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Key Points:
- Review drought prediction based on statistical, dynamical, and hybrid methods
- Summarize advances in predicting different types of drought
- Discuss current challenges and future prospects in drought prediction

Correspondence to:
Z. Hao,
haozc@bnu.edu.cn

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Seasonal Drought Prediction: Advances, Challenges, and Future Prospects

Zengchao Hao[1], **Vijay P. Singh**[2], **and Youlong Xia**[3]

[1]Green Development Institute, College of Water Sciences, Beijing Normal University, Beijing, China, [2]Department of Biological and Agricultural Engineering and Zachry Department of Civil Engineering, Texas A&M University, College Station, TX, USA, [3]I.M. System Group at Environmental Modeling Center, National Centers for Environmental Prediction, College Park, MD, USA

Abstract Drought prediction is of critical importance to early warning for drought managements. This review provides a synthesis of drought prediction based on statistical, dynamical, and hybrid methods. Statistical drought prediction is achieved by modeling the relationship between drought indices of interest and a suite of potential predictors, including large-scale climate indices, local climate variables, and land initial conditions. Dynamical meteorological drought prediction relies on seasonal climate forecast from general circulation models (GCMs), which can be employed to drive hydrological models for agricultural and hydrological drought prediction with the predictability determined by both climate forcings and initial conditions. Challenges still exist in drought prediction at long lead time and under a changing environment resulting from natural and anthropogenic factors. Future research prospects to improve drought prediction include, but are not limited to, high-quality data assimilation, improved model development with key processes related to drought occurrence, optimal ensemble forecast to select or weight ensembles, and hybrid drought prediction to merge statistical and dynamical forecasts.

1. Introduction

Drought is among the most disastrous natural hazards and occurs in virtually all geographical areas. Severe drought events in recent decades, including 2010–2011 East Africa drought, 2011 Texas drought, 2012 U.S. Central Great Plains drought, and 2012–2015 California drought, have caused huge losses to agriculture, society, and ecosystems with profound impacts on crop production and water supply (Dutra et al., 2013; Hoerling et al., 2014; Nielsen-Gammon, 2012; Peterson, Hoerling, et al., 2013; Seager et al., 2015). Extensive impacts of drought in past decades at regional and global scales call for improved capability to cope with drought (Below et al., 2007; Sheffield & Wood, 2012; Smith & Katz, 2013). Drought prediction plays a key role in drought early warning to mitigate its impacts.

Drought is a complicated phenomenon and is among the least understood natural hazards due to its multiple causing mechanisms or contributing factors operating at different temporal and spatial scales (Kiem et al., 2016). The evolution and multiple contributing factors of drought is shown in Figure 1. The figure shows that the precipitation deficit due to natural climate variability may lead to reduced runoff and soil moisture, resulting in reduced streamflow with negative impacts on socio-economic sectors. Drought mostly originates from precipitation deficit, while in certain cases it may result from the anomaly of other variables, such as temperature or evapotranspiration (Cook et al., 2014; Livneh & Hoerling, 2016; Luo et al., 2017). Specifically, high temperature may lead to increased evaporation and reduced soil moisture, causing drought in agricultural sectors. Moreover, drought may not be a purely natural hazard, for human activities such as land use changes and reservoir operation may alter hydrologic processes and affect drought development (Van Loon, Gleeson, et al., 2016). Overall, the development and evolution of drought result from complicated interactions among meteorological anomalies, land surface processes, and human activities.

Drought may occur with multiple processes driving its onset, persistence or recovery, happening at a wide range of time scales (subseasonal/weekly, seasonal, multiyear, or decadal) and across different spatial scales (local, regional, continental, and global) (Kam, Sheffield, & Wood, 2014a). Drought is commonly characterized at the seasonal time scale. Recently, it has been highlighted that drought may occur at the subseasonal scale. For example, the 2012 central U.S. drought with rapid onset in May is generally referred to as flash drought (typically occurs for a few days or weeks), which results from concurrent soil moisture deficit and anomalously

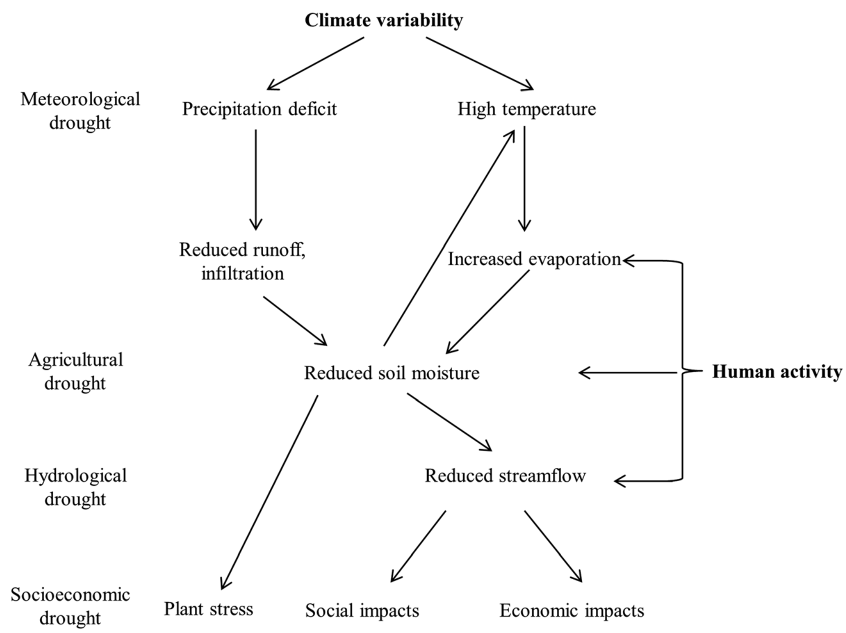

Figure 1. Interaction of different variables in the hydrological cycle during drought (derived from National Drought Mitigation Center, University of Nebraska-Lincoln, U.S.A., http://drought.unl.edu/DroughtBasics/TypesofDrought.aspx).

high temperatures (and increased evaporation) (Hoerling et al., 2014; Mo & Lettenmaier, 2015; Wang et al., 2016). In addition, certain regions have suffered from drought at multiyear or decadal time scales. For example, the 2001–2009 drought in southeast Australia is the worst drought on record since 1900 with below median rainfall for several years (Dijk et al., 2013; Kiem et al., 2016). Drought may occur at different spatial scales, usually with large spatial extent that may reach continental scales (Hannaford et al., 2011; Sheffield et al., 2009). For example, the African drought of early 1980s is among the most spatially extensive drought events and covered over 11×10^6 km^2 (Sheffield et al., 2009).

Due to its complexity with diverse origins and occurrence at different temporal and spatial scales, drought prediction has presented a major challenge to climatologists and hydrologists as well as decision and policy makers. Generally, three types of methods have been used for drought prediction: statistical, dynamical, and hybrid methods (Mariotti et al., 2013; Mishra & Singh, 2011; Pozzi et al., 2013). The statistical prediction method uses empirical relationships of historical records, taking different influencing factors as predictors. With the increased computational capability and improved understanding of climate, drought prediction has been tackled more with state-of-the-art general circulation models (GCMs), which provide drought prediction based on the physical processes of the atmosphere, ocean, and land surface. The past decade has also witnessed the development of hybrid prediction methods that combine forecast from both statistical and dynamical methods.

Drought prediction generally refers to the prediction of drought severity (e.g., values of a specific drought indicator). In certain cases drought prediction also refers to other properties, such as drought duration and frequency (Sharma & Panu, 2012; Wetterhall et al., 2015), or phases, such as drought onset, persistence, and recovery. In this study, we mainly focus on the prediction of drought severity at the seasonal time scale, which centers around the current drought prediction efforts and is particularly related to the operational early warning to mitigate drought impacts.

This study reviews recent advances in drought prediction methods and discusses the challenges and future prospects. The basics of drought types and indices are provided in section 2, followed by drought mechanisms and predictability in section 3. Recent advances in drought prediction with statistical and dynamical methods are reviewed in sections 4 and 5, respectively, along with the recently developed hybrid prediction method in section 6. The challenges and future prospects for drought prediction are summarized in sections 7 and 8, followed by conclusions in section 9.

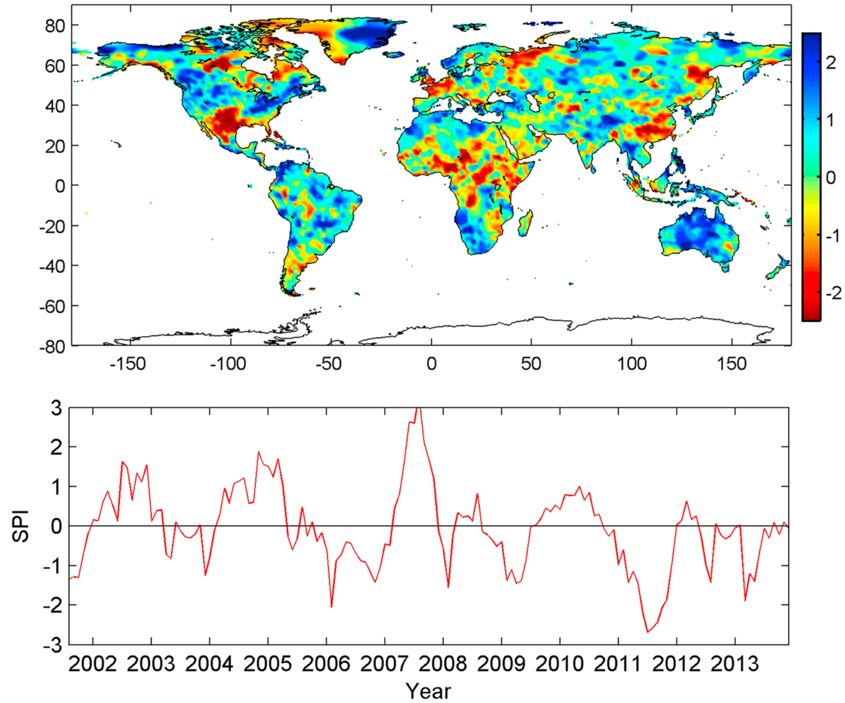

Figure 2. Meteorological drought monitoring based on SPI computed with monthly precipitation from Global Precipitation Climatology Centre (GPCC) for July 2011 at the (top) global scale and (bottom) one grid from 2002 to 2013 in Texas.

2. Drought Types and Indices

Traditionally, drought can be classified into meteorological, agricultural, hydrological, and socioeconomic drought, based on both physical and socioeconomic factors (Wilhite & Glantz, 1985). Before one can make drought predictions, a quantitative variable or indicator needs to be defined to measure drought conditions of a specific type. Scores of univariate and multivariate drought indicators based on individual or multiple hydroclimatic variables have been developed in past decades (Hao & Singh, 2015; Hayes et al., 2011; Mishra & Singh, 2010; Zargar et al., 2011), such as the Standardized Precipitation Index (SPI) (McKee et al., 1993). However, a universally accepted drought indicator to characterize drought condition does not exist. Drought categories (e.g., “moderate” drought) can also be used to characterize drought, based on threshold values of the indicators. For example, the U.S. Drought Monitor (USDM) labeled drought intensity with multiple drought categories to characterize drought conditions, including abnormally dry (D0), moderate drought (D1), severe drought (D2), extreme drought (D3), and exceptional drought (D4), with D4 being the most intense (Svoboda et al., 2002). However, there is still inconsistency in determining the threshold of indicators (e.g., $\text{SPI} < -1$) to define a drought (Hao, Hao, Singh, Xia, et al., 2016; Quiring, 2009; Steinemann et al., 2015).

2.1. Meteorological Drought

Meteorological drought is related to the precipitation deficit over a prolonged period of time. The commonly used meteorological drought indicators include SPI (McKee et al., 1993), Percent of Normal Precipitation (PNP) (Hayes et al., 2011), and Palmer Drought Severity Index (PDSI) (Palmer, 1965). For example, SPI is commonly used to track meteorological drought with negative SPI values indicating drier than normal conditions. An example of meteorological drought based on SPI computed with monthly precipitation from Global Precipitation Climatology Centre (GPCC) version 7 (Schneider et al., 2015) (with respect to the climatology 1960–2011) for July 2011 is shown in Figure 2 (top). Large regions in Texas, U.S. A. and Africa with drought condition are shown from this figure. In addition, the SPI values from 2008 to 2011 for a grid in Texas are shown in Figure 2 (bottom). The low SPI values during 2011 indicate the severe drought condition that is the most extreme on record in Texas (Nielsen-Gammon, 2012).

The meteorological drought (or precipitation deficit) is generally caused by persistent anomalies in large-scale atmospheric circulation patterns due to anomalous sea surface temperatures (SSTs) or other remote conditions (Dai, 2011). For example, the precipitation deficit over North America is primarily associated with the SST variability in the tropical Pacific with certain contributions from the SST variability in the Atlantic at the annual time scale (Schubert et al., 2009, 2016; Seager et al., 2005). The meteorological drought does not result from a single cause but a combination of multiple causes. Other factors, such as land surface interactions or feedbacks (e.g., reduced soil moisture and increased temperature) may also contribute to the atmospheric anomaly or occurrence of meteorological drought (Dai, 2011; Fernando et al., 2016; Kam, Sheffield, & Wood, 2014b; Koster & Suarez, 1995). For example, it has been shown that the 1930s Dust Bowl drought in the United States was caused by anomalous tropical SST during that decade, while interactions between the atmosphere and land surface increased the drought severity (Schubert et al., 2004a).

Since meteorological drought is dominated by the precipitation process, its prediction is commonly performed based on the medium to long-range climate forecast (Yoon et al., 2012). A variety of statistical methods have also been devoted to meteorological drought prediction based on large-scale atmospheric circulation patterns as natural precursors. The prediction of precipitation (or meteorological drought) plays an important role in the prediction of other types of drought, since the water deficit may propagate to other components of the hydrological cycle.

2.2. Agricultural Drought

Agricultural drought is commonly related to the deficit in soil moisture, which affects plant production and crop yield. Due to the lack of observation networks of soil moisture, hydrological models have been commonly used to obtain soil moisture data for characterizing and predicting agricultural drought. Commonly used agricultural drought indicators are mostly based on soil moisture simulations (Heim, 2002), including the Soil Moisture Percentile (SMP) (Sheffield et al., 2004), Crop Moisture Index (CMI) (Palmer, 1965), Soil Moisture Deficit Index (SMDI) (Narasimhan & Srinivasan, 2005), Normalized Soil Moisture (NSM) (Dutra et al., 2008), and Standardized Soil moisture Index (SSI) (Hao et al., 2014).

The agricultural drought is generally caused by the previous precipitation deficit and/or increased temperature resulting in increased evapotranspiration from the bare soil and plant (as shown in Figure 1) (Sheffield et al., 2004; Van Loon, 2015). It may delay and prolong effects of meteorological drought (Nicholson, 2000; Wu et al., 2002). The agricultural drought prediction is commonly performed based on indices derived directly from soil moisture or other indices related to soil moisture (e.g., crop yield) (Dutta et al., 2013; Sun et al., 2012).

2.3. Hydrological Drought

Hydrological drought is generally related to the deficit of surface runoff, streamflow, reservoir, or groundwater level. Since it is directly linked to drought impacts, it is argued that more attention is needed to study the hydrological drought (Cloke & Hannah, 2011; Mishra & Singh, 2010; Pozzi et al., 2013). The commonly used hydrologic drought indicators include Palmer Hydrologic Drought Index (PHDI) (Palmer, 1965), runoff or streamflow percentile, Standardized Runoff Index (SRI) (Shukla & Wood, 2008), or reservoir level (Hayes et al., 2011).

Though droughts originate from the insufficiency of precipitation, the evolution of drought from meteorological to hydrological (and agricultural) drought is not instantaneous and is dominated by complicated physical mechanisms. As such, not all meteorological droughts may lead to hydrological droughts. Though the causative mechanism is mainly related to antecedent precipitation deficit, other factors may affect the occurrence of hydrological drought, such as low water storage, and low temperatures and snow accumulation (Van Loon & Van Lanen, 2012). Overall, the occurrence of hydrological drought is mainly controlled by both the climate and catchment characteristics (Van Lanen et al., 2013), and its prediction necessitates meteorological forcing (particularly precipitation and temperature) and initial catchment conditions.

2.4. Socioeconomic Drought

Socioeconomic drought is associated with the supply and demand of some economic goods (e.g., water, food grains) (Wilhite & Glantz, 1985), which incorporates features or impacts of the other three types of drought. Drought impacts span a wide range of societal (e.g., health), economic (e.g., water supply,

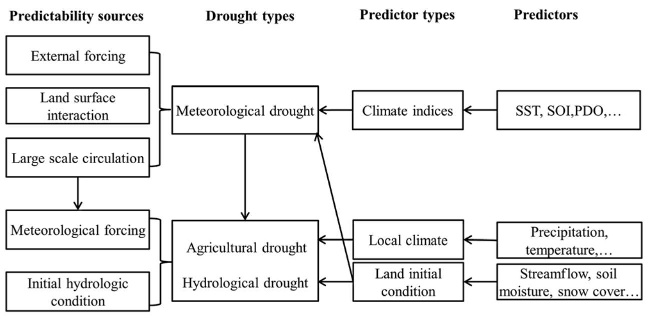

Figure 3. Predictability sources of different types of drought and commonly used predictors for statistical drought prediction at the seasonal time scale.

agricultural production, and recreation), and environmental (e.g., forest productivity and wildfires) systems. In past decades, a large number of drought indicators have been developed for meteorological, agricultural, and hydrological droughts, while few efforts have been devoted to the characterization of socioeconomic drought (Blair & Buytaert, 2016; Van Loon, Stahl, et al., 2016). Crop yield, water supply shortage, and water quality have been commonly used for characterizing the socioeconomic drought (Mosley, 2015; Quiring & Papakryiakou, 2003). Meanwhile, certain indicators (e.g., Social Water Stress Index (SWSI)) have been developed to evaluate water scarcity to account for environmental and social factors for water use, supply, and vulnerability (Pedro-Monzonís et al., 2015), which can be used to characterize socioeconomic drought.

The definition of socioeconomic drought highlights the strong interaction between drought and human activities. The incidence of socioeconomic drought could be affected by changes in the frequency of physical events, changes in societal vulnerability to water shortages, or both (Wilhite, 2000). It is generally hard to quantify drought impacts due to the slow onset, multiple socioecological interactions, and imprecise definitions (Collins et al., 2016). Currently, there are limited studies on socioeconomic drought prediction. Certain types of data, such as crop yield, water quality, wildfire occurrence, or remotely sensed vegetation stress, are related directly or indirectly to drought impacts, and prediction of these quantity can be regarded as approximations of socioeconomic drought prediction (Gudmundsson et al., 2014; Tadesse et al., 2014; Yu et al., 2014).

3. Drought Mechanism and Predictability

The goal of drought prediction research is to improve our understanding of the physical mechanism of drought and improve the prediction skill through fully utilizing the sources of predictability (Huang et al., 2016). Several processes affecting the precipitation producing phenomena (or the ultimate cause of meteorological drought) often act over relatively large geographic distances through large-scale atmospheric motions (e.g., Hadley circulation and Walker circulations, Rossby wave), which are generally forced by SST anomaly, land surface interactions/feedbacks, and natural and anthropogenic changes in radiative forcings (or external factors superimposed on natural climate variability) (Schubert et al., 2016). These forcing factors provide certain degree of meteorological drought predictability (shown in Figure 3) (Heim & Brewer, 2012; Kingston et al., 2015; Mueller & Seneviratne, 2012; Rodríguez-Fonseca et al., 2015; Wood et al., 2015).

The source of atmosphere or climate predictability at the seasonal time scale results from slowly varying boundary conditions, such as SST and land surface characteristics (e.g., soil moisture, high-latitude snow cover, and sea ice), which may provide more skillful seasonal forecast to the extent that these boundary conditions and associated climate impacts are predictable (Goddard et al., 2001; Roundy & Wood, 2015). A major advance in drought (or climate) prediction has been the discovery of teleconnections between hydroclimatic anomalies and SST phenomena (Schubert et al., 2004b), for which the combined ocean-atmosphere El Niño–Southern Oscillation (ENSO) phenomenon (with periods of 2–7 years) provides the most important source of seasonal predictability. ENSO affects seasonal climate over wide areas, including North and South America, east and south Africa, India, Indonesia, southwest Asia and Australia (Schubert et al., 2016; Smith et al., 2012). The statistically significant correlation (at the 0.05 significance level) between the precipitation from GPCC version 7 and the Niño 3.4 SST index (representing the ENSO variability) for different seasons is shown in Figure 4. It can be seen that the correlation is high in many regions around the globe (as listed above) with seasonal differences (Doblas-Reyes et al., 2013), which shows an empirical estimate of the potential signal from ENSO for seasonal forecast. More information on global impacts of ENSO can be found at NOAA Climate Prediction Center (CPC) (e.g., http://www.cpc.noaa.gov/products/analysis_monitoring/impacts/cold.gif). The SST anomaly has been recognized as the external driver of large-scale drought conditions in different regions, which has significantly improved forecasting capabilities, especially in regions or seasons with strong teleconnection (Hoerling & Kumar, 2003; Kallis, 2008; Schubert et al., 2016; Seager & Hoerling, 2014).

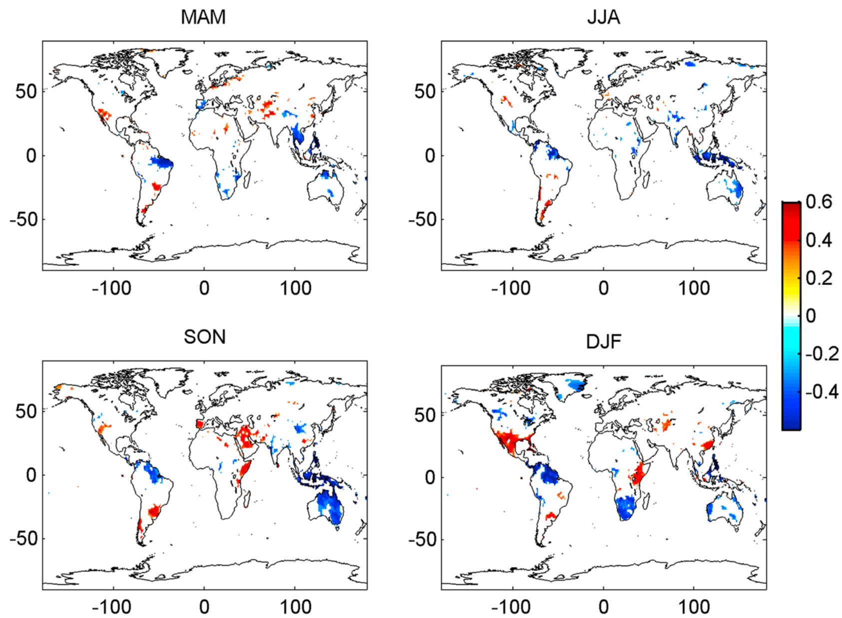

Figure 4. Correlation coefficients (statistically significant at 0.05 significance level) between monthly precipitation from GPCC and Niño 3.4 SST index for different seasons March–April–May (MAM), June–July–August (JJA), September–October–November (SON), and December–January–February (DJF) at the global scale.

For example, for drought in the United States, Pacific SST anomalies associated with ENSO or Pacific Decadal Oscillation (PDO) often provides dominating forcing, while the SST anomaly in the Atlantic ocean and Indian ocean have been shown to provide certain predictability (Cook et al., 2007; Hoerling & Kumar, 2003; Hoerling et al., 2009; McCabe et al., 2004).

Meanwhile, regional land surface characteristics (e.g., soil moisture, vegetation, snow cover) have also been shown to strengthen or weaken drought severity and affect drought development (Koster et al., 2017; Schubert et al., 2007; Su & Dickinson, 2017; Yuan & Wood, 2013). Soil moisture, for instance, may contribute to the weather (or climate) prediction either through its direct impact on the water and energy balance, or through its memory characteristic affecting atmospheric variability and land surface hydrology (Evans et al., 2017; Koster et al., 2004; Nicolai-Shaw et al., 2016; Seneviratne et al., 2010). It has been shown to affect the precipitation and temperature variability in several key regions (e.g., transitional zones between wet and dry climates) and may provide useful information for improving climate prediction on a seasonal basis through land-atmosphere interactions (shown in Figure 1) (Dirmeyer et al., 2009; Koster et al., 2000; NRC, 2010; Seneviratne, Lüthi, et al., 2006; van den Hurk et al., 2012). One important mechanism of land surface interactions between soil moisture deficit and temperature in certain regions is that, with the antecedent dry condition, the reduced local evapotranspiration may lead to increased sensible heat flux contributing to a positive feedback between high temperature and drought (Durre et al., 2000; Fischer et al., 2007; Hao, Hao, Singh & Ouyang, 2017; Koster et al., 2009; Lyon & Dole, 1995; Mueller & Seneviratne, 2012; Seneviratne et al., 2010). Evidence has shown that both dynamical forcings from remote sources and local forcings (anomalous local surface boundary conditions) contribute to the extreme heat wave-drought (e.g., 1980 and 1988 U.S. summer drought) with relative importance depending on the evolution of the events, in which land-atmosphere feedbacks contribute to the persistence and magnitude of drought (Ferguson et al., 2010; Koster et al., 2003; Lyon & Dole, 1995; Schubert et al., 2004b). For example, Hong and Kalnay (2002) found that for the 1998 Oklahoma-Texas drought, large-scale drought conditions during April–May 1998 were established by SST anomalies, and soil moisture anomalies started to play an important role in maintaining the drought in June 1998 with most of the water deficit in July explained by regional positive feedback associated with lower evaporation and precipitation.

Moreover, external forcing factors of drought (or climate) include the natural variations in solar radiations (or volcanic activities) and human-induced changes in greenhouse gases (GHG) and land use (Doblas-Reyes

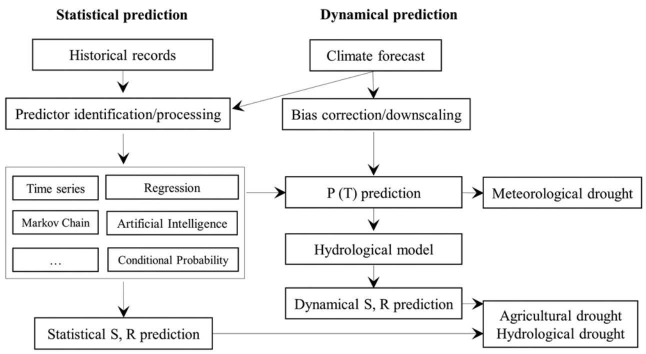

Figure 5. A schematic framework of statistical and dynamical drought prediction methods (precipitation, temperature, soil moisture, and runoff are abbreviated as P, T, S, and R, respectively).

et al., 2013; Stockdale et al., 2010). For example, Cook et al. (2009) showed that the inclusion of forcings from human land degradation in the GCM, represented by the reduction in vegetation cover and the addition of soil dust aerosol sources due to crop failure, was necessary to reproduce the anomalous features of the Dust Bowl drought in the 1930s in United States, highlighting the impact of human land degradation on drought.

At last, drought may also result from internal atmospheric variability without strong external forcings (Kumar et al., 2013). For example, studies have shown that the 2012 drought in the United States resulted mostly from natural variations in weather and may be driven by atmospheric noise without clear forcings from the SST anomaly (Hoerling et al., 2014; Kam et al., 2014). For the seasonal prediction, certain processes, such as the development of the synoptic system in the atmosphere that usually occurs at short time scales, are sources of the unpredictable noise (Stockdale et al., 2010).

Agricultural and hydrological drought prediction is commonly achieved through the hydrological simulations with predictability determined by both meteorological forcings and initial land surface conditions (shown in Figure 3), which will be introduced in section 5.2. Overall, there are several processes related to drought occurrences with varying importance depending on regions, seasons, and time scales. Substantial efforts have been devoted to the understanding of drought-causing mechanisms and predictability, while there are still challenges in explaining drought formulation, maintenance, and termination (Bonsal et al., 2011). The following sections will introduce how different approaches were employed to utilize these sources of predictabilities for predicting different types of drought.

4. Statistical Methods for Drought Prediction

A schematic framework of the statistical drought prediction is shown in Figure 5. For statistical prediction, usually a variety of predictors is first identified from historical hydroclimatic records (including oceanic, atmospheric, and land components) and are then fed to different statistical models to predict different types of droughts. The selection of predictors and different statistical models are introduced in the following sections.

4.1. Selection of Predictors

For the statistical prediction of drought, predictors are generally obtained from historical observations (or reanalysis) that are already known prior to the prediction period. With advances in the weather and climate forecast, predictors may also be obtained from dynamical forecast for the prediction of hydroclimatic variables (Chowdhury & Sharma, 2009; Foster & Uvo, 2010; Lang & Wang, 2010; Marcos et al., 2017; Sahu et al., 2016; Schick et al., 2017; Stephenson et al., 2005). This is also related to the Model Output Statistics (MOS) of climate forecast, which will be introduced afterward in section 5.1.2.

4.1.1. Identification of Predictors

Drought is a multifaceted natural phenomenon with a large number of influencing factors and thus a wealth of atmospheric, oceanic, and hydrologic predictors is generally required for the statistical prediction of drought. These influencing factors may be at play in different regions and seasons. Thus, identification of suitable predictors that explain large variances of the predictand in target periods is the first step in statistical drought prediction.

Understanding physical mechanisms of drought provides the basis for selecting suitable predictors. For example, the propagation of drought signal from precipitation deficit to other types of drought implies that meteorological drought indicators may be used as the predictors (or precursors) for agricultural and hydrological drought prediction (Hao, Hao, Singh, Sun, et al., 2016; Wong et al., 2013). A variety of techniques can also be used for identifying predictors, including the correlation analysis and composite analysis. Correlation analysis based on Pearson's correlation coefficient (or other measures of dependence) is the most commonly used tool for diagnosing and selecting potential predictors. Usually, significant correlation coefficients between the predictand and influencing factors imply the potential to include these factors as predictors. It is recommended that plausible mechanisms are explored together with the correlation analysis to identify suitable predictors, since screening a large number of potential predictors with correlation analysis may lead to inauthentic correlations (Brown & Ward, 2013).

There are a variety of factors contributing to drought occurrences and developments. It is usually expected that all predictors are incorporated without omitting useful information for prediction purposes. However, accounting for all potential variables at multiple lags (or sites) may yield a huge number of predictors, while too many predictors may lead to model overfitting that may decrease the predictive performance. Moreover, predictors are usually mutually correlated, and incorporating strong mutual correlation may lead to poor estimate of model parameters (Wilks, 2011). To address these issues, statistical criteria are often needed to select predictors objectively. The Akaike information criterion (AIC) and Bayesian information criterion (BIC) are commonly used in different statistical models for selecting predictors (Singh, 2016).

4.1.2. Typical Predictors

A variety of predictors from the atmosphere, ocean, and land have been identified for drought prediction in different regions and seasons, mainly including the large-scale climate indices that reflect the atmosphere-ocean circulation pattern (e.g., SST, Southern Oscillation Index (SOI), PDO, and North Atlantic Oscillation (NAO)), local climate variables (e.g., precipitation and temperature), and land initial conditions (e.g., persistence). Commonly used predictors for different types of drought are shown in Figure 3.

The large-scale teleconnection patterns have been shown to be an important driving factor of drought occurrence in different regions. As such, climate indices may be used as potential predictors for precipitation (or meteorological drought) prediction in regions with strong teleconnections (Bonaccorso et al., 2015; Magno et al., 2014; Morid et al., 2007; Özger et al., 2012; Santos et al., 2014). The large-scale teleconnection patterns have also been shown to affect hydrological conditions (through the effect on precipitation, temperature, or other meteorological variables) (Chiew & Mcmahon, 2002; Wanders & Wada, 2015) and have been used for predicting hydrological drought and agricultural drought (or streamflow and soil moisture) in different regions (Kingston et al., 2013; Kuss & Gurdak, 2014; Nicolai-Shaw et al., 2016; Ryu et al., 2010; Trambauer et al., 2013, 2015).

The second type of predictors mainly consists of local climate variables (e.g., precipitation, temperature) that reflect the local-to-regional driver, especially for agricultural and hydrological droughts. With precipitation deficit and high temperature (possibly increased evaporation), soil moisture may be depleted leading to agricultural drought. Thus, these contributing factors of local climate variables may provide useful information for agricultural (or hydrological) drought prediction in the subsequent period (Maity et al., 2016). For example, the previous meteorological drought may provide useful predictive information for the subsequent hydrological drought prediction (Hannaford et al., 2011; Haslinger et al., 2014; Li et al., 2016; Maity et al., 2016; Nalbantis & Tsakiris, 2009; Wang et al., 2011; Wong et al., 2013). These predictors mainly consider the temporal dependence between the target drought indicator and contributing factors in antecedent periods. The diagnosis of lagged temporal correlations between agricultural (or hydrological) drought and local climate variables in antecedent periods is generally required. In addition, the spatial coherence of drought over wide areas may provide useful predictors for the hydrological drought prediction, based on information from other regions. For example, Hannaford et al. (2011) proposed a novel methodology for drought forecast by predicting “drought from drought” that uses spatial coherence of drought to facilitate early warning in Europe.

The land initial conditions (e.g., the persistence of hydroclimatic variables reflecting the memory) can also be used as predictors for drought prediction. For example, the high-latitude Eurasian snow cover has been used as a predictor for the precipitation (or meteorological drought) prediction in China and Europe (Brands et al., 2012; Wang et al., 2017). For a catchment, the initial condition of streamflow provides useful information for the future forecasting of streamflow, and thus antecedent streamflow is commonly used as predictors in a statistical framework (Hao, Hao, Singh, Sun, et al., 2016; Sun et al., 2014). A salient property of soil moisture is its high persistence ranging from a few weeks to months (Entin et al., 2000; Koster, Mahanama, Livneh, et al., 2010; Seneviratne, Koster, et al., 2006; Wu & Dickinson, 2004). As such, the persistence of soil moisture can be used as a potential predictor for the future prediction of agricultural drought. Using the initial condition or the persistence as predictors is not confined to the drought prediction based on hydroclimatic variables, such as precipitation, soil moisture, or streamflow (Hao et al., 2014; Lyon et al., 2012; Turco et al., 2017). A variety of drought indicators also show a certain degree of persistence, such as SPI and PDSI, and thus the persistence provides useful predictive information in this regard.

These types of predictors may be used together for drought prediction, depending on regions, seasons, or variables to be predicted. For meteorological drought prediction, multiple climate indices (e.g., from different oceans) can be used as climate precursors for prediction purposes. Statistical methods for agricultural and hydrological drought prediction generally involve predictors of all these three types. For example, the predictors from large-scale climate indices, antecedent precipitation, and streamflow can be fed into a statistical model for the hydrological drought (or streamflow) prediction (Hao, Hao, Singh, Sun, et al., 2016; Wang, Robertson, & Chiew, 2009).

4.1.3. Predictor Processing

For many cases, there are multiple predictors to be incorporated in a prediction model for drought prediction. For example, statistical prediction of precipitation (or meteorological drought) in a specific region may involve a large number of predictors, such as SST, geo-potential height, SOI, PDO index, or Multivariate ENSO Index (MEI). To reduce the dimensionality, multiple predictors may be combined for statistical drought prediction. The Principal Components Analysis (PCA) and Canonical Correlation Analysis (CCA) are among the commonly used methods for the dimension reduction (Mortensen et al., 2017). For example, when there is a large number of predictors (e.g., fields of SST) (Brown & Ward, 2013), the PCA is commonly used to reduce the dimension (or compressing data) to avoid overfitting and multicollinearity, which may be combined with a multiple linear regression model for climate prediction (Funk et al., 2014; Mortensen et al., 2017). When the response variable is a vector (or multiple response variables) with multiple predictors, the CCA method can be used to find correlated patterns between predictor and predictand fields for climate prediction (Hwang et al., 2001; Sohn & Tam, 2016).

4.2. Statistical Methods

The commonly used statistical methods (or data-driven methods) include time series model, regression model, artificial intelligence model, Markov Chain model, and conditional probability model, which are also shown in Figure 5. The key of the statistical prediction is to establish suitable models to characterize temporal or spatial dependences between the predictand and predictors. These models provide different ways to explore the complex relationships between the drought indicator to be predicted and an array of predictors in previous periods.

The prediction from a model is commonly compared with a reference (or baseline) prediction for assessing the prediction skill. A number of reference drought prediction, including the climatology prediction, persistence prediction, and random prediction (Wilks, 2011), can be simply achieved by using historical records. The climatology prediction can be achieved if the climatological average of the target period is used, while the persistence prediction is defined when records of the antecedent period is used as prediction. When the prediction is obtained from relative frequency in the climatology, it is termed as the random prediction. For drought prediction based on SPI of certain time scales (e.g., 6 month SPI), resampled historical records of the target period can be combined with antecedent observations to obtain the baseline prediction of SPI (Lyon et al., 2012), which can also be applied to other univariate and multivariate drought indicators (Hao, Hao, & Singh, 2016; Hao et al., 2014).

4.2.1. Time Series Model

The main time series modeling technique is the Autoregressive Integrated Moving Average (ARIMA) framework. For a time series X_t (drought indicator to be predicted), a nonseasonal ARIMA (p,d,q) can be expressed as

$$\left(1-\varphi_1 L-\ldots-\varphi_p L^p\right)(1-L)^d X_t=\left(1+\theta_1 L+\ldots+\theta_q L^q\right)\varepsilon_t \quad (1)$$

where ε_t is the error term that is independent, identically distributed from a normal distribution with zero mean; L is the lag operator; the nonnegative integer p is the order of the Autoregressive (AR) model; d is the degree of differencing; and q is the order of the Moving Average (MA) model.

Drought indices, such as SPI and PDSI, generally possess a long memory property, either through the accumulation (e.g., 6 month SPI) or the autoregressive component (e.g., PDSI). As such, the ARIMA model is suitable for drought prediction based on these drought indices for different time scales (e.g., 3 and 6 month SPI) (Durdu, 2010; Mishra & Desai, 2005). For the prediction based on SPI, the model relies highly on the persistence, and drought prediction performance is relatively better for long lead time for SPI of longer time scale. The ARIMA model has also been applied to other drought indicators, including Palmer drought index (Rao & Padmanabhan, 1984) and standardized streamflow index (Fernández et al., 2009; Modarres, 2007). The main limitation of this model is that it assumes a linear relationship between the predictand and predictors, and thus, it generally falls short in capturing nonlinear characteristics (e.g., the response of soil moisture to precipitation deficit). In addition, other factors affecting drought occurrences are not considered in the time series model, since it is based only on the persistence of a specific indicator.

4.2.2. Regression Model

Linear regression is a traditional method for statistical prediction in hydrology and climatology. A basic formulation of the multiple linear regression model for drought prediction with respect to two predictors X and Z can be expressed as (1 month lead):

$$Y_t = AX_{t-1} + BZ_{t-1} + \varepsilon_t \tag{2}$$

where Y_t is the predictand (or dependent variable) in the form of drought indicator series; X_{t-1} and Z_{t-1} are covariates (or independent variables) that provide the predictive information of Y_t; A and B are regression coefficients; and ε_t is the error term.

In contrast to the time series model that predicts drought severity based solely on the persistence of certain drought indicators, the regression model seeks to establish the relationship between predictand and other variables that may contribute to the predictive information of drought developments. The regression model has been used to model the relationship between drought indices to be predicted and a suite of predictors (e.g., SOI and PDO) (Barros & Bowden, 2008; Liu & Juárez, 2001; Panu & Sharma, 2002; Sun et al., 2012). Due to the high persistence of the drought indicator, the autoregressive component (e.g., Y_{t-1} for 1 month lag) is commonly used in the regression framework. In this case, the drought indicator is predicted based on linear combinations of antecedent drought conditions through a lagged term as well as external factors related to drought conditions of the target period. The regressive model in equation (2) is generally limited by the assumption of linear relationships between the predictand and predictors. Several nonlinear regression models, such as the locally weighted polynomial regression (LWPR), have been employed for modeling nonlinear relationships for prediction purposes (Hwang & Carbone, 2009; Liu & Hwang, 2015).

These regression models mainly work with the predictand in the continuous case (e.g., continuous SPI or PDSI). When the predictand is in the form of drought categories, the traditional regression model would not work, and the categorical modeling framework (logistic regression or ordinal regression model) is generally needed. For the simplest case with a binary drought category (i.e., drought occurs or not), the logistic regression model can be applied to estimate the probability of drought occurrences (Hao, Hao, Xia, et al., 2016; Regonda et al., 2006).

Define a binary response variable Y ($Y = 1$ or 0). The distribution function of Y is expressed as the probability $P(Y = 1) = \pi$ of success and $P(Y = 0) = 1 - \pi$ of failure. The objective is to estimate the conditional distribution of Y with respect to the predictor X. The binary logistic regression model can be used in this case, which is expressed as (Agresti, 2007):

$$\text{logit}(\pi) = \log\left(\frac{\pi}{1-\pi}\right) = \alpha + \beta_1 x_1 + \ldots + \beta_k x_k \tag{3}$$

where α and β are parameters; $\alpha + \beta_1 x_1 + \ldots + \beta_k x_k$ is the linear combination of explanatory variables; logit(π) is the link function that links the response variable Y with the predictor X. The commonly used link function is the logit which is defined as logit (π) = log(π/(1 − π)). Note that a linear relationship is assumed between the transformed response logit (π) (but not the response Y itself) and explanatory variables.

When there are three or more drought categories (e.g., multiple categories D0–D4 in the USDM), the ordinal regression model can be used for the prediction of multiple drought categories with respect to a suite of predictors. For m drought categories, denote $F_j = P(Y \leq j)$ the cumulative nonexceedance probability of drought category j (j = 1, 2,..., $m - 1$). By substituting F_j into the logit link function, the ordinal regression model is expressed as (Agresti, 2007; Hao, Hong, et al., 2016):

$$\log\left(\frac{P(Y\leq j)}{1-P(Y\leq j)}\right) = \alpha_j + \beta_1 x_1 + \ldots + \beta_k x_k \tag{4}$$

where $\boldsymbol{\alpha}$ = [α_1, α_2,..., α_{m-1}] is the intercept parameter; $\boldsymbol{\beta}$ = [β_1,..., β_k] is the regression coefficient.

The ordinal regression model has been employed to predict USDM drought categories based on a suite of predictors, such as precipitation, soil moisture, evaporation, runoff, or climate indices (Hao, Hao, Xia, et al., 2016). The potential limitation in predicting multiple drought categories is that a large number of parameters may be involved. A potential solution is to combine several categories to keep the model parsimonious (Hao, Xia, et al., 2017). For example, the USDM categories can be grouped into two drought categories (e.g., drought more severe than D2 or not) and the logistic regression model can be employed to predict the probability of drought occurrences with fewer parameters. Currently, several drought information systems are based on the drought categories (Hao, Yuan, et al., 2017; Lawrimore et al., 2002; Svoboda et al., 2002). The logistic or ordinal regression model can be applied for drought category prediction in these systems.

4.2.3. Artificial Intelligence Model

In many cases, the complicated interaction in the hydroclimatic system cannot be characterized by linear models. The Artificial Intelligence (AI) (or machine learning, soft computing) models, including Artificial Neural Network (ANN), Fuzzy Logic (FL), Support Vector Regression (SVR) or Support Vector Machine (SVM), Genetic Algorithm (GA) or Genetic Programming (GP), and wavelet transformation, can be used to model complex interactions of hydroclimatic variables for a variety of applications (Bourdin et al., 2012; Fahimi et al., 2016; Nourani et al., 2014; Rhee & Im, 2017; Wang, Chau, et al., 2009; Yaseen et al., 2015). Several AI models, including the ANN (Mishra & Desai, 2006; Mishra et al., 2007; Morid et al., 2007), SVM (Ganguli & Reddy, 2014), and wavelet transformation (Maity et al., 2016; Özger et al., 2011), have been used to model complicated and nonlinear interactions between drought indicators and influencing factors for drought prediction.

The ANN model is capable of modeling the nonlinear dependence between drought indicator and other variables and has been widely used for drought prediction (Barua et al., 2012; Mishra et al., 2007; Mishra & Desai, 2006; Morid et al., 2007; Santos et al., 2014; Yang et al., 2015). An ANN model generally consists of three components, an input layer (i.e., a suite of predictors), a hidden layer that consists of a nonlinear function to map inputs into outputs, and an output layer (i.e., the target drought variable or indicator to be predicted). There are certain limitations of ANN methods, including local maxima and overfitting. The SVM or SVR is similar to ANN for drought prediction in that the input of predictors is mapped to a hidden space (and then to the output space) to minimize the error function for training, but differs from ANN in that these spaces are transformed into higher dimensions using kernel functions, in which the mapping functions become linear (Bourdin et al., 2012). It is able to learn from a much smaller data set for training based on the linear optimization and is capable of handling a large number of variables. Thus, the SVM may overcome certain limitations of the ANN method to some extent for drought prediction (Ganguli & Reddy, 2014). An alternative way to perform drought prediction is to decompose drought indicator series into several components and the prediction can be performed for each subseries. The wavelet transform is such a method for decomposing original series into different resolution levels and is commonly blended with other methods to facilitate statistical modeling. Specifically, based on decomposed series, statistical methods can be applied to predict each series to facilitate drought prediction with the hybrid method, such as the wavelet-ANN (or SVR) (Belayneh et al., 2014; Deo et al., 2016; Kim & Valdés, 2003), wavelet FL (Özger et al., 2012), and wavelet GP (Mehr et al., 2014), which in general shows improved prediction ability of different drought indicators. Other attempts combining advantages of different models have also been explored, such as ARIMA-ANN (Mishra et al., 2007) and ANN-FL (Bacanli et al., 2009). The AI model is favorable for drought prediction when the relationship between the predictor and predictand is complicated.

4.2.4. Markov Chain Model

In many cases, drought condition is classified into different states (e.g., two states of wet and dry) or categories with a specific threshold (Lawrimore et al., 2002; Steinemann & Cavalcanti, 2006; Svoboda et al., 2002; Zink et al., 2016). The problem of drought prediction in this case can be formulated as the transition from the wet or normal state to the dry state (or the other way around) and thus the transition probability has to be modeled. This can be handled with the Markov Chain (MC) model based on the stochastic process with a countable state space, in which future states are assumed to depend only on the current state.

The drought prediction with the model is based on the "transition probability" which is defined as the conditional probability of a drought category C_{n+1} for a period $n + 1$ given the drought category C_n for the period n (Steinemann, 2003). Specifically, the transition probability of C_{n+1} in category j given C_n in category i can be expressed as

$$M_{ij} = P(C_{n+1} = j | C_n = i) \tag{5}$$

The estimation of transition probabilities in equation (5), which is the element of the transition matrix M, can be achieved through the conditional frequency, that is,

$$\overline{M}_{ij} = \frac{m_{ij}}{m_i} \tag{6}$$

where m_{ij} is the number of transitions from category j at time $n + 1$ ($C_{n+1=}j$) to category i at time n ($C_n = i$); m_i is the total number of transitions from category i to other categories.

The MC model has been commonly used for drought prediction based on drought states of different indicators, including Palmer drought index (Lohani & Loganathan, 1997), SPI (Cancelliere et al., 2007; Paulo & Pereira, 2007, 2008) and Standardized Hydrological Index (SHI) (Sharma & Panu, 2012). The transition matrix M can be used for drought prediction of the next step based on the current period (i.e., first-order MC model). It can be extended to higher-order MC models for the prediction of multiple categories or states (e.g., wet, normal, and dry) (Avilés et al., 2015). The MC model enables the prediction of transitions of drought states based on the historical records of an indicator.

4.2.5. Conditional Probability Model

The joint distribution has been commonly used to characterize the joint behavior of multiple drought variables, from which the conditional distribution can be constructed to model the predictand conditioned on predictors. A variety of studies have been conducted for the prediction of hydroclimatic variables based on the joint distribution (Khedun et al., 2014; Liu et al., 2015; Wang, Robertson, & Chiew, 2009; Wu et al., 2011; Yan et al., 2012). For example, streamflow prediction can be achieved by constructing a joint distribution of streamflow of the target period and several predictors, such as precipitation, streamflow, and climate indices in previous time steps (Liu et al., 2015; Souza Filho & Lall, 2003; Sun et al., 2014). The multivariate distribution function can be used for statistical drought prediction by establishing the conditional distribution of the variable of interest with other predictors that may provide predictive information (Cancelliere et al., 2007; Hao, Hao, Singh, Sun, et al., 2016; Madadgar & Moradkhani, 2013).

The conditional distribution of a drought indicator Y with respect to a suite of variables $X_1, X_2, \ldots, X_n$ can be expressed with a function F as (Hao & Singh, 2016)

$$F(Y | X_1, X_2, \ldots, X_n) \tag{7}$$

where Y is the predictand; X is any factor that may provide the predictive information of Y. There are a variety of choices for the function F (e.g., parametric distributions, copula models, entropy models, and nonparametric models), which can be used to construct the joint distribution of the predictand Y and predictor X (Hao & Singh, 2016).

The advantage of the conditional probability model in drought prediction is that nonlinear dependences between the predictand and predictors can be modeled and probabilistic prediction can be achieved from the conditional distributions. The temporal dependence (different time lags) and cross-variable dependence of different locations (spatial dependence) can be modeled with the function F for drought prediction. The main disadvantage of this type of model is that when a relatively large number of predictors are involved, the joint distribution in high dimensions is difficult to build. Though certain models may be used for statistical inference of multiple variables (e.g., multivariate normal distribution), they are generally limited in the dependence modeling in high dimensions. The recently developed vine copula is capable of modeling flexible dependences of multiple drought indicators and influential factors (Aas et al., 2009; Bedford & Cooke, 2002; Kurowicka & Joe, 2011) and may be used for addressing this issue for drought prediction.

5. Dynamical Methods for Drought Prediction

The dynamical method for drought prediction is based on climate models and/or hydrologic models that simulate physical processes of the atmosphere, ocean, and land. Due to the model bias and coarse resolution of climate model forecast, the post- processing technique and multimodel ensemble technique have been commonly used to improve the prediction skill. Dynamical prediction of hydrological and agricultural drought at seasonal time scales is generally achieved based on hydrological models driven by climate forecast with prediction skill depending on both the climate forcings and initial conditions. The framework of dynamical methods for drought prediction is also shown in Figure 5.

5.1. Seasonal Climate Forecast

5.1.1. Forecast From GCMs

With the increase of our understanding of the climate system and computational capabilities, the physically based GCMs have been employed for weather and climate forecasts that are available from a variety of climate forecast systems, such as NCEP Climate Forecast System Version 2 (CFSv2) (Saha et al., 2014) or European Center for Medium Range Weather Forecasting (ECMWF) seasonal forecast system 4 (SYS4) (Molteni et al., 2011). The seasonal climate forecasts usually range from several weeks to a year and are typically available at the monthly time scale and 1° spatial resolution (Crimmins & McClaran, 2016; Doblas-Reyes et al., 2013; Wanders & Wood, 2016). Season predictions of precipitation and temperature can be used to compute drought indicators for meteorological drought prediction (Dutra et al., 2014; Mo & Lyon, 2015; Steinemann, 2006; Yoon et al., 2012; Yuan & Wood, 2013). The key to the seasonal prediction of drought is the accurate prediction of precipitation and temperature. Though significant progress has been made in climate forecasting (e.g., prediction of ENSO several months ahead) due to better climate models and additional observations, seasonal precipitation forecast has only marginally improved, and the overall prediction skill of precipitation and temperature outside the tropics is still low due to the chaotic nature of the ocean-atmospheric system and the currently limited physical understanding (Kirtman & Pirani, 2009; NRC, 2010; Saha et al., 2014; Smith et al., 2012).

Currently, the prediction skill of precipitation or meteorological drought highly depends on strong circulation patterns, and evidences have shown that the seasonal prediction is more skillful with the active ENSO (NRC, 2010). For example, in the United States, the seasonal climate forecast of winter precipitation has been improving due to its connection with SST and pressure anomalies, while the prediction skill for the summer growing season is still limited (Crimmins & McClaran, 2016; Quan et al., 2006; Tian et al., 2014). Except for drought severity, few studies assessed the predictability of certain drought phases, such as the onset and recovery. For instance, Yuan and Wood (2013) showed that only less than 30% of the drought onsets over global scales can be detected by climate forecast.

5.1.2. Postprocessing Forecast From GCMs

Raw climate forecasts from GCMs are generally biased relative to observations with systematic errors, and their resolution is too coarse (aproximately hundreds of kilometers) to be used as direct inputs for agricultural and water management. The postprocessing of dynamical forecast, including bias correction and downscaling, is commonly applied before using the model outputs for climate (or drought) prediction.

Traditionally, the Model Output Statistics (MOS) technique has been commonly used for the bias correction of weather forecast from numerical weather prediction (NWP) models, which is likely due to the computational intensiveness and the high dimensionality that prohibit model parameter calibrations (Wood & Schaake, 2008). The basis of MOS technique is that historical records of observations and forecast (or hindcast) for a retrospective verification period can be used to develop forecast equations by using dynamical model outputs as predictors (i.e., to calibrate forecasts). This can be achieved with a variety of statistical models, such as multiple linear regression, logistic regression, quantile regression, and Bayesian Model Averaging (BMA) (Mendoza et al., 2015; Wilks, 2011). MOS has also been employed in the bias correction of seasonal climatic forecast in recent decades to relate observations with raw dynamical forecasts for improving the forecast reliability and accuracy. The commonly used approaches include linear scaling and quantile (or distribution) mapping. The linear-scaling approach corrects the mean of climate forecast based on the mean of both observations and forecasts, while the quantile mapping approach corrects the distribution function of climate forecasts to match the distribution function of observations (Crochemore et al., 2016; Maraun, 2016; Teutschbein & Seibert, 2012). In addition, due to the course resolution and low temporal resolution of climate forecast, the downscaling is required to provide regional drought information at finer temporal and spatial scales (Fowler et al., 2007; Tian et al., 2017). Statistical downscaling aims to establish the statistical relationship between large-scale climate forecast and local-scale observations, while dynamical downscaling employs GCM outputs to provide initial and boundary conditions for regional climate models (RCM) for the generation of forecast at local scales (Maraun et al., 2010; Tian et al., 2014). The commonly used statistical downscaling method includes bilinear interpolation, quantile mapping (Wood et al., 2004), analogue approach (Maurer & Hidalgo, 2008), and Bayesian methods (Luo et al., 2007), among others. For the meteorological drought prediction, the precipitation forecast from GCMs should generally be downscaled (and bias corrected) to assess the prediction skill at regional scales (Sohn et al., 2013; Yoon et al., 2012). For the agricultural and hydrological drought prediction, climate forecast downscaled to finer temporal and spatial resolutions is needed to drive hydrologic models for predicting soil moisture and streamflow.

5.1.3. Multimodel Ensemble Forecast

The multimodel ensemble has also been used to improve seasonal forecast skill. The uncertainty linked to initial conditions and models are taken into account through the use of an ensemble of simulations with different initial conditions from each model and the use of several models as ensemble members, respectively (Doblas-Reyes et al., 2005). The rationale behind this approach is that the error cancellation can be achieved through running multimodels, while uncertainties in the initial condition can be addressed by running ensembles of forecasts with different initial conditions (Hagedorn et al., 2005; Sikder et al., 2016). The recent advances of multimodel ensembles, including the Development of a European Multimodel Ensemble System for Seasonal-to-Interannual Prediction (DEMETER) system (Palmer et al., 2004) and North American Multimodel Ensemble (NMME) (Becker et al., 2014; Bolinger et al., 2016; Infanti & Kirtman, 2014; Kirtman et al., 2014), have uncovered new opportunities for climate and drought prediction in different regions (Ma et al., 2015; Mo & Lyon, 2015; Roundy et al., 2014; Wanders et al., 2017; Yuan & Wood, 2013). The advantage of the multimodel ensemble is that it generally performs better than the individual models and provides probabilistic drought prediction with uncertainty quantification (Kirtman et al., 2014; Yuan, Wood, et al., 2015). Except for the commonly used ensemble mean, certain merging techniques of multimodel ensemble, such as the BMA (Casanova & Ahrens, 2009; Ma et al., 2016; Raftery et al., 2005), linear regression (Wanders & Wood, 2016), and nonhomogeneous Gaussian regression (NGR) (Bogner et al., 2017; Gneiting et al., 2005), have been used to obtain the merged forecast with unequal weights for different members to improve the drought (or climate) prediction skill (DelSole et al., 2013; Luo & Wood, 2008).

An important application of the multimodel weather and climate forecast is the quantification of uncertainty. The multimodel approach essentially combines predictions from different forecast systems to produce an estimate of the forecast probability density function (PDF). In addition, the variance or “spread” of ensembles has also been used as a measure of uncertainty. It has been shown that a multimodel ensemble may result in the similarity of or overconfidence in the seasonal forecast, due to similar atmospheric or oceanic components (Yuan & Wood, 2012). Usually, the variance within the model ensemble members has to be included to ensure realistic representations of the ensemble uncertainty and to prevent overconfident forecast (Wanders & Wood, 2016).

Though great strides have been made based on the multimodel ensemble, the seasonal prediction skill may not be satisfactory in certain regions or seasons. For example, the observation and 1 month (and 3 month) lead prediction of drought based on the precipitation anomaly from NMME at 1° resolution for August 2012 in the United States is shown in Figure 6. From the observation, severe drought conditions with negative precipitation anomaly reside in large regions in the midwest and the Great Plains. It can be seen that the 1 month forecast shows useful prediction skill for the 2012 drought in the United States, while the 3 month lead prediction shows limited skill.

5.2. Seasonal Hydrologic Forecast

5.2.1. Hydroclimatic Forecast

Agricultural and hydrological droughts are generally related to soil moisture, runoff, and groundwater, which are commonly predicted by hydrological models. Traditionally, the Ensemble Streamflow Prediction (ESP) method has been employed by National Weather Service (NWS) for hydrologic forecast since the1970s (Day, 1985), in which the streamflow prediction is achieved by driving hydrologic models with historical observations in the target period. Different methods have been proposed for selecting or weighting different historical records based on climate indices or dynamical forecast from GCMs (Carpenter & Georgakakos, 2001; Hamlet & Lettenmaier, 1999; Wang et al., 2011; Werner et al., 2004; Yao & Georgakakos, 2001). The ESP prediction mainly relies on the land surface memory, and the prediction skill generally decreases after the 1 month lead time in many regions around the world (Shukla et al., 2013; Yuan, Wood, et al., 2015).

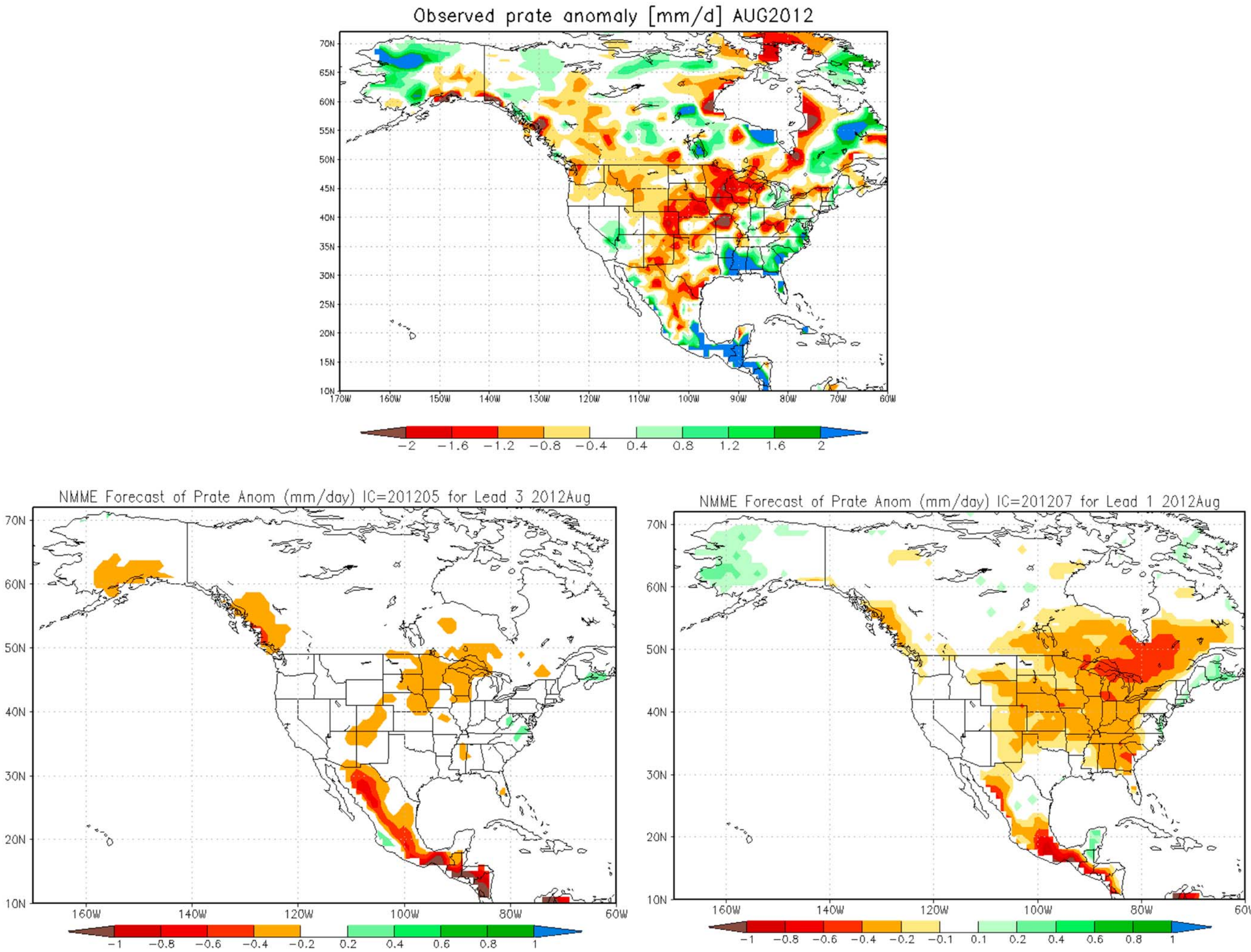

Figure 6. The observation and 1 month (3 month) lead prediction of precipitation anomaly (mm/d) based on ensemble mean from NMME for the period August 2012. The observation and prediction are obtained from National Centers for Environmental Prediction (NCEP), NOAA (ftp://ftp.cpc.ncep.noaa.gov/NMME/real-time_anom/ENSMEAN, http://www.cpc.ncep.noaa.gov/products/NMME/archive/2012070800/current/images/NMME_ensemble_prate_us_lead1.png).

With the progress in climate forecasts from state-of-the-art models, the advancement of seasonal hydrologic forecast has been witnessed by driving hydrological models with climate forecast as forcing variables (Shukla et al., 2014; Wood et al., 2002, 2004). Recently, the climate forecasts from CFSv2, ECMWF, or NMME have been used as inputs to drive hydrologic models to predict agricultural and hydrological drought (Fundel et al., 2013; Li et al., 2008; Luo & Wood, 2007; Samaniego et al., 2013; Sheffield et al., 2014; Shukla et al., 2014; Trambauer et al., 2013; Zhang et al., 2016). An example of 1 and 3 month lead drought prediction based on soil moisture percentile at one-eighth spatial resolution for March 2010 in the United States is shown in Figure 7, which was obtained from the NCEP/EMC NLDAS Seasonal Hydrological Forecast System jointly developed by Princeton University and the University of Washington. The forecasts from CFSv2 after bias correction and downscaling were used as forcing variables to drive the VIC hydrologic model to predict soil moisture (Luo & Wood, 2008). The soil moisture percentile was computed based on the soil moisture climatology from 1979 to 2011. The drought condition for this period mainly resided in the northwestern and midwest U.S. regions, which is clearly shown from the 1 month lead prediction mainly due to the high persistence of soil moisture. The 3 month lead prediction performed relatively well in detecting drought condition in large areas of northwestern and midwest regions.

The potential limitation of the hydrologic model for hydrologic prediction is that even with the identical forcing variables, substantially different simulations may be produced (Guo et al., 2006; Mo, Chen, et al., 2012; Wang et al., 2011). To reduce errors from hydrologic models or meteorological forcings, the

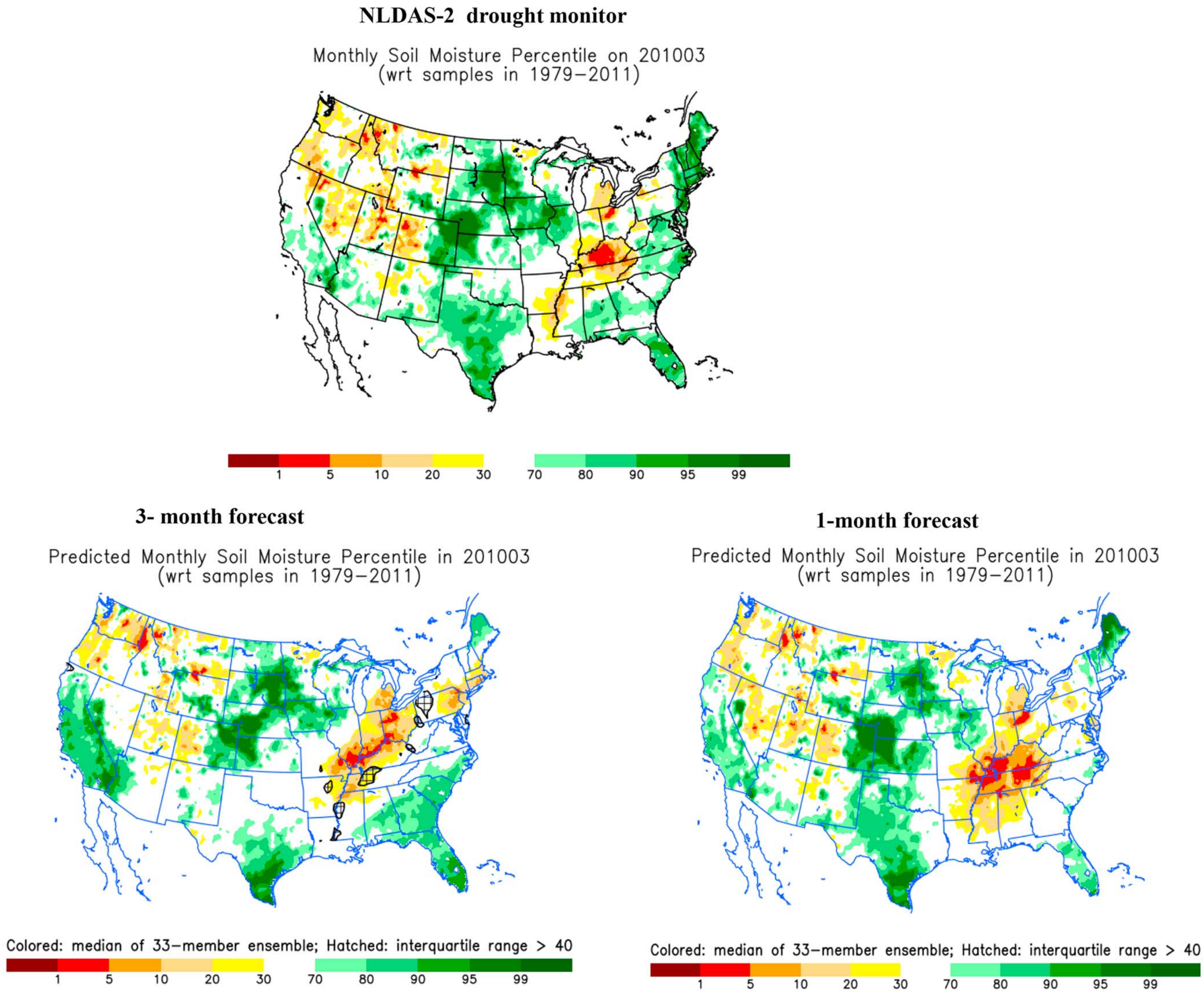

Figure 7. The 1 and 3 month lead prediction and observation of soil moisture percentile for the period March 2010. The observation and prediction can be obtained from http://www.emc.ncep.noaa.gov/mmb/nldas/drought/ or http://drought.geo.msu.edu/research/forecast/smi.monthly.php.

postprocessing of hydrological forecast has also been conducted to increase the forecast skill and reliability (Shi et al., 2008; Wood & Schaake, 2008; Yuan, Wood, et al., 2015). In addition, the multimodel ensemble of hydrological simulations has been developed and employed for drought prediction to reduce uncertainties (Duan et al., 2007; Huijgevoort et al., 2013; Mo & Lettenmaier, 2014a; Nijssen et al., 2014; Wang, Bohn, et al., 2009).

The hydrological forecast relies on the dynamical prediction performance of precipitation and temperature, which are among the most decisive variables of the hydrological budget. An issue with the hydroclimatic forecast is that the error in climate forecast may propagate to the hydrological forecast through the rainfall-runoff process, which may mask values of skillful climate forecast and impose challenges to skillful agricultural and hydrological drought prediction (Samaniego et al., 2016). Thus, an important task for using hydroclimatic forecast for hydrological and agricultural drought prediction is to assess whether improvements in precipitation and temperature forecasts from GCMs will result in the improved ability of forecasting soil moisture or streamflow (Mo & Lettenmaier, 2014b; Mo, Shukla, et al., 2012; Thober et al., 2015). This requires the investigation of when and where the climate forecast and initial condition provide useful skill for hydroclimatic forecast.

5.2.2. Initial Hydrological Conditions (IHCs) and Climate Forcing

The prediction skill of seasonal hydroclimatic forecast depends on both the initial hydrological conditions (IHCs) from the catchment before the forecast period and future seasonal climate forecasts (CFs) (Arnal et al., 2017; Emerton et al., 2016; Li et al., 2009; Mendoza et al., 2017). The initial catchment condition, including the water stored in snow, soil, or groundwater, controls the streamflow generation and may contribute to the prediction skill (Mahanama et al., 2012; Staudinger & Seibert, 2014; Yuan et al., 2016). For example, the stored water may affect catchment response to the meteorological forcing during the target period of forecast (Koster, Mahanama, Yamada, et al., 2010; van Dijk et al., 2013). Thus, the initial condition is an important source of hydrologic predictability at the seasonal time scale, depending on the season and region. For the ESP prediction with meteorological forcings sampled from historical records, the forecast skill solely depends on the initial condition. As such, the ESP (and reverse ESP; Wood & Lettenmaier, 2008) prediction of different hydrologic variables is commonly used to assess the relative role of initial conditions and meteorological forcings (Shukla et al., 2013; Yuan et al., 2013).

Sources of predictability from initial condition and climate forecast have been assessed at regional and global scales and are shown to depend on the region, season, lead time, and basin size (Shukla et al., 2013; van Dijk et al., 2013; Yossef et al., 2013). The prediction skill of streamflow varies significantly across rainfall-runoff and snowmelt-driven regimes (Sinha & Sankarasubramanian, 2013). For example, snow played a critical role in streamflow predictability for up to a few months lead time in the western United States (Maurer et al., 2004). In addition, relatively high prediction skill from initial conditions may be achieved during the transition between dry and wet seasons (van Dijk et al., 2013). Wood and Lettenmaier (2008) showed that in northern California, USA, initial conditions provide streamflow prediction skill for up to 5 months during the transition from wet to dry seasons, whereas climate forecast information is critical during the reverse transition. This partly implies that the initial condition may provide useful prediction after the onset of drought, whereas it may not perform as well in predicting the onset (or recovery) (Thober et al., 2015; Yuan, Roundy, et al., 2015). The role of initial condition also varies with the lead time of prediction. Based on hydrologic forecasting experiments in Ohio River basin and the Southeast United States, Li et al. (2009) showed that initial conditions control the forecast skill up to 1 month, while the climate forecast plays a dominant role for longer lead time, as is confirmed by studies in other regions (Mo & Lettenmaier, 2014b; Shukla & Lettenmaier, 2011; Sinha & Sankarasubramanian, 2013; Thober et al., 2015; Yuan et al., 2013). They also reported that the impacts from IHCs are stronger for large basins at short lead times, while small basins are more sensitive to climate forcings. Better initialization of the catchment/hydrological condition and improved meteorological forecast skill are needed for enhancing the prediction capability of agricultural and hydrological drought.

6. Hybrid Methods for Drought Prediction

Statistical and dynamical prediction methods differ in several aspects, including resources for development and capability to model complicated interactions and nonstationary conditions. The following section first introduces the comparison of statistical and dynamical methods, followed by a discussion of hybrid prediction through merging forecasts from both methods.

6.1. Comparison of Statistical and Dynamical Methods

Statistical methods based on multiple predictors without consideration of physical processes remain a useful choice for the drought prediction. The salient advantage of statistical methods is that they are generally simple to implement and operate with less computational resources. However, statistical methods rely on the relationships between the predictand and predictors in historical records, which is not guaranteed in a changing climate (or nonstationarity of climate) (Schepen et al., 2012; Smith et al., 2012). Therefore, the prediction performance may not be satisfactory if changes in the climate (or unprecedented conditions) are not adequately captured from historical records. In addition, due to the limitation in representing physical processes, the statistical methods generally fall short in modeling complicated interactions in hydroclimatic systems. Usually, a statistical method is particularly useful in providing a baseline level of skill, which the complicated dynamical models aim to exceed (Kirtman et al., 2013).

The dynamical forecast using GCMs or hydrological models is based on the physical processes of weather and climate systems and is capable of providing multiple aspects of drought properties within the hydrologic

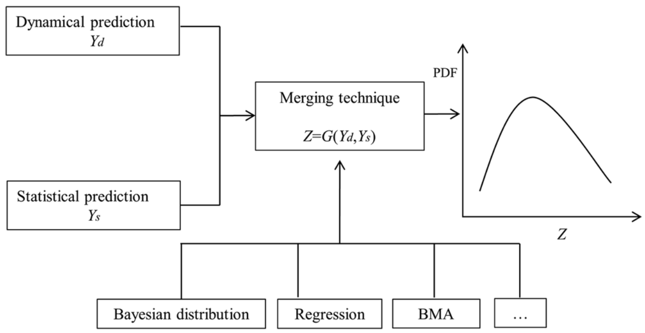

Figure 8. A schematic framework of hybrid drought prediction based on the drought indicator *Z* by merging dynamical forecast (Y_d) and statistical forecast (Y_s) with the function *G*.

cycle, such as precipitation, temperature, soil moisture, and runoff. The advantage of dynamical methods is that they are physically based and are capable of capturing nonlinear interactions of the atmosphere, land, and ocean (Schepen et al., 2012). As such, dynamical forecast is capable of predicting the unprecedented conditions and is adaptable to the nonstationarity of the climate. However, the dynamical forecast is generally computationally demanding with intensive investments in data assimilation, which requires much more time for model building and parameterizations, and suffers from model biases (Stockdale et al., 2010).

Generally, it is hard to determine which method is eventually the best, and the predictive skill always depends on the season, region, and lead time (Schepen & Wang, 2015).There is, however, a clear advantage of dynamical methods over statistical methods in hydrologic prediction if the precipitation forecast from GCM is skillful (Mo, Shukla, et al., 2012; Roundy et al., 2015). Moreover, for the prediction of long lead time, the predictive skill of dynamical methods is generally higher than that of statistical methods (Trambauer et al., 2015). When the prediction skill of climate forecast from GCM is low, the statistical prediction may provide a useful forecast. Various studies have shown that the two types of methods may complement each other (Block & Rajagopalan, 2009; Mo & Lyon, 2015; Quan et al., 2012). Overall, statistical and dynamical methods are complementary in drought (and climate) prediction in that the improved understanding from successful statistical forecasts may lead to better dynamical models, and vice versa (Crochemore et al., 2017; Kirtman et al., 2013).

6.2. Combination of Statistical and Dynamical Methods

The hybrid statistical-dynamical drought prediction mainly involves two steps: calibrating climate forecast to correct the bias (and ensemble spread) of GCM forecasts, and merging forecast from multiple sources (Lim et al., 2011; Robertson et al., 2013; Schepen et al., 2014; Wang et al., 2012). A schematic framework of the hybrid drought prediction to merge different forecasts is shown in Figure 8. The commonly used merging techniques, including the regression model, Bayesian posterior distribution, and BMA, can be employed to obtain probabilistic prediction. The regression method can be used straightforward to incorporate multiple indicators from climate forecast and statistical forecast (or observations) with the aim to obtain coefficient parameters of each forecast in a linear combination manner (Block & Rajagopalan, 2009; Hao, Hao, Xia, et al., 2016; Ribeiro & Pires, 2015; Wang et al., 2017). The Bayesian posterior distribution can be used to update the dynamical forecast with the prior distribution derived from the statistical forecast (Coelho et al., 2004; Luo et al., 2007). In addition, the two types of forecasts can also be combined through BMA to obtain the optimal weight of each member to form a unique prediction (Madadgar et al., 2016; Pokhrel et al., 2013; Schepen et al., 2014). For example, the hybrid statistical-dynamical method, based on calibration, bridging, and merging (CBaM), has been shown to provide improved forecasts of climate variables through postprocessing GCM outputs based on the Bayesian joint probability model (for calibration and bridging) and BMA (for merging) (Bennett et al., 2016; Schepen et al., 2014; Schepen & Wang, 2015). For this method, "bridging" represents the statistical prediction using GCM's forecasts of climate indices as predictors to produce alternative forecasts and "merging" is used to optimally combine different forecasts. Combining dynamical forecast with predictors from observations in a statistical prediction framework is also termed hybrid statistical-dynamical prediction in certain cases (Humphrey et al., 2016; Lang & Wang, 2010; Stephenson et al., 2005; Wang et al., 2017). Exploring the merging techniques of statistical and dynamic forecasts to combine advantages of both methods is important to drought prediction for achieving improved prediction skill.

7. Challenges in Drought Prediction

Despite substantial advances in drought prediction, there are still challenges in predicting the full aspects of drought onset, severity, development, and recovery, especially for long lead time and under a changing environment. A few challenges in drought prediction are discussed here.

7.1. Skillful Drought Prediction for Long Lead Time

One challenge of the climate forecast from coupled GCMs is that the precipitation forecast quickly loses skill after 2 weeks because of the inherent chaotic nature of the atmosphere (Lavers et al., 2009; Smith et al., 2012; Yuan et al., 2011). There are large uncertainties in the precipitation forecast, and skillful climate forecast beyond the 1 month lead is still a prevailing challenge (Mcevoy et al., 2015; Saha et al., 2014; Weisheimer et al., 2009; Wood et al., 2015; Yuan et al., 2013). This leads to limitations of reliable drought prediction of long lead time, especially in midlatitude (or extratropics) regions in which the climate predictability is low (Sohn & Tam, 2016). Currently, it is only expected to have some drought predictability on seasonal and longer time scales in regions where SSTs play a substantial role in driving precipitation and temperature variability (Schubert et al., 2016).

The SST forcing is an important contributing factor to drought and may provide the best prospects for drought prediction of long lead time (Seager & Hoerling, 2014). The statistical drought prediction of long lead time is commonly achieved through incorporating climate indices (e.g., SST) as predictors, or using the periodic nature of hydroclimatic variables (Barros & Bowden, 2008; Mishra & Singh, 2011). For the dynamical prediction, successful drought forecast on the seasonal and longer time scales require the successful prediction of SST, simulations of the global circulation response to SST anomalies, as well as taking into account land-atmosphere interactions that convert meteorological drought to agricultural and hydrological drought (Schubert et al., 2007). In addition, evidences have shown that for the interannual and longer time scales, SST anomalies affect the timing of drought onset while land-atmosphere feedbacks (primarily during the warm seasons) predominately govern the magnitude and persistence of drought (Ferguson et al., 2010; Schubert et al., 2008; Seager et al., 2008). This has important implications for the long-term drought prediction in regions with substantial coupling between land and atmosphere.

7.2. Drought Prediction in a Changing Environment

The rise in temperature will increase the water holding capacity of and evaporation to the atmosphere, resulting in changes of precipitation extremes (Prudhomme et al., 2014). Global warming from natural and anthropogenic factors has accelerated the hydrological cycle, resulting in more extremes, including drought, and a strong tendency of the wet areas getting wetter and dry areas getting drier (Dai, 2011; Held & Soden, 2006; Seager et al., 2010; Trenberth et al., 2014). Human activities change the global climate not only through the emission of greenhouse gases (GHG), but also through change in land use and land cover (LULC). The altered water cycle due to the climate change and human activities (Huntington, 2006; Milly et al., 2007) imposes challenges to drought prediction.

The statistical relationship between the predictor and predictand from historical records is generally assumed stationary for the statistical prediction. However, this may not be valid under climate change, due to the temporal variabilities involving trends, oscillatory behavior, and sudden shifts shown from hydroclimatic records (Mishra & Singh, 2011; Nicholls, 2001; Sveinsson et al., 2003). Accordingly, the drought prediction with traditional statistical models may not perform as well in this case. For example, Rajagopalan et al. (2000) investigated the teleconnection of summer U.S. drought (represented with PDSI) in response to SST patterns linked to ENSO and found potential nonstationarities in the relationship at different periods during the twentieth century. This implies that statistical prediction models developed based on teleconnection responses (i.e., drought) and SST for earlier periods may not be successful in the following periods. Efforts are needed to exploit the predictability associated with these nonstationary behaviors (NRC, 2010) and to improve existing models to incorporate nonstationary features for drought prediction.

Drought is essentially a hydroclimatic, socioeconomic. and environmental event with human and natural drivers. Global and local changes (including change in climate, LULC, and water consumption) can have significant impacts on the hydrological cycle and all types of drought, especially hydrological drought. For example, the hydrological drought (or streamflow) is not only affected by the climate and catchment characteristics but also human activities, such as irrigation or operation of dams and reservoirs (Di Baldassarre et al., 2017; He et al., 2017; Seibert et al., 2016). Human activities, such as extracting groundwater or water transfer over long distances, may also induce drought and are thus required to be incorporated in drought modeling and diagnosis (Mote et al., 2016; Pielke et al., 2011; Van Loon, Stahl, et al., 2016). For example, it has been shown that human activity of water consumption has intensified hydrological droughts worldwide (Wada et al., 2013).

Current drought prediction efforts mostly focus on natural aspects of climate or hydrology, while studies on the integration of human aspects in drought prediction are rare but growing (Van Loon, 2015; Wada et al., 2017; Yuan et al., 2017).

8. Future Prospects

To improve drought prediction, efforts are still needed in the understanding of drought mechanisms and predictability in different regions or seasons. Apart from this, several future aspects that may contribute to the improved drought prediction are listed as follows.

8.1. Data Assimilation

Both statistical models and dynamical models rely heavily on accurate observations. Statistical models mostly rely on high-quality data to capture relationships in historical observations for prediction purposes. For the dynamical forecast, GCMs are generally initialized from observed states in the ocean, land, and atmosphere domains for the seasonal climate prediction (Infanti & Kirtman, 2017), and high-quality data is of particular importance to specify initial conditions for hydrologic forecasts based on a hydrologic model (Lettenmaier, 2017). Apart from enhancing the skill from weather or climate forecast, the increased skill of hydrological forecast likely necessitates improved precipitation estimation and initial hydrological conditions (Shukla et al., 2013; van Dijk et al., 2013). Data assimilation (DA) provides a useful method in this regard to merge different observations with model simulations to provide accurate initial conditions for hydroclimatic forecasting (including drought prediction) (Kumar et al., 2006; Liu et al., 2012; Tang et al., 2016). A variety of land data assimilation systems (LDAS) have been developed in recent decades, such as the NLDAS in the United States (Mitchell et al., 2004; Xia, Peters-Lidard, et al., 2014; Xia, Ek, et al., 2014) and the Global Land Data Assimilation System (GLDAS) (Rodell et al., 2004), and they play an important role in drought early warning. For example, the recently developed Coupled Land and Vegetation Data Assimilation System (CLVDAS) can generate initial conditions of both soil moisture and leaf area index (LAI), and thus can provide unique opportunities to predict ecohydrological droughts (Sawada & Koike, 2016). Improving data assimilations is expected to generate better initializations of climatic and hydrologic models and obtain improved prediction skill for drought.

8.2. Remote Sensing and Drought Prediction

Remote sensing products provide consistent temporal and spatial measurements of multiple hydroclimatic variables, including precipitation, soil moisture, snow, and vegetation conditions, at regional and global scales (AghaKouchak et al., 2015; Tang et al., 2009; Wardlow et al., 2012, 2016). Despite the disadvantages of biases and short records, the wide coverage of remote sensing products play an important role in monitoring drought especially for the regions with sparse or no observations (e.g., Africa) (Masih et al., 2014; Mwangi et al., 2014; Sheffield et al., 2008), and in assessing land-atmosphere interactions (Roundy & Santanello, 2017).

Remote sensing products have been employed to aid drought prediction either through statistical or dynamical models (Nijssen et al., 2014; Sheffield et al., 2014; Svoboda et al., 2002). For the statistical prediction, drought indices from remote sensing products (e.g., NDVI) have been commonly used as the predictand for drought prediction mostly achieved with regression models (Asoka & Mishra, 2015; De Linage et al., 2014; Funk & Brown, 2006; Liu & Juárez, 2001; Tadesse et al., 2014). For example, the NDVI is the most commonly used vegetation index for characterizing drought conditions and is available from different satellite remote sensing platforms. Accordingly, predicting NDVI based on hydroclimatic variables (and climate indices) can provide drought early warning information in different regions (Tadesse et al., 2014). In addition, remote sensing products have been used as predictors to facilitate the statistical drought prediction (Dutta et al., 2013; Vicente-Serrano et al., 2006). For the dynamical prediction, remote sensing products have been combined with other products (e.g., through DA) to form a near-real time and long-term record to drive hydrologic models for agricultural and hydrological drought prediction. It is expected that with the improved accuracy and extended records of remote sensing products, there are promising opportunities to use the products for drought prediction through either providing predictors (or predictands) for statistical models or providing initial conditions for climatic or hydrologic models.

8.3. Improved Model Development

Currently, climate models may not perform well in simulating key processes, such as teleconnection and land-atmosphere coupling, which are related to the generation of extremes. For example, the land-atmospheric interactions or feedbacks, which have been shown to be important factors for drought occurrence, have not been fully understood and reproduced by GCMs (Taylor et al., 2012). Thus, a pressing need is to improve the atmospheric and land models to incorporate key processes related to extremes, which involve increasing model resolutions and parameterizing subgrid scale processes with novel approaches (Koster et al., 2017; WCRP, 2015). Moreover, many processes related to human activities, such as pumping, irrigation, land use change, urbanization, and deforest, are not well quantified and have rarely been included in either offline hydrologic models or coupled climate forecast system. Incorporating these human impacts through adding related components, such as reservoirs, is needed to improve drought prediction. For example, Yuan et al. (2017) assessed the hydrological drought prediction in the Anthropocene with human interventions incorporated in the post processing of streamflow. Overall, continuous efforts are needed in the development of GCMs and hydrologic models to account for key physical processes and human influences through incorporating more components of the Earth system with finer resolutions (Wood et al., 2011, 2015; Yuan, Wood, et al., 2015).

8.4. Optimal Ensemble Forecast

The multimodel ensembles have been commonly used in hydroclimatic forecast in the past decade, which can be achieved by perturbing initial conditions (e.g., SST or wind stress), running the model with different start dates, and performing forecast with multiple climatic or hydrologic models (Yuan, 2016). Ensemble mean with equal weight has been widely used and evaluated to show added values of the prediction skill with respect to the single model. Meanwhile, the combination of ensembles can be achieved by assigning weights to different ensembles based on the quality of forecast. Evidences have shown that by combining models through optimal weights, the multimodel forecast skill is significantly improved compared to the equally weighted mean (e.g., for longer lead times in extratropics) (Wanders & Wood, 2016). Currently, research gaps still exist in robustness of spreads across multimodels, and a related task is to figure out why and when certain ensemble members are more skillful than the ensemble mean (Wood et al., 2015). Selecting or weighting ensembles by conditioning on different phases of teleconnections, such as ENSO, PDO, and NAO (Wood et al., 2015; Zimmerman et al., 2016), is a promising method in this regard. Further research is needed in evaluating the spread information on drought statistics in ensemble modeling systems (Hoerling et al., 2014), and in investigating the formulation of the optimal selection/weight of ensemble members to improve drought prediction.

8.5. Hybrid Drought Prediction

Previous efforts have been devoted to the combination of forecasts from multiple dynamical or statistical models. In the past decade, the hybrid statistical-dynamical prediction has attached much attention to integrate the prediction skill from both models. It has been shown that the best forecast can be achieved by combining all sources of predictions to support informed decision making (Coelho et al., 2006; Doblas-Reyes et al., 2013). Since the calibration of climate forecast is an important component of the hybrid prediction, the development of novel postprocessing techniques of climatic and hydrologic forecast is an essential task to improve drought prediction. In addition, merging techniques of different forecasts from either dynamical or statistical models need to be further investigated to achieve an optimal combination. The development of hybrid drought prediction models and the evaluation of their performance in different regions and seasons for different drought types would bring new opportunities in improving drought prediction capability.

8.6. Prediction of Drought Impacts

Many models have been employed to forecast meteorological drought and its propagation to agricultural and hydrological droughts; however, there are rather limited studies on the prediction of drought impacts (or socioeconomic drought). Though various studies have been devoted to the prediction of drought signals based on different indicators, these prediction results are generally not directly linked to the impacts of drought on the society or ecosystem (Bachmair, Svensson, et al., 2016). Exploring the indicators that are linked directly to drought impacts would be important for meeting this challenge to facilitate drought impact prediction. The availability of several drought impact inventories, such as the U.S. Drought Impact Reporter (DIR) and European Drought Impact report Inventory (EDII) (Bachmair, Stahl, et al., 2016; González Tánago et al., 2016; Stagge et al., 2015; Stahl et al., 2016), which collect drought impacts from agriculture to water quality, provide alternatives for predicting drought impacts in the U.S. and Europe. For example, the USDM can be predicted with the ordinal regression model through integrating lagged USDM categories and a suite of drought indicators from statistical and/or dynamical forecast (Hao, Hao, Xia, Singh, et al., 2016). In addition, Blauhut et al. (2016) predicted drought impact occurrences based on logistic regression with predictors integrating traditional drought indices and information of land use and water resources.

The prediction of drought impacts can also be achieved through predicting indicators that are directly linked to drought impacts, such as crop yield, as stated in section 2. Statistical methods, such as regression model and conditional probability model, can be applied to establish the relationship between hydroclimatic variables and crop yield (or other indicators) for predicting drought impacts (Nadolnyak & Vedenov, 2013; Sen & Boken, 2005; Vicente-Serrano et al., 2006). For example, the crop yield can be predicted with a regression model during the growing season based on yield affecting variables, including climate or weather observations, satellite products and drought indices (Boken, 2000; Boken & Shaykewich, 2002; Kumar & Panu, 1997). The dynamical model can also be applied to predict the drought impact based on crop yield by linking climate forecasts, hydrologic models, and crop models (Shafiee-Jood et al., 2014). Due to the different formats of data sources related to drought impacts, novel methods that handle both the qualitative and quantitative data are needed for predicting drought impacts.

8.7. Probabilistic Drought Prediction

The probabilistic drought prediction with uncertainty quantification is needed to facilitate drought early warning. Due to the chaotic nature of the climate system and limitation of the current prediction capability, it is generally appropriate to characterize forecasts in a probabilistic way. In addition, end users' decision making generally requires probabilistic forecasts with quantitative information regarding forecast uncertainty (Demargne et al., 2014). A probabilistic forecast can be characterized in different forms, including the full PDF, the probability of falling in different categories, or the ensemble mean and variance (Stockdale et al., 2010). Providing the PDF of forecasts of drought indicators, from which the prediction interval and the probability of exceeding (or below) a certain threshold can be achieved (Behrangi et al., 2015; Hao, Hao, Singh, Sun, et al., 2016; Mendoza et al., 2015; Pan et al., 2013; Scheuerer, 2014), is popular in probabilistic drought prediction.

With advances of dynamical forecast from multiple climatic and hydrologic models, the probabilistic drought prediction is generally achieved through the multimodel ensemble, from which the sample of ensemble members can be used to obtain the probabilistic information of drought prediction. In addition, statistical models can also be used to achieve the probabilistic drought prediction by deriving the distribution of the predictand. For example, the BMA can be used to calibrate and merge forecast to produce probabilistic distributions of the forecast (Raftery et al., 2005). For the regression model, the probabilistic forecast of the predictand can be constructed through distributional assumptions of error terms (Hao, Hong, et al., 2016; Hwang & Carbone, 2009). For the conditional probability model, probabilistic forecasts can be achieved by constructing conditional distribution functions of the predictand with respect to predictors (Hao, Hao, Singh, Ouyang, & Cheng, 2017; Liu et al., 2016). Probabilistic drought prediction provides more values than a deterministic forecast and is easier for decision makers to understand.

9. Conclusions

This study reviewed recent developments of seasonal drought prediction methods from statistical and dynamical perspectives. The large scale circulation patterns, land surface interactions, and land initial conditions provide important predictability of drought at the seasonal time scale. Meanwhile, a variety of important contributing factors, including local climate, evaporation changes, and human activities may maintain or amplify different types of drought (Schubert et al., 2016; Peterson, Heim, et al., 2013). Seasonal drought prediction mainly focuses on fully utilizing these predictability sources or contributing factors operating at local, continental, or global scales to facilitate drought prediction at seasonal time scales. For the statistical prediction, these predictability sources and contributing factors are mainly represented as oceanic, atmospheric, or hydrologic predictors and are then fed to a forecast model with the key task to model linear or nonlinear relationships between the predictand and predictors. For the dynamical prediction, GCMs and hydrologic models parameterize physical processes in climatic and hydrologic systems for predicting droughts of different types. Comparison of dynamical and statistical prediction methods reveals the differences in the requirement of computing resources and ability to model complicated interactions. This motivates the integration of both methods to combine drought forecasts from different sources for improving drought prediction.

It has been generally well recognized that drought occurrence is associated with anomalous moisture transport that is linked to large-scale climate phenomena through atmosphere-ocean teleconnection with drought severity and duration affected by land surface feedback, which may also be influenced by human activities or global warming (Peterson, Heim, et al., 2013; Yuan, Roundy, et al., 2015). Despite substantial progress in the understanding of drought-causing mechanisms and modeling of drought from statistical and dynamical approaches, challenges of drought prediction still exist and may hinder the achievement of the upper limit of predictabilities. The current skill of drought forecasting at the seasonal time scale is mainly limited to tropical or subtropical regions due to its strong teleconnection with ENSO, or relies on land surface memory in midlatitude regions (Pozzi et al., 2013). There is still deficiency in skillful seasonal precipitation (or meteorological drought) prediction for long lead time due to the chaotic nature of the atmosphere, which also affects the skillful prediction of agricultural and hydrological droughts. Natural and anthropogenic climate change has altered the hydrological cycle and poses challenges to drought prediction due to the nonstationarity in hydroclimatic interactions, which necessitate the building of statistical and dynamical models to capture complex interactions and incorporate human activities. Improved drought prediction requires a deep understanding of drought mechanism, refined observations from data assimilation, better models through parameterizing key components in natural and anthropogenic systems, novel methodologies to select ensembles and combine forecasts from multiple sources, and suitable uncertainty quantification through probabilistic prediction. These efforts are of particular importance for improving drought prediction, especially in regions or seasons with low climate or drought predictability.

We stress that drought prediction studies will benefit not only the drought research community but also other sectors related to natural hazards, such as flood or wildfire (Gill & Malamud, 2014). For example, wildfires can occur and spread easily during drought conditions, leading to the destruction and degradation of forest ecosystems. Thus, the improved prediction of drought may contribute to the wildfire prediction (Gudmundsson et al., 2014; Stagge et al., 2015). Moreover, statistical and dynamical methods presented in this study would also benefit the prediction of other hydroclimatic phenomena or extremes, such as flood. At last, the transition of drought prediction to decision makers is an essential element in early drought warning and risk management. Apart from the investment into better data, models, and methodologies in drought prediction, it is of equal importance to enhance the coordination and communication between scientists and decision makers and deliver drought prediction information in a user friendly manner.

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