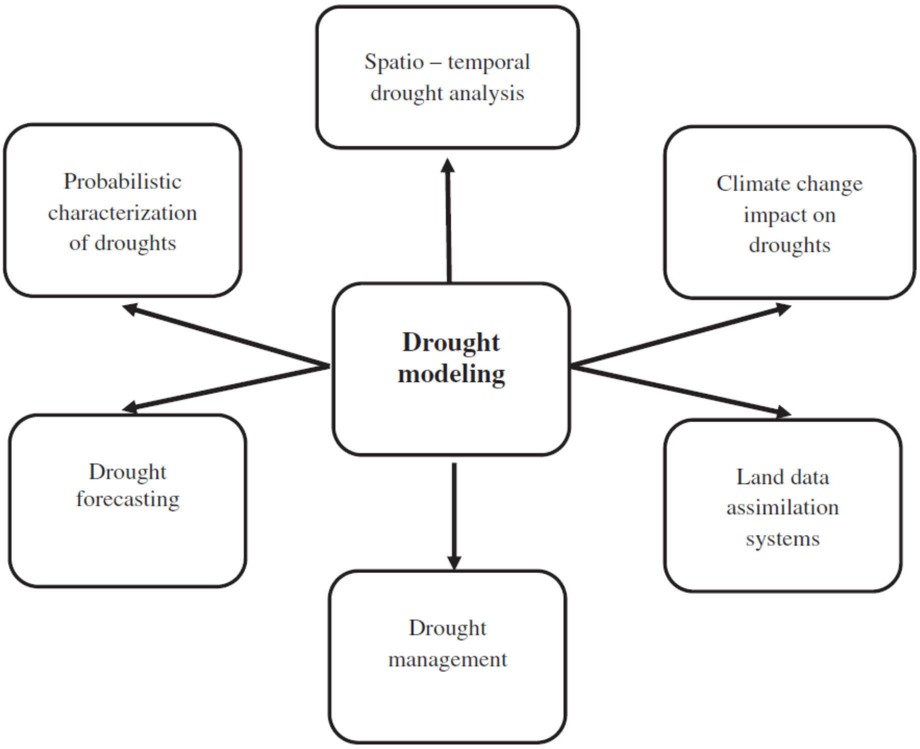

Figure 3 Components of the drought modelling ecosystem (Source: Mishra & Singh, 2011)

Statistical drought prediction is based on the relationship between drought indices and a variety of potential predictors; these include large-scale climate mode indices, local climate variables and land initial conditions (Figure 4); these are data-driven methods (e.g. time series; regression; artificial intelligence; Markov Chain; conditional probability modelling approaches).

Dynamical drought prediction is based on seasonal climate forecasting systems derived from climate models and/or hydrologic models that simulate interactions between the ocean, atmosphere and land (Figure 4);

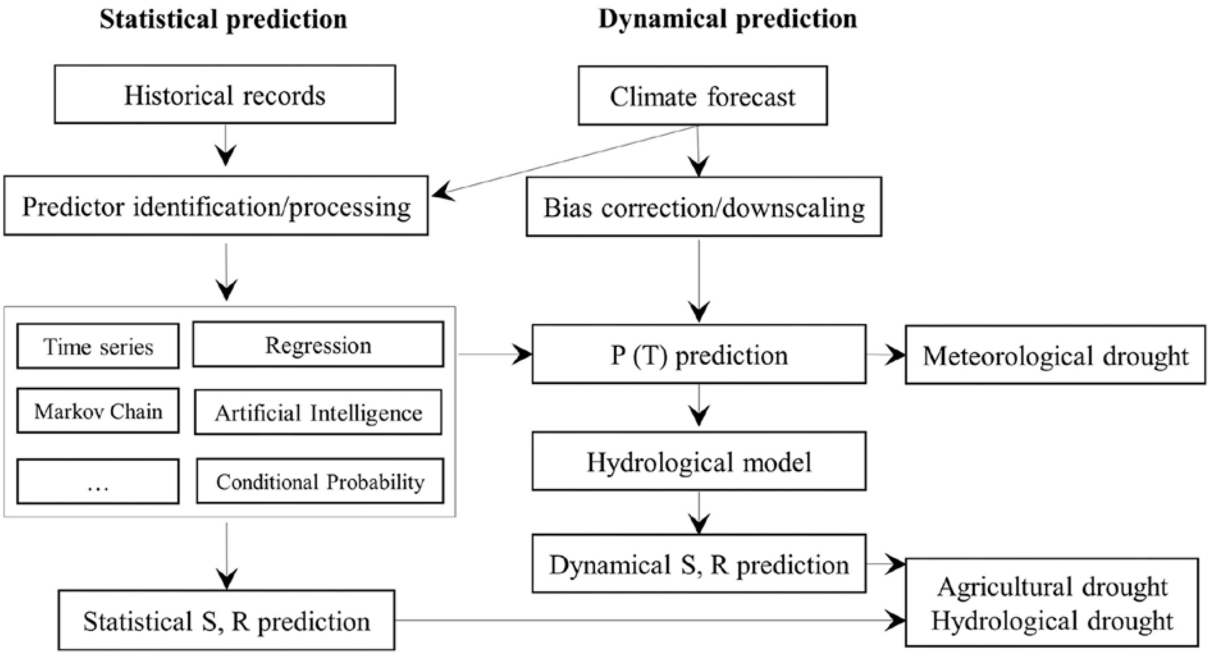

Figure 1 A schematic framework of statistical and dynamical drought prediction methods (precipitation, temperature, soil moisture, and runoff are abbreviated as P, T, S, and R, respectively) (Source Hao et al. 2018)

Hybrid drought prediction methods use a combination of statistical and dynamical prediction methods (Figure 5); they include hybrids between machine learning models or between data pre-processing techniques and machine learning models. These approaches combine the merits of each individual model and reportedly perform better (i.e. have better prediction accuracies) than the stand alone methods. They have been extensively applied in drought forecasting in recent decades and are proving useful for short-term (e.g. rapidly evolving flash droughts; see Lorenz et al., 2018) and medium-term drought forecasting, plus multi-step ahead prediction. Hybrid approaches incorporating large scale climate indices also offer promise for long lead-time drought forecasting (Mishra and Singh, 2011) and are likely to be applicable under changing environmental conditions including climate change (Fung et al., 2019).

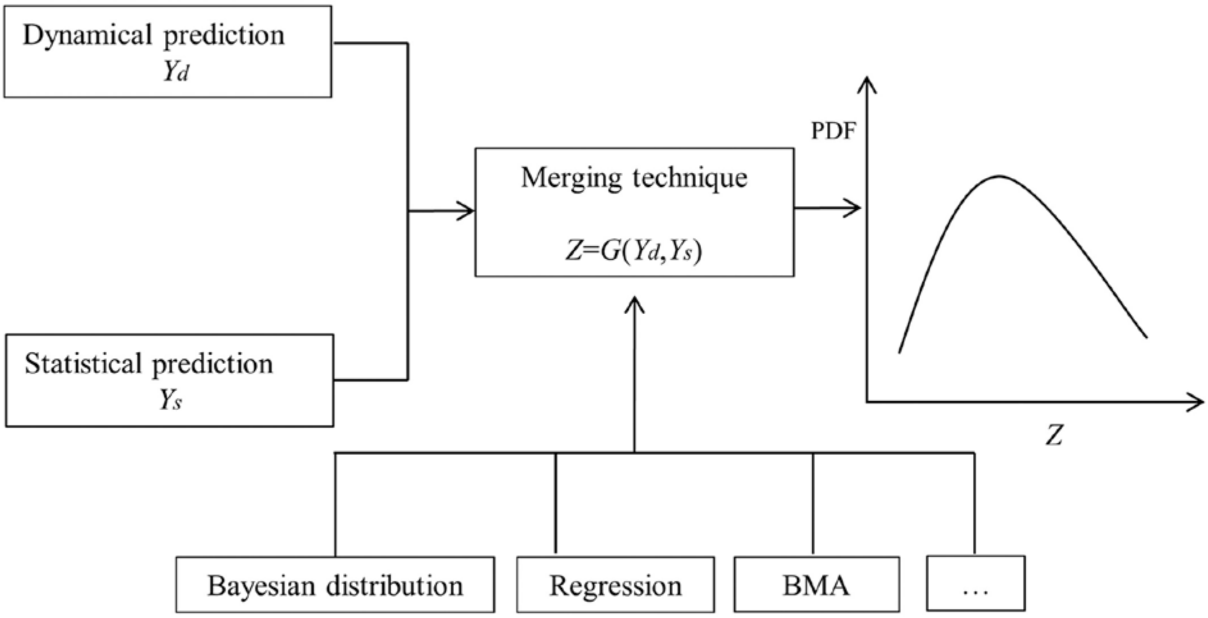

Figure 2 A schematic framework of hybrid drought prediction based on the drought indicator Z by merging dynamical forecast (Yd) and statistical forecast (Ys) with the function G (Source Hao et al. 2018)

Ongoing gaps and challenges in drought forecasting, identified by the NOAA Drought Task Force in 2016, include improving the objectivity of inputs into drought monitoring tools; ensuring accurate data collection from gauge-based observation networks and real-time merging of in-situ observations and (bias-corrected) satellite data; improvements in prediction of the full drought cycle (onset, duration, severity, recovery); improved understanding of key governing processes in the coupled ocean-atmosphere-land system and their predictability; developing hydrological seasonal prediction systems; and development of a seamless ensemble-based drought monitoring and prediction system.

Drought Outlook products

Applied modes

1. **US Monthly and Seasonal Drought Outlooks**

The US Drought Portal, hosted by the National Integrated Drought Information System (NIDIS), contains a number of national (USA) outlook and forecast products include the **US Monthly and Seasonal Drought Outlooks**, which predict whether drought will emerge, stay the same or get better over the next 30 days and next three months, respectively (details in Appendix A).

Also available are:

- **Seasonal Climate Forecasts**: Worldwide predictions for temperature and precipitation from the International Research Institute for Climate and Society (IRI) at Columbia University.
- **Drought Termination and Amelioration**: maps show the probability of precipitation and the amount of precipitation to ameliorate or end a drought.
- **Temperature and Precipitation Outlooks**: temperature and precipitation forecasts for one to six months ahead.
- **GFS Soil Moisture Anomaly**: predictions for the upcoming 1–2 weeks.
- **Streamflow Forecast Maps**: forecasts of percent of monthly average flow (spring, summer) compared to data from 1981–2010.
- **National Significant Wildland Fire Potential Outlook**: Seasonal fire potential; also available is a 3-8 Day Fire Weather Outlook: map layers depict watches and warnings, weather outlooks, spot forecasts.

These products are produced by the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center (CPC) and are developed by merging data from a number of sources: CPC temperature and precipitation outlooks; long lead forecasts such as the National Centres for Environmental Prediction (NCEP) Climate Forecast System (CFS) and the North American Multi-Model Ensemble (NMME) system; short-term weather forecasts from NCEP and ECMWF; and current conditions from the US Drought Monitor, which itself incorporates measurements of climatic, hydrological and soil conditions plus reported impacts and observations from more than 350 contributors across the USA (NOAA Drought Task Force, 2016).

2. Global Drought Analysis and Prediction Tools

The International Research Institute for Climate and Society (IRI) at Columbia University, in collaboration with the CPC and University of Maine, has developed a set of Global Drought Analysis and Prediction Tools (NIDIS, 2019).

Of these, the core forecast tool is the **Global Drought Prediction Tool – NMME Multi-Model Ensemble SPI Forecast**, which provides probabilistic forecasts of meteorological drought risk using future Standardized Precipitation Index (SPI) for a range of accumulation periods (3, 6, 9 or 12 months) for the globe based on monthly precipitation predictions from six NMME models (Appendix A) and the initial observed condition derived from the associated **Global Drought Analysis Tool**. This tool reports SPI values generated from monthly precipitation totals calculated from a gridded dataset (resolution: 1.0 degree lat/long) combining global retrospective and real-time

CPC Gauge - OLR Blended (GOB) daily precipitation analysis, accumulated to monthly.

The Global Drought Prediction Tool – NMME Multi-Model Ensemble SPI Forecast tool provides several map display options:

- Scale: global and regional (e.g. Australia, Asia, Pacific)
- Map type: SPI value, probability
- SPI period: 3, 6, 9 and 12 months
- Lead time: 1 or 2 months
- Probability of non-exceedance: 0.05 to 0.95 (increments of 0.05)

3. World Bank Global Forecast Drought Tool

The World Bank Global Forecast Drought Tool, presented as global/regional forecast drought severity and drought risk maps, builds on the IRI's prototype Global Drought Analysis and Prediction Tools, providing probabilistic forecasts of meteorological drought risk using the SPI as an indicator of drought (IRI and World Bank, 2019). These are based on monthly precipitation predictions from nine NMME models (Appendix A) and initial observed SPI conditions (see above, Global Drought Analysis Tool). For example, a six-month Standardized Precipitation Index (SPI6) drought forecast is produced by combining observed precipitation for the prior three months with the forecasted seasonal rainfall for the next three months.

Two types of drought forecast maps can be produced using the tool (see Appendix B for examples):

i. **Forecasted Drought Severity**: drought severity can be predicted for a user-specified likelihood. This information informs decision-makers—particularly in agricultural and water resources planning sectors—about the probability of rainfall deficit or surplus and whether drought conditions are likely to develop, worsen or improve;
ii. **Drought Risk**: these maps show the probability that the forecast SPI value for a particular period will be equal to or lower than a user-selected drought severity level (i.e. the risk of a certain magnitude of drought level happening).

Drop down menus in both products provide choices about the type and scale of information displayed:

- Scale: global and regional (e.g. Australia, Asia, Pacific)
- Map type: drought risk, drought severity
- Drought severity levels: seven categories (severe wetness–severe drought; Table 2)
- Probability of drier conditions (user set values: 0–100%)

Maps display the likelihood of a drought as severe as or worse than the level selected, according to the relevant SPI threshold (e.g. Table 2).

Table 1 Six month Standard Precipitation Index (SPI6) thresholds used in mapping drought risk of a certain severity or worse (Source: IRI and World Bank, 2019).

SPI6 Value	Drought Severity	Frequency
2.0	Severe Wetness	1 in 43-year event
1.5	Intermediate Wetness	1 in 23-year event
1.0	Moderate Wetness	1 in 11-year event
0.0	Normal	2 in 3-year event
-1.0	Moderate Dryness	1 in 11-year event
-1.5	Intermediate Dryness	1 in 23-year event
-2.0	Severe Dryness	1 in 43-year event

The global drought tool has been developed to better inform drought action and preparedness—hence, drought risk reduction—particularly in vulnerable countries. It provides timely seasonal forecasts, within the context of the current hydro-meteorological conditions, which enable the development of drought conditions and the risk of its evolution in the short-/near-term to be monitored.

This tool provides a standardized objective approach, consistent over space and time, which facilitates regional monitoring and forecasting of drought risks. Users of the tool can investigate current and future drought conditions through a simple and effective user visualisation interface. The tool also provides a quantitative measure of the risk/likelihood of drought occurrence and/or intensification, which is of critical value to decision makers in climate vulnerable countries.

It is anticipated that such tools may also drive regional/national programs to develop targeted data collection programs and build drought risk assessment and management capacity (IRI and World Bank, 2019).

Research modes – in development

There have long been calls for a Global Early Warning System for drought (e.g. Pozzi et al., 2013); however, it is unclear whether this function is fully operationalised by the World Bank Global Forecast Drought Tool. It is likely that further extension and decision support systems need to also be in place to ensure that warnings are effected and that regionally appropriate and timely drought planning and management practices are implemented.

Potential value of a Northern Australia Drought Outlook product

Development of a prototype drought outlook tool for northern Australia is feasible once the Combined Drought Index (CDI)—currently under development for drought monitoring purposes through the Northern Australian Climate Program (NACP)—is fully developed, verified and operationalised. This, in conjunction with the Bureau of Meteorology's new Australian Community Climate and Earth-System Simulator (ACCESS) model, provides scope to develop a prototype tool based on the simplified drought forecasting approach of IRI's World Bank Global Forecast Drought Tool (IRI and World Bank, 2019).

For example, one way to produce an automated Drought Outlook for Australia would be to use the seasonal (next 3 months) precipitation forecasts from ACCESS-S1, together with the existing drought areas as defined by the Drought Monitor, and draw regions based on a set of criteria which would be evaluated at every grid point:

- If currently in drought and probability of getting above XX mm of rainfall in the next 3 months is < YY1 %, then "Drought Persists"
- If currently in drought and probability of getting above XX mm of rainfall in the next 3 months is > YY1 % then "Drought remains but improves"
- If currently in drought and probability of getting above XX mm of rainfall in the next 3 months is > YY2 % then "Drought removal likely"

Where XX would be a function of location and perhaps also the season. YY1 and YY2 would be set percentages that are the same across the whole country, noting that YY2>YY1.

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Appendix A: Table of drought forecasting research papers reviewed (A1: Statistical methods; A2: Dynamical methods; A3: Hybrid methods)

A1: Statistical drought forecasting methods (ordered by country)

Author	Countries Examined	Temporal Scale	Predictand	Input Sources	Method	Results	Validation
Funk et al. (2014)	Africa	Seasonal	Rainfall deficits	Western Pacific gradient (WPG) and central Indian Ocean index (CIO)	Principal component analysis (PCA)	Predictions based on these simple indices can be used to support regional forecasting efforts and land surface data assimilations to help inform early warning and guide climate outlooks.	Cross-validated
Masinde et al. (2018)	Africa	Daily	Effective Drought Index (EDI)	Indigenous knowledge on droughts forecast indicators from the literature Primary data collected from a series of structured interviews from five communities	Artificial Neural Networks (ANNs) Fuzzy System	Integration framework, called 'itiki'	Root Mean Square Error (%RMSE) and Regression (R)
Seibert et al. (2017)	Africa	Monthly	Streamflow	Streamflow data, climate indices and gridded sea surface temperature anomalies	Multiple linear models, artificial neural networks, random forest regression trees	Multiple linear models showed the best forecast skill overall. Standardised streamflow was predictable with lead times up to 12 months. El Nino and customised indices, representing sea surface temperature in the Atlantic and Indian oceans, were important teleconnection predictors for the region. Antecedent streamflow was a strong predictor in small catchments (with median 42% explained variance), whereas teleconnections exerted a stronger influence in large catchments.	Leave-one-out cross validation Receiver operating characteristic (ROC)
Deo et al. (2017a)	Australia	Monthly	SPI	Monthly rainfall Climate indices and sea surface temperature (SST)	Regression splines (MARS), least square support vector machine (LSSVM), and M5Tree	MARS and M5Tree models outperformed LSSVR, and highlighted the importance of periodicity as a predictor variable for SPI-modelling	Root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (r^2)

Author	Countries Examined	Temporal Scale	Predictand	Input Sources	Method	Results	Validation
						Drought forecasting was dependent on proper combination of predictor variables and scaled with the geographic location of study sites	
Deo et al. (2017b)	Australia	Monthly	Monthly effective drought indices (EDIs)	Monthly precipitation	Wavelet-based drought model using the extreme learning machine (W-ELM), W-ANN and W-LSSVR algorithm	Wavelet pre-processing of the predictor dataset enhanced forecast skill of drought models W-ELM was computationally efficient and outperformed traditional ELM, LSSVR, ANN and their wavelet-equivalent counterparts (W-ANN, W-LSSVR)	Coefficient of determination (r^2) Willmott's Index of agreement (WI) Nash–Sutcliffe coefficient (E_{NS}) Percentage peak deviation (P_{dv}) Root MSE (RMSE) Mean absolute error (MAE)
Rahmat et al. (2017)	Australia	Monthly	SPI	Monthly rainfall	Non-homogeneous Markov chain model	Drought severity class predictions were similar for all clusters The developed model predicted drought situations 1 month ahead reasonably well; 2 and 3 months ahead predictions should be used with caution until the models are developed further	Compare observed and predicted SPI
Chen et al. (2016)	China	seasonal	SPEI3	Daily precipitation and 2-m air temperature (maximum and minimum temperature)	Copula-based probabilistic forecasting models	Seasonal variation in drought persistence and severity was identified. For example, modelling indicated a higher probability of occurrence of seasonal droughts after the occurrence of more severe seasonal droughts; extreme drought in winter tended to persist with higher probability till spring; and extreme drought in autumn might not last into winter.	Compared observed droughts in each season and the central 95 % intervals of the predicted droughts

Author	Countries Examined	Temporal Scale	Predictand	Input Sources	Method	Results	Validation
Alexander et al. (2019)	Ethiopia	Seasonal	Precipitation	Gridded precipitation from Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) NMME precipitation predictions SST, sea-level pressure (SLP), surface-air temperature (SAT), and precipitable water content (PWC)	Principal component regression (PCR) Multiple-linear regression	Statistical approaches specific to the local region showed higher prediction skill at the sectoral decision-making scale compared with dynamic approaches; potential in regions currently vulnerable to highly variable spatial precipitation patterns.	Pearson correlation, hit score, extreme miss score, and rank probability skill score (RPSS)
Totz et al. (2017)	Europe	Seasonal	Precipitation anomalies	Gridded precipitation from the “European Climate Assessment and Data Set Project” Sea ice concentration (sic) from the Met Office Hadley Centre Snow cover extent (sce) provided by NOAA Sea surface temperatures (sst) from the Met Office Hadley Centre Geopotential height (gph) at 500 mb Sea level pressure (slp) Atmospheric data are from National Centers for Environmental Prediction (NCEP)/National Center for Atmospheric Research (NCAR) Hindcast experiments from the North American Multimodel Ensemble	Canonical Correlation Analysis Cluster-based empirical forecast method	The prediction method performed better in terms of time and pattern correlation than dynamic forecast models or a canonical correlation analysis-based prediction method in the Mediterranean and European regions	Cross-validated correlation between the hindcasts and observations
Turco et al. (2017)	Europe	seasonal	SPEI6	Two-meter air temperature from GHCN-CAMS Monthly gridded precipitation from CPC Merged Analysis of Precipitation	Statistical empirical method: ensemble streamflow prediction system (ESP, an ensemble based on reordering historical data)	Dynamical forecast showed higher skill in probabilistically identifying drought occurrence. ESP is a computationally fast alternative to dynamical prediction applications for drought prediction.	Pearson correlation coefficient ROC area skill score (ROCSS)

Author	Countries Examined	Temporal Scale	Predictand	Input Sources	Method	Results	Validation
Ganguli and Reddy (2014)	India	Monthly	SPI	Monthly area-weighted precipitation from rainfall stations Multivariate ENSO Index (MEI), Indian Ocean Dipole Mode (IOD) and Atlantic Multidecadal Oscillation (AMO)	Support vector machine (SVM)-copula approach	The SVM-copula approach improved drought prediction capability and provided estimation of uncertainty associated with drought predictions.	Continuous ranked probability score (CRPS) Nash–Sutcliffe efficiency
Kim et al. (2012)	Korea	Monthly Weekly	SWSI	Average air temperature and total precipitation forecasts Global Data Assimilation and Prediction System (GDAPS)	Water balance model: as a rainfall–runoff model to generate streamflow series from the given meteorological input series Ensemble (monthly) Deterministic forecasting (weekly)	Weekly outlook with GDAPS may be useful Monthly drought outlook is expected to improve as climate forecast accuracy increases	Hit ratio: calculates the number of times the forecast category coincides with the actual occurrence category during a test period Contingency tables: represents relative frequencies or counts in each category Regional regression
Abdourahamane and Acar (2019)	Niger	Seasonal	Meteorological drought SPI3	Monthly precipitation from rainfall stations Monthly Southern Oscillation Index (SOI), South Atlantic sea surface temperature (SST), relative humidity (RH), and Atlantic sea level pressure (SLP), sourced from the National Oceanic and Atmosphere Administration (NOAA)	Fuzzy rule-based modelling Clustering technique	Some discrepancy in the influence of SOI and SLP on drought occurrence, while the effect of SST and RH were space independent, being significantly correlated (at alpha < 0.05 level) to the SPI-3. The implemented fuzzy model showed better forecast skills than a decision tree-based forecast model.	Mean absolute error (MAE), Nash-Sutcliffe efficiency (NSE), and coefficient of determination R^2
Ali et al. (2018b)	Pakistan	Monthly	SPI	Rainfall from the Pakistan Meteorological Department	Ensemble-Adaptive Neuro Fuzzy Inference System (ensemble-ANFIS)	Ensemble-ANFIS provides confidence bounds for forecasted drought properties Ensemble-ANFIS uncertainty-based information is useful for drought-risk forecasting Ensemble-ANFIS model can generate information for strategic decision-making	Mean square error (MSE) Correlation coefficient (r) Willmott's Index (WI) Nash-Sutcliffe coefficient (ENS) Root mean square error (RMSE) Mean absolute error (MAE) Legates-McCabe's (LM)

Author	Countries Examined	Temporal Scale	Predictand	Input Sources	Method	Results	Validation
Ali et al. (2018a)	Pakistan	Monthly	SPI	Precipitation (PCN), mean monthly temperature (T) and mean monthly relative humidity (H) from the Pakistan Meteorological Department SOI	Committee extreme learning machine (Comm-ELM) model in respect to a committee particle swarm optimization-adaptive neuro fuzzy inference system (Comm-PSO-ANFIS) and committee multiple linear regression (Comm-MLR)	Climate parameters and seasonality factor incorporated for enhanced accuracy Comm-ELM model was evaluated in a drought prone, agricultural region of Pakistan	Mean square error (MSE) Correlation coefficient (r) Willmott's Index (WI) Nash-Sutcliffe coefficient (ENS) Root mean square error (RMSE) Mean absolute error (MAE) Legates-McCabe's (LM)
Ali et al. (2019)	Pakistan	Monthly	SPI	Precipitation (PTCN), temperature (T), humidity (H), southern oscillation index (SOI), sea surface temperatures (Nino3SST, Nino3.4SST, Nino4SST), pacific decadal oscillation (PDO), Indian ocean dipole (IOD), El-Nino southern oscillation Modoki index (EMI), southern annular mode (SAM)	Multivariate empirical mode decomposition model integrated with simulated annealing and Kernel ridge regression algorithms (i.e., MEMD-SA-KRR)	Hybrid model provides significant hydrological and water management implications	Mean square error (MSE) Correlation coefficient (r) Willmott's Index (WI) Nash-Sutcliffe coefficient (ENS) Root mean square error (RMSE) Mean absolute error (MAE) Legates-McCabe's (LM)
Turco et al. (2019)	Spain	Seasonal	SPEI	Burned area GHCN-CAMS (1948–near present, 0.5 degree resolution) CHIRPS for precipitation data (1981–near present, 0.05 degree resolution) GHCN-CAMS for two-meter air temperature	Logistic regressions	Summer fires can be forecast months in advance with this strategy	Relative operating characteristic (ROC)
Carbone and Dow (2005)	USA	Monthly	Long lead forecasts of the likelihood of exceeding drought thresholds that would trigger water use restrictions	Historical temperature and precipitation	Incorporating long lead forecasts with joint probabilities of monthly temperature and precipitation using resampling strategy	Forecasts show the likelihood of exceeding drought thresholds that would trigger water use restrictions. The methods illustrate how long lead fore-casts can be extended and customized into secondary products that address issues of greater relevance to water resource managers	
Hwang and Carbone (2009)	USA	Monthly	PDSI SPI	Historical climate record and seasonal temperature and precipitation records	Locally weighted polynomial (LWP) function	Kuiper skill scores of PDSI indicated good forecast performance with up to 3-month lead time and	General cross-validation statistics (GCV)

Author	Countries Examined	Temporal Scale	Predictand	Input Sources	Method	Results	Validation
						improvements for 1-month-lead SPI forecasts. NOAA CPC climate outlook improved the forecast skill by up to 40%, though the degree of improvement varied by season and forecast lead time.	
Lyon et al. (2012)	USA	Seasonal	SPI PDSI	Global Precipitation Climatology Center (GPCC) (1901–2007, 0.5 degree resolution) US–Mexico gridded precipitation (1948–2011, 1.0 degree resolution) Climate division precipitation time series	Monte Carlo resampling	Inherent persistence of drought allows potentially useful predictive information out to several months' lead time.	
Unganai et al. (2013)	Zimbabwe	Seasonal	Seasonal forecast model termed the binary' or drought/no drought' (SPI-1)	Monthly rainfall data from the national Meteorological Services Indian Ocean Dipole (IOD) index and El Nino-Southern Oscillation (ENSO)	Target audience and participatory climate risk assessment Probabilistic drought forecasts	Drought risk information is critical for rainfed agriculture production systems.	Contingency table of Standardized Precipitation Index (SPI) and historical crop yield

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A2: Dynamical drought forecasting methods (ordered by country)

Author	Countries Examined	Temporal Scale	Predictand	Input Sources	Method	Output/Outcome	Validation
Bowden et al. (2016)		Monthly	SPI	Precipitation	Weather Research and Forecasting (WRF)	Regional climate generated by WRF has the largest improvement over reanalysis for SPI correlation with observations as drought timescale increases WRF improves the timing and intensity of moderate to extreme wet and dry periods, even in regions with homogenous terrain	Historical case comparison
Mwangi et al. (2014)	Africa	Seasonal	SPI	Dynamical model European Centre for Medium-Range Weather Forecasts (ECMWF) Rain gauge data	ECMWF seasonal forecast system-4 (SYS-4)	Complementing the original ECMWF precipitation forecasts with SPI provides additional information on the spatial extent and intensity of drought event.	Anomaly correlation coefficient (ACC) Continuous ranked probability score (CRPS) Relative operating characteristic (ROC) Qualitative assessment at forecast meetings
Lim et al. (2009)	Australia	Seasonal	Rainfall	Indo-Pacific sea surface temperatures (SSTs) Rainfall anomalies	Predictive Ocean and Atmospheric Model for Australia (POAMA)	Springtime rainfall over eastern Australia, and major drought events are predictable up to a season in advance	Contingency table, and proportion correct, hit rate, and false alarm rate
Ma et al. (2018)	China	Monthly and seasonal	SPI3 SSI1	Gridded daily temperature and precipitation Climate hindcast data from North American Multi-Model Ensemble (NMME) Monthly streamflow datasets from Distributed Time-Variant Gain Hydrological Model (DTVGM)	SPI3 was produced using NMME climate forecasts, and SSI1 using DTVGM forced by NMME climate forecasts	Predicting meteorological droughts more than 2 months in advance became difficult because of complex climate mechanisms. However, hydrological drought forecasts could show some skills up to 3-6 month leads due to memory of ICs during cold and dry seasons. During wet seasons, there are no skillful hydrological predictions from lead month 2 onwards because of the dominant role of meteorological forcings.	Anomaly correlation (AC) and Brier score (BS) or Brier skill score (BSS)

Kim et al. (2012)	Korea	Monthly Weekly	SWSI	Average air temperature and total precipitation forecasts Global Data Assimilation and Prediction System (GDAPS)	Water balance model: as a rainfall–runoff model to generate streamflow series from the given meteorological input series Ensemble (monthly) Deterministic forecasting (weekly)	Weekly outlook with GDAPS may be useful; monthly drought outlook is expected to improve as the climate forecast accuracy increases	Hit ratio: calculates the number of times the forecast category coincides with the actual occurrence category during a test period Contingency tables: represents relative frequencies or counts in each category Regional regression
Kang and Sridhar (2018)	US	Weekly	Standardized Soil Moisture index (SSI), the Multivariate Standardized Drought Index (MSDI), and the Standardized Baseflow index (SBI)	Weekly-to-seasonal meteorological inputs are provided by the Climate Prediction Center (CPC) and Climate Forecasting System version 2 (CFS v2)	Soil and Water Assessment Tool (SWAT) and Variable Infiltration Capacity (VIC)	Eight weeks lead time forecasting showed good drought predictability from both SWAT and VIC models for MSDI simulations Accuracies of drought predictions decreased after eight weeks Low prediction performance even for first eight weeks when using only one variable (i.e., SSI and SBI)	Drought area agreement (%); DA
Luo and Wood (2007)	US	Monthly	Soil moisture index	Precipitation, temperature, North America Land Data Assimilation System (NLDAS) data (RS)	NCEP's Climate Forecast System(CFS)	DMAPS successfully predicted the evolution of droughts several months in advance	Root mean square difference (RMSD)
Luo and Wood (2008)	US	Daily and monthly	Precipitation, soil moisture, and streamflow	Precipitation, temperature, Streamflow, North America Land Data Assimilation System (NLDAS) data (RS), CFS data, DEMETER data	NCEP's Climate Forecast System(CFS), CFS + European Union's Development of a European Multimodel Ensemble System for Seasonal-to-Interannual Prediction (DEMETER), Ensemble Streamflow Prediction (ESP)	The multimodel CFS+DEMETER forecast was significantly better than the ESP forecast during the first two months of the forecasts The advantage was marginal to moderate when only CFS forecast was used	Ranked probability score (RPS)
McEvoy et al. (2016)	US	Seasonal	Evapotranspiration anomalies	Climate Forecast System version 2 (CFSv2) reforecast data for 1982-2009	Climate Forecast System version 2 (CFSv2) reforecast and METDATA	Moderate forecast skill of ET0 for leads of up to 5 months; consistently better than precipitation skill over most of contiguous United States (CONUS). ET0 anomaly forecasts can improve and complement existing seasonal drought forecasts.	METDATA to evaluate CFSRF skill Climate Forecast System Reanalysis and Modern Era Retrospective-analysis for Research and Applications to test the sensitivity of observations to forecast skill

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A3: Hybrid drought forecasting methods (ordered by country)

Author (yr)	Countries Examined	Temporal scale	Predictand	Input sources	Method	Result	Validation
Mwangi et al. (2014)	Africa	Seasonal	SPI	Dynamical model European Centre for Medium-Range Weather Forecasts (ECMWF) Rain gauge data		Complementing the original ECMWF precipitation forecasts with SPI provided additional information on the spatial extent and intensity of drought events	Anomaly correlation coefficient (ACC) Continuous ranked probability score (CRPS) Relative operating characteristic (ROC) Qualitative assessment at forecast meetings
Shukla et al. (2014)	Africa	Monthly	precipitation and soil moisture	High-quality atmospheric observations	Soil moisture (SM) scenarios simulated using the Variable Infiltration Capacity (VIC) hydrologic model forced with climate scenarios describing the upcoming season	SM forecasts initialised with start-of-season (SOS) SM conditions resulted in useful SM forecast skill (> 0.5 correlation) at 1-month and, in some cases, 3-month lead times. End-of-season forecast skill improved when forecast initialized with midseason SM conditions. SM forecasts here were more skilful than those generated using the Ensemble Streamflow Prediction (ESP) method, in which forecast skill was solely driven by initial hydrological conditions. The skill of this agricultural drought forecast system in forecasting spatial patterns of SM anomalies was generally greater (> 0.8 correlation) during drought years (when the standardized anomaly of MAM precipitation was below 0).	Spearman rank correlation
Yuan et al. (2013)	Africa	Monthly	SPI6 soil moisture percentile	Climate Forecast System, version 2 (CFSv2), and the Variable Infiltration Capacity (VIC) land surface model	Bayesian space-time downscaling and Weibull plotting position statistics	This system was generally more skilful than climatology out to 3–5 months and indicated more heterogeneity for soil moisture relative to SPI6.	Brier score (BS) and Brier skill score (BSS)
Robertson et al. (2013)	Australia	Seasonal	Streamflow	Simulations from monthly water partition and balance model (WAPABA)	Bayesian joint probability (BJP) modelling approach	The hybrid forecasting system produces forecasts that are more skilful than the existing operational practice of the Australian Bureau of Meteorology and as reliable	Compared to forecasts made using the existing operational practice of the Australian Bureau of Meteorology

Author (yr)	Countries Examined	Temporal scale	Predictand	Input sources	Method	Result	Validation
Schepen and Wang (2015)	Australia	Seasonal	Streamflow	Experimental dynamic forecasting system at the Bureau of Meteorology (GR4+ Bayesian Total Error Analysis)	Bayesian model averaging (BMA) quantile model averaging (QMA)	The BMA merged forecasts for these events can have unusually wide and bimodal distributions QMA merged forecasts for these events were narrower, unimodal and generally more smoothly shaped, and potentially more easily communicated to and interpreted by forecast users	Leave-five-years-out cross-validation Continuous ranked probability score (CRPS) Root mean square error in probability (RMSEP) PIT uniform probability plots
Schepen et al. (2012)	Australia	Seasonal	Rainfall	GCM ensembles Large-scale circulations in the tropical Pacific and Indian Ocean regions Australian Water Availability Project (AWAP)	Bayesian model averaging (BMA)	Merged statistical-dynamical forecasts represent a significant improvement in terms of maximizing spatial and temporal coverage of skilfulness and are reliable in representing forecast uncertainty	Leave-one-out cross-validation Root mean squared error in probability (RMSEP) Generalized skill score Continuous ranked probability score (CRPS)
Liu et al. (2018)	China	Monthly	SPI3	Dataset of observed daily precipitation amounts (1961–2014, 0.5 degree resolution) NCEP Climate Forecast System Version 2 (CFSv2) (y 1948-present, 2.5 degree resolution) National Oceanic and Atmospheric Administration (NOAA) high-resolution SST (1981-present, 0.25 degree resolution)	Empirical orthogonal function (EOF) analysis	Performed well in simulating and predicting drought development, but was less effective in predicting drought severity	Simple stepwise regression
Ma et al. (2015)	China	Seasonal	SPI3	Multiple climate models from the North American Multimodel Ensemble (NMME) project Observed daily precipitation ENSO Phase	Two-parameter gamma probability density function	Drought forecast skill for the model ensemble mean was higher than that of individual ensemble members; best performing was the North American Multimodel Ensemble grand ensemble. Predictability was higher than forecast skill, indicating room for improvement in drought forecasting. Higher drought predictability and forecast skill were found over regimes where ENSO has significant impact.	Anomaly correlation (AC) Brier Score (BS) False alarm rate (FAR) Hit rate (HR) Equitable Threat Score (ETS)

Author (yr)	Countries Examined	Temporal scale	Predictand	Input sources	Method	Result	Validation
Xu et al. (2019)	China	Monthly	Precipitatio n	Precipitation forecasts from NMME Observed data from 518 meteorological stations	Downscaling of the NMME using wavelet transformation, support vector machine (WSVM) and wavelet random forest (WRF) methods	This approach increased the Pearson's correlation coefficient by 0.05–0.3 and reduced root mean square error (RMSE) by 18–40mm (21–33%) for individual models. Wavelet machine learning methods were shown to be superior to traditional quantile mapping (QM) approach for both spatial and seasonal patterns.	The Pearson's correlation coefficient (PCC) and root mean square error (RMSE)
Zhang et al. (2017)	China	monthly	Real-time evolution of soil moisture (SM) drought	Climate model (CFSv2)-based forecast (MONIT+CFSv2) real-time land surface states historical climate traces ensemble streamflow prediction (ESP)-based forecast (MONIT+ESP)	Variable Infiltration Capacity model (VIC)	Skilful CFSv2 climate forecasts (CFs) were only found for the first month. The satellite-aided monitoring provided a reasonable estimate of forecast initial conditions (ICs) in real-time mode.	VIC has been effectively calibrated and validated with high-quality ground observations from the China Meteorological Administration (CMA) and the Bureau of Hydrology (BoH) The Bias Correction and Spatial Downscaling (BCSD) method is used for bias-correct and downscale CFSv2 monthly reforecasts. root-mean-square error (RMSE)-based skill score (SSRMSE) is introduced to quantitatively assess the MONIT+CFSv2 ensemble forecast skill relative to that of MONIT+ESP
Rhee and Yang (2018)	Fiji	Monthly	SPI6	APEC Climate Center Multi-Model Ensemble seasonal climate forecast and machine learning models of Extra-Trees and Adaboost	Hybrid drought prediction models	Hybrid models generally showed better performance than simple bias corrected forecasts; this was especially the case for a model based on Extra-Trees, which was trained using Weather Research Forecasting (WRF) model outputs.	In-situ data and bias-corrected dynamic downscaling of historical climate data from the Weather Research Forecasting (WRF) model were used as reference data
Yuan and Wood (2013)	Global	Monthly	SPI6	Monthly mean precipitation forecasts from multiple climate models developed in the NMME phase-I and phase-II project	Biases of monthly predicted precipitation were corrected through quantile mapping Parametric distributions were used to correct precipitation forecasts exceeding the lower and upper bounds of the observed climatological distributions	Climate models increased the global mean probability of drought onset detection relative to the climatology forecast by 31–81%, but only increased the associated threat score by 21%–50% due to a high false alarm ratio. Missed drought events were associated with low potential predictability and a weak antecedent El Nino-Southern Oscillation signal.	Observed monthly precipitation were used for bias correction and validation

Author (yr)	Countries Examined	Temporal scale	Predictand	Input sources	Method	Result	Validation
Chen et al. (2017)	Korea	Monthly	SPI3	Monthly precipitation data from meteorological stations	Discrete-time finite state-space hidden Markov model (HMM) aggregated with the Representative Concentration Pathway 8.5 (RCP) precipitation projection (HMM-RCP)	Point forecasts derived as HMM-RCP forecast mean values and measured by forecasting skill scores showed greater accuracy than those from either conventional models or a climatology reference model across a range of lead times. The HMM-RCP provided a probabilistic forecast with acceptable skill levels for different drought categories, even at long lead times.	Forecast skill score (SS) Ranked probability score (RPS) Relative operating characteristic (ROC)
Kang and Sridhar (2018)	USA	Weekly	Standardized Soil Moisture index (SSI), Multivariate Standardized Drought Index (MSDI), and Standardized Baseflow index (SBI)	Weekly-to-seasonal meteorological inputs provided by the Climate Prediction Center (CPC) and Climate Forecasting System version 2 (CFS v2)	Soil and Water Assessment Tool (SWAT) and Variable Infiltration Capacity (VIC) models	Eight weeks of lead time forecasting showed good drought predictability from both the SWAT and VIC models for the MSDI simulations; however, the accuracies of drought predictions significantly decreased after eight weeks. Drought forecasting using only one variable showed relatively low prediction performances, even within the first eight weeks.	Drought area agreement (%); DA
Lorenz et al. (2018)	USA	Weekly	Depicted drought intensification	Observations and forecast model output from the Climate Forecasting System (CFS) including weekly anomalies in precipitation, potential evapotranspiration, dew point depression, and soil moisture computed over different time lags	Modified standard logistic regression using Non-Negative Logistic Regression (NNLR)	Inclusion of CFS model output contributed only a very modest increase in skill due to limited skill in the CFS forecasts themselves.	Brier Skill Score (BSS)
Madadgar et al. (2016)	USA	Monthly	Precipitation	American Multi-Model Ensemble (NMME) model simulations Decadal Oscillation (PDO), Multivariate ENSO Index (MEI) Atlantic Multidecadal Oscillation (AMO)	Expert Advice (EA) algorithm was used to combine dynamical and analogue-year statistical components	Improved seasonal precipitation predictions (3–5 month lead time) by 5–60% relative to NMME simulations The hybrid framework performed better in predicting below-normal precipitation than above-normal precipitation	The observed reference precipitation was based on a gridded station-based data record developed for western U.S. forecasting and verification purposes

Author (yr)	Countries Examined	Temporal scale	Predictand	Input sources	Method	Result	Validation
Otkin et al. (2013)	USA	Weekly	ESI	Remotely sensed thermal infrared imagery	Evapotranspiration (ET) was estimated from remotely sensed thermal infrared imagery	Large negative change anomalies were indicative of rapidly drying conditions were either coincident with the initiation of drought identified in the U.S. Drought Monitor (USDM) or lead the USDM drought depiction by several weeks, depending on which ESI composite and time-differencing interval was used.	Drought classifications in the USDM and standard precipitation-based drought indicators
Otkin et al. (2014)	USA	Weekly	RCI	Thermal infrared remote sensing imagery	Atmosphere–Land Exchange Inverse (ALEXI) surface energy balance model	Initial appearance of negative RCI values indicative of rapid increases in moisture stress preceded the identification of severe-to-exceptional drought in the USDM by more than four weeks. RCI may provide useful drought early warning capabilities for alerting stakeholders of increased risk of drought development over sub-seasonal time scales.	Drought classifications in the USDM
Quan et al. (2012)	USA	Monthly	SPI6	Global Precipitation Climatology Center (GPCC) monthly gridded precipitation (1982–2008, 1.0 degree resolution)	Empirical and dynamical predictions (unconditioned and conditioned on SST) using atmospheric climate simulations of the atmospheric component [Global Forecast System (GFS)] of the coupled model [Climate Forecast System (CFS)] (i.e. dynamical models forced by observed global SSTs)	Unconditioned forecast skill for drought was least during a wet season and greatest during a region's climatological dry season and/or when and where precipitation is ENSO-sensitive. Little additional skill relative to the uninitialized SST-forced simulations was realised in fully coupled initialized model at seasonal scale, but the prediction skill of monthly forecasts was improved.	Simulation and hindcast datasets diagnosed
Yan et al. (2017)	USA	Seasonal and inter-annual	Soil moisture	Precipitation, maximum and minimum temperature (1979-2015) from the Phase 2 of the North American Land Data Assimilation Systems (NLDAS-2) derived from the North American Regional Reanalysis (NARR) (32 km spatial resolution; three hour temporal resolution) Blended microwave soil moisture climate change initiative (CCI) products	Combined dynamical and statistical probabilistic drought forecasting model using a copula function	This drought forecasting system showed significantly improved seasonal drought forecasting skill and potential to facilitate drought preparation and declaration some three months before official state drought declarations	U.S. Geological Survey (USGS) streamflow data, and No Regulation No Irrigation (NRNI) streamflow data provided by Bonneville Power Administration (BPA) [https://www.bpa.gov/power/streamflow/]

Author (yr)	Countries Examined	Temporal scale	Predictand	Input sources	Method	Result	Validation
				v02.2 and the Advanced Microwave Scanning Radiometer2 (AMSR2) soil moisture products			

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Appendix B Drought Outlook Products

Name	Operated by	Spatial Scale	Temporal Scale	Functions	Description	Input Sources	Ground Truthing	Refs.
Climate Prediction Center's (CPC) Monthly Drought Outlook	NOAA CPC, available through the US Drought Portal	National	Forecasts out to 1 month and 3 months	Maps of predicted drought conditions, relative to current month	monthly and seasonal/3-month drought forecasts	CPC temperature and precipitation outlooks; long lead forecasts such as the National Centres for Environmental Prediction (NCEP) Climate Forecast System (CFS) and the North American Multi-Model Ensemble (NMME) system; short-term weather forecasts from NCEP and ECMWF; and current conditions from the US Drought Monitor (which itself incorporates measurements of climatic, hydrological and soil conditions plus reported impacts and observations from more than 350 contributors across the USA)	US Drought Monitor is ground-truthed based on reported impacts and observations from more than 350 contributors across the USA	NOAA Drought Task Force (2016)
Global Drought Prediction Tool – NMME Multi-Model Ensemble SPI Forecast	IRI (Columbia University), NOAA CPC, University of Maine	Global	3, 6, 9, 12-month	• Maps of probabilistic forecasts of SPI • Maps of SPI value	• Probability: shows the probability (0,1) of SPI ≤ Threshold • SPI Value: shows the SPI ≤ Probability of Non-Exceedance	CMC1-CanCM3 CMC2-CanCM4 COLA-RSMAS-CCSM4 GFDL-CM2.5-FLOR-A06 NASA-GMAO-062012 NCEP-CFSv2	CPC GOB Combined Retrospective and Real-Time Blended Daily Precipitation Data Accumulated to Monthly and Regridded to 1.0 deg. lat/lon, U. S. Climate Prediction Center	
Global Forecast Drought Tool	IRI (Columbia University), World Bank	Global	6 month (combines the prior 3 months of observed precipitation and forecasted upcoming 3 months of seasonal rainfall)	• Maps of meteorological drought risk using SPI • Maps of predicted drought severity or risk.	• Drought severity: probability of drier conditions, e.g. 90%, it is 90% likely that the SPI observed over that 6-month period will be drier than the value presented in the map. • Drought risk: probabilities that the forecast SPI value will be equal to or lower than a user-selected drought severity level.	North American Multi-Model Ensemble (NMME) forecast precipitation (1.0°, monthly, May 2016), using data from these models: • CMC1-CanCM3 • CMC2-CanCM4 • NCAR-CESM1 • COLA-RSMAS-CCSM4 • GFDL-CM2.1-aer04 • GFDL-CM2.5-FLOR-A06 • GFDL-CM2.5-FLOR-B01 • NASA-GMAO-062012 • NCEP-CFSv2	Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) v.2 (gridded 0.05°, monthly, Jan 1981 to near-present)	Lyon et al., (2012) Quan et al. (2012)

Example 1: Climate Prediction Centre’s monthly drought outlook product (Available at: https://www.drought.gov/drought/)

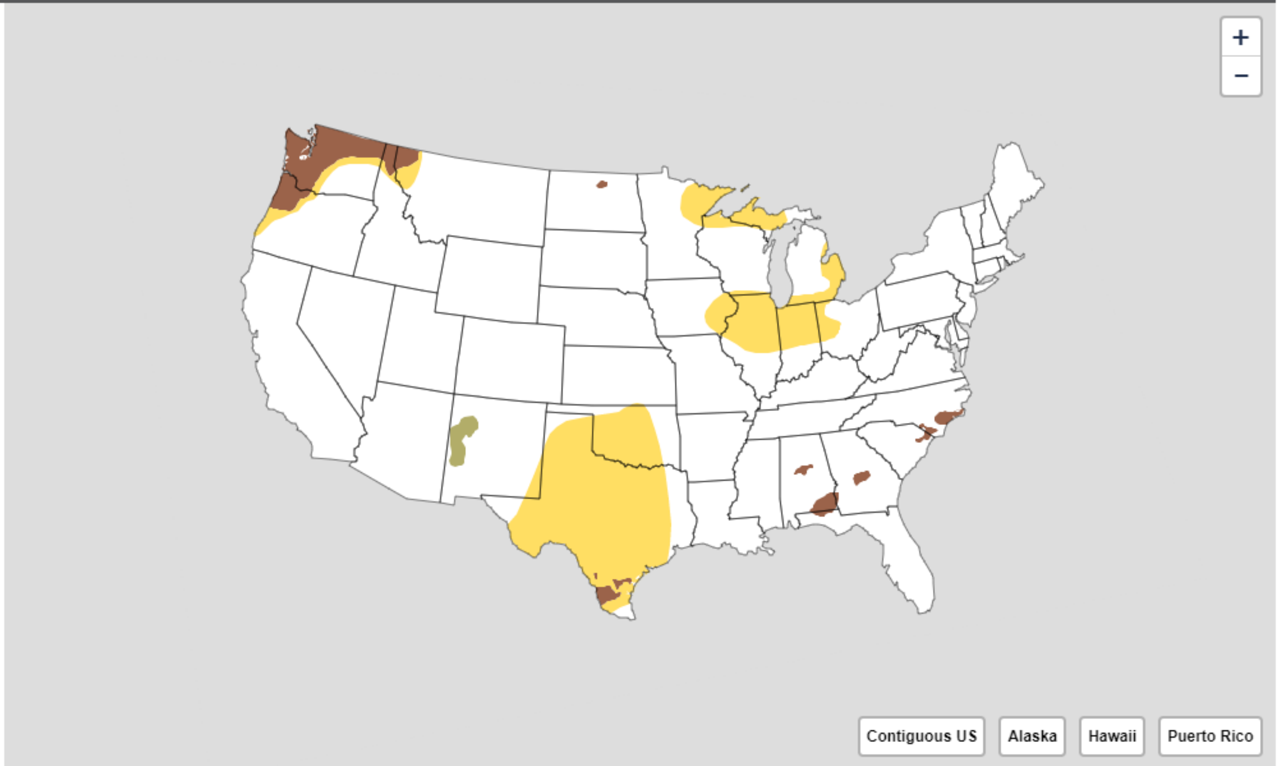
Current Drought Monitor | **August Drought Outlook** | Drought Outlook through November

The drought outlook for August 2019.

The Climate Prediction Center’s (CPC) Monthly Drought Outlook is issued at the end of each month. The outlook predicts whether drought will emerge, stay the same or get better in the next month, based on the U.S. Drought Monitor conditions when the outlook was released on July 31, 2019.

Learn more about the US Monthly Drought Outlook

Drought persists Drought present on July 31, 2019 is expected to continue for August 2019.	**3.5%** of U.S.
Drought remains but improves Drought present on July 31, 2019 is expected to continue, but improve for August 2019.	**0.6%** of U.S.
Drought removal likely Drought present on July 31, 2019 is expected to be removed from the map in August 2019.	**2.4%** of U.S.
Drought development likely Abnormally dry conditions on July 31, 2019 are expected to intensify in August 2019.	**11.9%** of U.S.



Example 2: Climate Prediction Centre's seasonal drought outlook product (Available at: https://www.drought.gov/drought/)

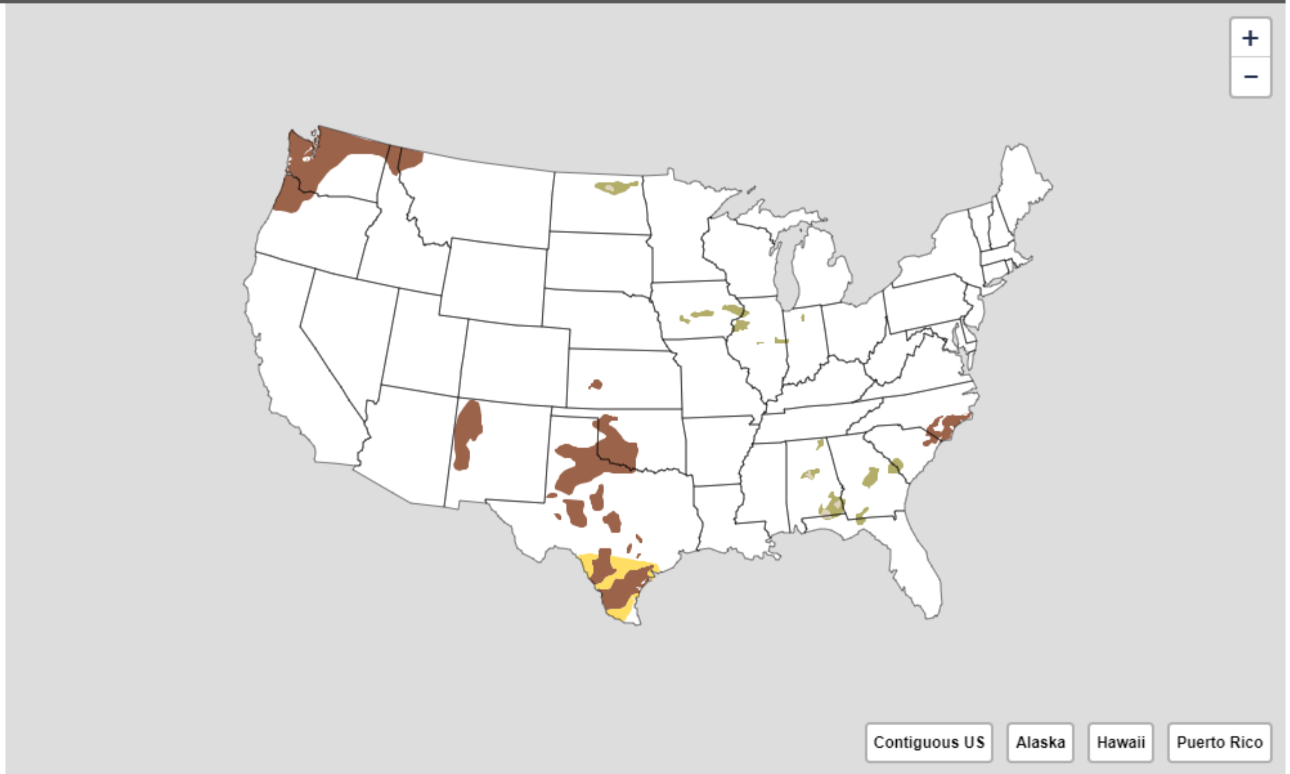
Current Drought Monitor | August Drought Outlook | **Drought Outlook through November**

The drought outlook through October 2019.

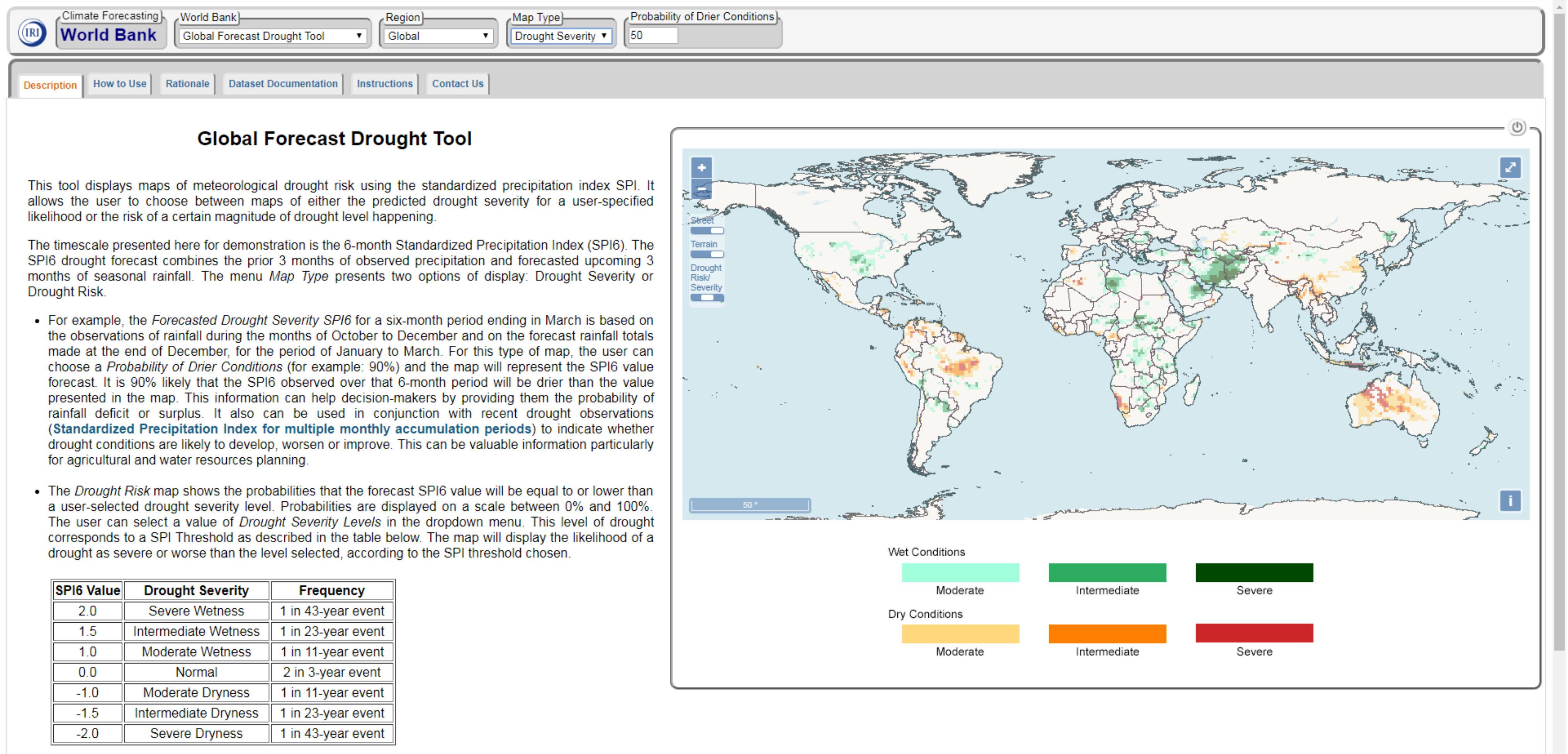
The Climate Prediction Center's (CPC) Seasonal Drought Outlook is issued monthly on the third Thursday of each month. The outlook predicts whether drought will emerge, stay the same or get better in the next three months, based on the U.S. Drought Monitor conditions when the outlook was released on August 15, 2019.

Learn more about the US Seasonal Drought Outlook

Drought persists Drought present on August 15, 2019 is expected to continue through October 2019.	**4.3%** of U.S.
Drought remains but improves Drought present on August 15, 2019 is expected to continue, but improve through October 2019.	**0.6%** of U.S.
Drought removal likely Drought present on August 15, 2019 is expected to be removed from the map by the end of October 2019.	**1.5%** of U.S.
Drought development likely Abnormally dry conditions on August 15, 2019 are expected to intensify by the end of October 2019.	**0.5%** of U.S.



Example 3: World Bank Global Forecast Drought Tool: Drought Severity



Climate Forecasting | World Bank | World Bank: Global Forecast Drought Tool | Region: Global | Map Type: Drought Severity | Probability of Drier Conditions: 50

Description | How to Use | Rationale | Dataset Documentation | Instructions | Contact Us

Global Forecast Drought Tool

This tool displays maps of meteorological drought risk using the standardized precipitation index SPI. It allows the user to choose between maps of either the predicted drought severity for a user-specified likelihood or the risk of a certain magnitude of drought level happening.

The timescale presented here for demonstration is the 6-month Standardized Precipitation Index (SPI6). The SPI6 drought forecast combines the prior 3 months of observed precipitation and forecasted upcoming 3 months of seasonal rainfall. The menu *Map Type* presents two options of display: Drought Severity or Drought Risk.

- For example, the *Forecasted Drought Severity SPI6* for a six-month period ending in March is based on the observations of rainfall during the months of October to December and on the forecast rainfall totals made at the end of December, for the period of January to March. For this type of map, the user can choose a *Probability of Drier Conditions* (for example: 90%) and the map will represent the SPI6 value forecast. It is 90% likely that the SPI6 observed over that 6-month period will be drier than the value presented in the map. This information can help decision-makers by providing them the probability of rainfall deficit or surplus. It also can be used in conjunction with recent drought observations (**Standardized Precipitation Index for multiple monthly accumulation periods**) to indicate whether drought conditions are likely to develop, worsen or improve. This can be valuable information particularly for agricultural and water resources planning.
- The *Drought Risk* map shows the probabilities that the forecast SPI6 value will be equal to or lower than a user-selected drought severity level. Probabilities are displayed on a scale between 0% and 100%. The user can select a value of *Drought Severity Levels* in the dropdown menu. This level of drought corresponds to a SPI Threshold as described in the table below. The map will display the likelihood of a drought as severe or worse than the level selected, according to the SPI threshold chosen.

SPI6 Value	Drought Severity	Frequency
2.0	Severe Wetness	1 in 43-year event
1.5	Intermediate Wetness	1 in 23-year event
1.0	Moderate Wetness	1 in 11-year event
0.0	Normal	2 in 3-year event
-1.0	Moderate Dryness	1 in 11-year event
-1.5	Intermediate Dryness	1 in 23-year event
-2.0	Severe Dryness	1 in 43-year event

Available at: https://iridl.ldeo.columbia.edu/maproom/Global/World_Bank/Drought_Monitor/index3.html?gmap=%5B10%2C5%2C2%5D&threshold=-1.5

Example 4: World Bank Global Forecast Drought Tool: Drought Risk

Climate Forecasting | World Bank | World Bank: Global Forecast Drought Tool | Region: Global | Map Type: Drought Risk | Drought Severity Levels: Intermediate Dryness

Description | How to Use | Rationale | Dataset Documentation | Instructions | Contact Us

Global Forecast Drought Tool

This tool displays maps of meteorological drought risk using the standardized precipitation index SPI. It allows the user to choose between maps of either the predicted drought severity for a user-specified likelihood or the risk of a certain magnitude of drought level happening.

The timescale presented here for demonstration is the 6-month Standardized Precipitation Index (SPI6). The SPI6 drought forecast combines the prior 3 months of observed precipitation and forecasted upcoming 3 months of seasonal rainfall. The menu *Map Type* presents two options of display: Drought Severity or Drought Risk.

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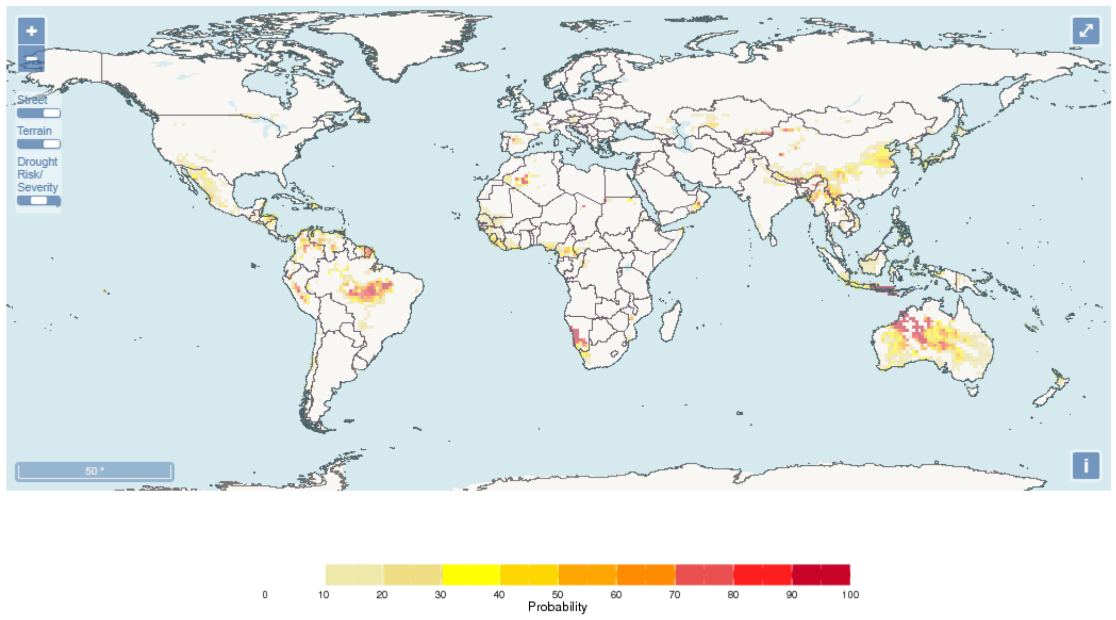
-1.0	Moderate Dryness	1 in 11-year event
-1.5	Intermediate Dryness	1 in 23-year event
-2.0	Severe Dryness	1 in 43-year event



Available at: https://iridl.ldeo.columbia.edu/maproom/Global/World_Bank/Drought_Monitor/index3.html?gmap=%5B10%2C5%2C2%5D&threshold=-1.5

Northern Australia Climate Program

For further information, click on the following links:

- For the MJO
- For weekly SSTs
- For easterly (and westerly) wind anomalies across the Pacific
- For sub-surface temperatures across the Pacific
- For ECMWF forecast products (note the web site for this output has changed)
- For 'plume' forecasts of SSTs in the central Pacific
- For a complete history of the SOI
- The Long Paddock
- Additional information on ENSO

USQ Research
Centre for Applied Climate Sciences

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