AN OVERVIEW OF DROUGHT MONITORING AND PREDICTION SYSTEMS AT REGIONAL AND GLOBAL SCALES

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The drought monitoring and prediction/forecast systems at regional and global scales are reviewed for both research and decision-making communities.

Drought has plagued civilizations throughout the course of human history. It is one of the most damaging natural hazards with profound impacts on different sectors, resulting in agricultural losses, water scarcity, and famine (Sheffield and Wood 2012; Smith and Katz 2013). Severe drought events in recent decades and huge damages, along with the potential increase of drought frequency and severity due to climate change (Dai 2011), have highlighted the urgent need for drought-prone countries to establish effective drought early-warning systems that incorporate accurate drought monitoring, reliable drought prediction, and effective information dissemination to assist decision-makers for drought planning and mitigation.

Drought is difficult to measure or even to define, which hinders approaches for accurate drought characterizations. The need to monitor complicated drought conditions has spurred a multitude of efforts to develop drought indicators based on different applications, regions affected, and data availability (Heim and Brewer 2012; Mishra and Singh 2010; Wilhite 2006), which take into account a variety of hydroclimatic variables, such as precipitation, soil moisture, streamflow, snow, groundwater, evapotranspiration, and vegetation. Meanwhile, reliable prediction of drought onset, development, and recovery are an important step toward effective early warnings, which can be achieved through either statistical approaches to explore empirical relationships in historical records or dynamical approaches based mostly on state-of-the-art general circulation models (GCMs).

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Extensive efforts have been devoted to drought information dissemination and monitoring and prediction studies in recent decades to reduce drought vulnerability through a proactive risk management approach. A suite of drought monitoring and prediction systems (DMAPS) has been developed to monitor and provide early warning of drought conditions at regional (Funk 2009; Luo and Wood 2007; Lyon et al. 2012; Sheffield et al. 2014; Svoboda et al. 2002; Wood and Lettenmaier 2006; Xia et al. 2014b) and global scales (Hao et al. 2014; Nijssen et al. 2014; Yuan et al. 2015a). These systems differ in several aspects (e.g., indicator, resolution) and play an important role in helping decision-makers for drought management. Meanwhile, scientific and technical challenges still exist in developing and implementing DMAPS, such as inconsistency in data availability, lack of universally accepted indicators, and limitation in drought prediction skill, which need to be addressed for improved drought planning and management.

The aim of this study is to provide an overview of the development of DMAPS at regional and global scales with focus on scientific and technical aspects, including advances and challenges in drought monitoring and prediction. The remaining sections introduce the basic components of drought monitoring and prediction in the development of DMAPS, provide recent developments of DMAPS at regional and global scales, discuss advances and challenges, and summarize our main conclusions.

OVERVIEW OF DROUGHT MONITORING AND PREDICTION.

Drought definition and indicator. The lack of precise and universally accepted definition of drought hinders the investigation of drought. Usually definitions of drought can be divided into four types, including meteorological, agricultural, hydrological, and socioeconomic drought, from the disciplinary perspective (Heim 2002; Keyantash and Dracup 2002; Wilhite and Glantz 1985). Various drought indices

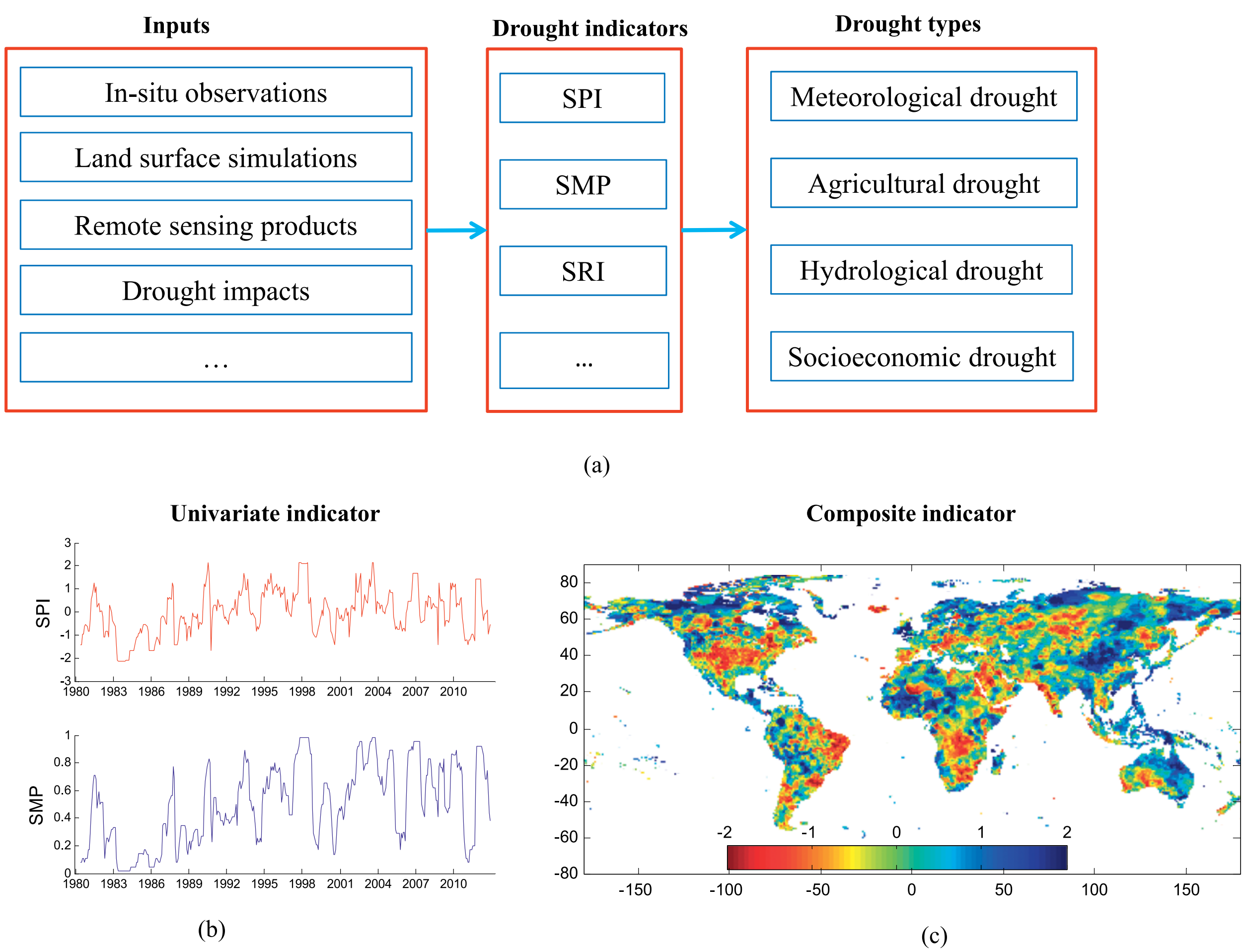

Fig. 1. (a) General concept in developing drought indicators to monitor different drought types with various inputs [SPI, soil moisture percentile (SMP), and standardized runoff index (SRI)]. (b) Monitoring meteorological and agricultural drought based on (top) SPI and (bottom) SMP. (c) Global drought monitoring for Aug 2012 with the composite indicator MSDI.

have been developed for characterizing each type with different inputs (Fig. 1a). Developing and selecting drought indicators that are widely accepted and suitable for specific regions and applications are basic elements of drought monitoring and prediction. The standardized precipitation index (SPI) was recommended at a World Meteorological Organization (WMO) meeting as the primary meteorological drought index to track the meteorological drought, while no consensus has been reached on standard indices for agricultural or hydrological drought monitoring (Hayes et al. 2011). A single drought indicator rarely works for all places/seasons for all types of drought, and a variety of multivariate or composite drought indices have been developed in the past decade by integrating a suite of hydroclimatic variables or indices for comprehensive drought monitoring (Figs. 1b,c; Hao and Singh 2015). Meanwhile, the threshold value of drought indicators, or the drought trigger, for defining drought categories or classes (e.g., moderate or severe drought) has also been studied to characterize drought conditions to aid drought response actions (Steinemann and Cavalcanti 2006; Steinemann et al. 2015). However, no consensus has been reached so far for an objective threshold value.

Drought monitoring. Traditional drought monitoring is generally based on in situ observations of hydroclimatic variables from observation networks at local scales, which falls short in drought characterization at regional scales due to sparse observation (e.g., soil moisture) networks. Substantial advances have been achieved in the availability of various datasets for monitoring drought, including remote sensing products, land surface model simulations, and impact data. Remote sensing provides continuous and consistent observations with increasing availability for drought characterizations at regional and global scales, especially for regions with no or sparse in situ observations (Hao et al. 2016d; Wardlow et al. 2015, 2012; Tang et al. 2009). These remote sensing products have led to new developments in drought monitoring, such as those based on the normalized difference vegetation index (NDVI), the evaporative stress index (ESI), and total storage anomaly measurements from the National Aeronautics and Space Administration (NASA)'s Gravity Recovery and Climate Experiment (GRACE; Anderson et al. 2011; Brown et al. 2008; Houborg et al. 2012; Kogan 1997; Mu et al. 2013; Thomas et al. 2014), for which improved accuracy with suitable corrections and extended record through integration with other sources of datasets are generally desirable. Moreover, accurate drought monitoring requires us to track the propagation of drought through the hydrological cycle. Land surface model (LSM) simulations provide opportunities to continuously track multiple hydrologic flux and state variables and are of particular importance in this regard for integrated drought modeling and analysis (Mo and Lettenmaier 2014; Sheffield et al. 2012; Shukla et al. 2011; Xia et al. 2014a). For example, the monitoring of the drought conditions on 20 September 2011 in the United States is shown with the total column soil moisture from the North American Land Data Assimilation System (NLDAS-2) in Fig. 2, in which the 2011 Texas drought is clearly identified. Monitoring drought impacts on the environment and society (e.g., crop yield failure, vegetation stress, and water quality degradation) also emerges and has been recognized as a critical component of drought early-warning systems (DEWS; Svoboda et al. 2002; Hayes et al. 2011; Lackstrom et al. 2013; Bachmair et al. 2016).

To characterize complicated processes and impacts of drought, integrated drought monitoring based on the composite or multivariate drought indicator from various sources has been used. The U.S. Drought Monitor (USDM), developed in 1999, is a landmark contribution in this regard, which blends multiple physical drought indicators and reported impacts with experts' inputs to characterize drought conditions. It has been widely used by media, researchers, policy makers and planners, water and natural resource managers, and authorities [e.g., U.S. Department of Agriculture (USDA)] for various applications, including drought relief allocation and disaster declarations and responses (Svoboda 2015; Svoboda et al. 2002). For example, a USDM map with severity labeled with categories from least to most intense (D0–D4) for the week of 28 August 2012 is shown in Fig. 3 (top). It clearly indicates the severe drought conditions that struck the central United States. Integration of various data sources without losing the advantages of USDM products is desirable and also an outstanding challenge (Wood et al. 2015). Certain efforts have been developed to address this need recently (Hao et al. 2016b,c; Xia et al. 2014b). For example, an ordinal regression approach has been proposed recently to model drought categories with respect to multiple drought indices by estimating probabilities of drought categories falling in each category (shown in Fig. 3, bottom left). The reconstructed percentage areas of different drought categories from this approach based on NLDAS-2 drought indices are shown in Fig. 3 (bottom right), which are generally close to the observations from USDM for the common period 1999–2013. Such

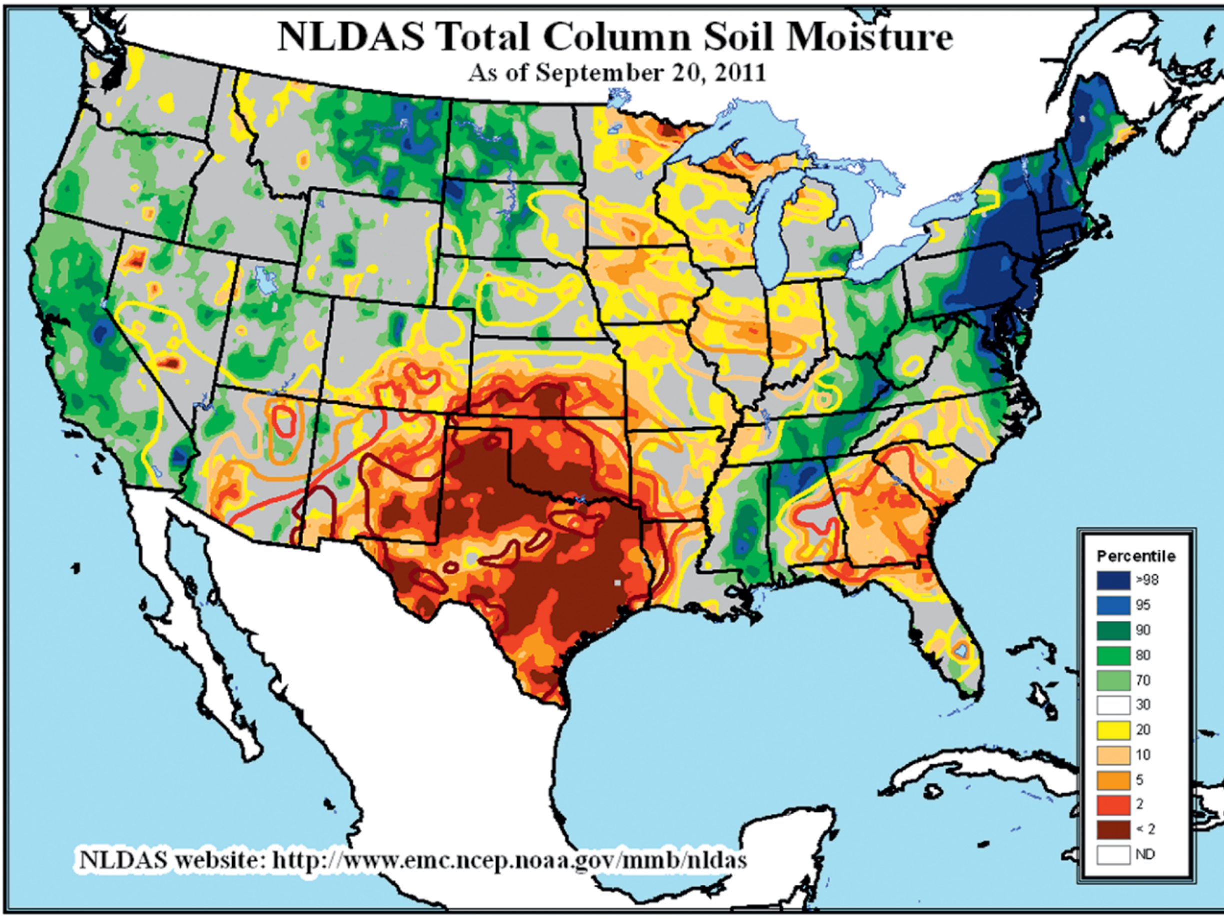

Fig. 2. Drought monitoring on 20 Sep 2011 in the United States based on total column soil moisture percentile (shading) from NLDAS-2 (courtesy of Eric Luebehusen).

constructions are useful for historical drought assessments in the United States for the period prior to the development of USDM. Research along this line also includes the reproducible and automated approaches for combining different physical indicators (Vicente-Serrano et al. 2010; Hao and Singh 2015; Mo and Lettenmaier 2014), such as the multivariate standardized drought index (MSDI) or the standardized precipitation evapotranspiration index (SPEI), for the integrated drought monitoring. For example, the MSDI (rescaled with the percentile approach; Hao et al. 2016a) for August 2012 at the global scale is shown in Fig. 1c, which is computed based on monthly precipitation and soil moisture data from the land surface reanalysis datasets Modern-Era Retrospective Analysis for Research and Applications (MERRA-Land; Reichle et al. 2011). Generally, the 2012 U.S. drought is captured by MSDI, though some differences in intensities may exist compared with USDM. Because of the limitation of individual drought indicators, usually a collection of them have to be continuously monitored. Moreover, the percentile-based approach allows for comparing and consolidating different drought indicators and has been commonly used in drought monitoring.

Drought prediction. Either based on statistical or dynamical approaches, the drought prediction problem essentially boils down to the forecast of several crucial meteorological variables (i.e., precipitation and temperature). Statistical approaches, such as the regression model and ensemble streamflow prediction (ESP), are mostly based on empirical relationships in historical records without considering underlying physical mechanisms and have been used in the development of several DMAPS (Hao et al. 2014; Lyon et al. 2012). These approaches remain useful partly due to their ease of implementation. Drought forecasts from these approaches are generally used as a baseline/benchmark for dynamical forecasts and may provide complementary forecast information in certain seasons and/or regions.

Dynamical approaches rely on GCMs (extended weather forecast models or seasonal climate models),

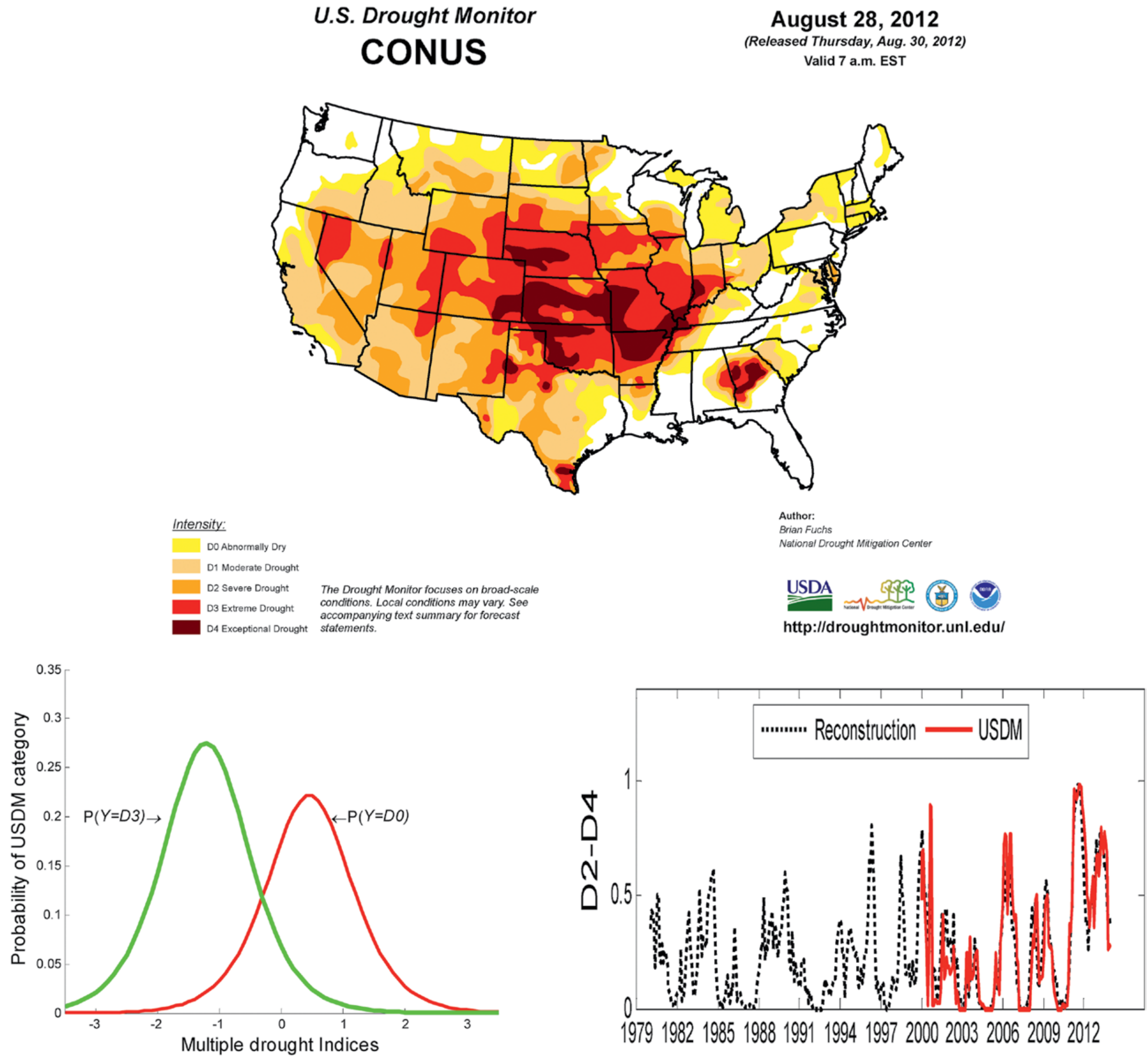

Fig. 3. (top) The U.S. Drought Monitor map for the week of 28 Aug 2012 [adapted from U.S. Drought Monitor website: http://droughtmonitor.unl.edu/; map courtesy of National Drought Mitigation Center (NDMC) of the University of Nebraska–Lincoln (UNL)]. (bottom left) Illustration of the ordinal regression approach to estimate probability of drought categories. (bottom right) Drought area percentage of drought categories (D2–D4) from USDM and reconstruction from the ordinal regression approach based on NLDAS-2 for the period 1979–2013 in Texas.

which are generally based on physical processes of atmosphere, ocean, cryosphere, and land surface and are the most advanced tools for climate (and meteorological drought) forecast (Quan et al. 2012; Yoon et al. 2012; Yuan and Wood 2013; Schubert et al. 2016). For these approaches, the seasonal climate predictability comes from the memory in tropical oceans via ocean–atmosphere teleconnections and from regional precursors such as stratospheric condition and soil moisture anomaly (Kirtman and Pirani 2009; Yuan et al. 2015a,b). Because of the limitation of coarse resolution and systematic model errors (Roundy et al. 2015), extra procedures, such as bias correction and downscaling, are required for coupling with the hydrologic model and matching the performance of statistical approaches. When driven by meteorological forcing from the dynamical climate forecast (or observations), hydrological models or land surface models can be used to transfer the climate anomaly to hydrological state/flux variations for agricultural and hydrological drought characterization (Mo et al. 2012b; Thober et al. 2015; Wood et al. 2002; Yuan et al. 2013). Meanwhile, characterizing uncertainties associated with hydroclimatic predictions from

Table 1. Examples of regional drought monitoring and prediction systems around the globe. Abbreviations indicate the following: combined drought indicator (CDI), comprehensive index (CI), evapotranspiration *E*, evaporative stress index (ESI), fraction of absorbed photosynthetically active radiation (fAPAR), normalized difference vegetation index (NDVI), precipitation *P*, runoff *R* (or streamflow), soil moisture *S*, standardized precipitation index (SPI), standardized soil moisture index (SSI), standardized runoff index (SRI), snow water equivalent (SWE), and soil moisture index (SMI).

System	Region	Indicator	Time scale	Resolution	Reference and/or website
U.S. Drought Monitor	United States	Category	Weekly	—	Svoboda et al. (2002); http://droughtmonitor.unl.edu/
North American Drought Monitor	North America	Category	Monthly	—	Lawrimore et al. (2002); www.drought.gov/nadm/
The Princeton U.S. Drought Monitoring and Prediction System	United States	Percentile of *P*, *S*, SWE, and *R*	Monthly	0.125°	Luo and Wood (2007); http://hydrology.princeton.edu/forecast/current.php
NLDAS Drought Monitor and Seasonal Drought Forecast	United States	Percentile (anomaly) of *P*, *E*, *R*, and SWE	Daily, weekly, monthly	0.125°	Sheffield et al. (2012); Xia et al. (2014b); www.emc.ncep.noaa.gov/mmb/nldas/drought; www.emc.ncep.noaa.gov/mmb/nldas/forecast/TSM/prob/
U.S. Monthly (Seasonal) Drought Outlook	United States	Drought tendency	Monthly, seasonal	—	www.cpc.ncep.noaa.gov/products/Drought/
University of Washington Surface Water Monitor	United States	SPI, SRI, percentile of *S*, *R*, and SWE	Weekly, monthly	0.5°	Wood (2008); Wood and Lettenmaier (2006); www.hydro.washington.edu/forecast/monitor
Evaporative stress index	United States, North America, and South America	ESI	Weekly, monthly	0.098°	Anderson et al. (2011); https://hrsl.ba.ars.usda.gov/drought/
U.S.–Mexico Drought Prediction Tool	United States and Mexico	SPI	Monthly	0.5°	Lyon et al. (2012); Quan et al. (2012); http://iridl.ldeo.columbia.edu/maproom/Global/Drought/N_America/index.html
African Drought Monitoring and Forecasting System (Africa Flood and Drought Monitor)	Africa	SPI, percentile of *S* and *R*, NDVI, and so on	Daily, monthly	0.25°	Sheffield et al. (2014); http://stream.princeton.edu/AWCM/WEBPAGE/interface.php?locale=en
European Drought Observatory	Europe	Drought tendency, SPI, *S*, fAPAR, CDI	Daily, 10 day, monthly	—	http://edo.jrc.ec.europa.eu/edov2/php/index.php?id=1000
Experimental Drought Monitor for India	India	SPI, SSI, SRI	Monthly	0.25°	Shah and Mishra (2015);
German Drought Monitor	Germany	Drought category based on SMI	Daily	4 km	Zink et al. (2016); www.ufz.de/droughtmonitor
Drought Monitoring System for China	China	Drought category, CI, SPI	Daily	—	http://cmdp.ncc-cma.net/en/

various sources is important for assessing the reliability of drought prediction products. The Hydrological Ensemble Prediction Experiment (HEPEX; www.hepex.org/) includes important initiatives in this regard toward improving ensemble forecasts and uncertainty quantification with various post-processing procedures for hydrologic forecast of rare events, including droughts and floods (Schaake et al. 2007; Demargne et al. 2014; Van Lanen et al. 2016). Because statistical and dynamical approaches come with specific strengths and limitations in their own rights, integration of both methods (or the hybrid statistical–dynamical method) can be included in the development of DMAPS for early warning.

REGIONAL DROUGHT INFORMATION SYSTEMS. In the past decades, the development of DMAPS has been achieved in many regions or countries (Heim and Brewer 2012), including the United States (Svoboda et al. 2002), Europe (e.g., European Drought Observatory; Acácio et al. 2013; Vogt et al. 2011), China, and Africa (Sheffield et al. 2014; Shukla et al. 2014). For example, in the United States, the National Integrated Drought Information System (NIDIS; www.drought.gov) provides a suite of drought systems and indicators for drought monitoring and forecasting, such as the North American Drought Monitor, U.S. Drought Monitor, and surface water supply index (SWSI). Certain regions or countries affected by recurring drought have not established comprehensive drought information systems, such as parts of South America (Pulwarty and Sivakumar 2014). Because of the diversity of climate across the world, the development and implementation of regional DMAPS need to be appropriate for the region in question (Heim and Brewer 2012; Svoboda et al. 2015). An example would be the DMAPS for the western United States that uses SWSI to incorporate snowpack information.

Table 1 lists parts of the regional DMAPS developed in recent years in different regions of the world, which monitor different aspects of drought, including the vegetation condition. This list is not meant to be comprehensive but illustrative of the recent development of DMAPS. At the regional scale (except for regions with sparse observation networks, such as Africa), monitoring and prediction of different components of the hydrological cycle can be achieved using hydrologic models (coupled with climate forecast) with a relatively long-term record, which is a salient nature of most regional systems in Table 1. An extended data record can generally be achieved by integrating ground observations, model simulations, and remote sensing products for drought modeling and assessment (Houborg et al. 2012; Sheffield et al. 2012). Accordingly, the comprehensive characterization of different aspects or types of drought is generally feasible. In the United States, for example, the Princeton DMAPS (Luo and Wood 2007) has been developed to take advantage of available observational networks, state-of-the-art land surface and climate models, and innovative statistical methods to monitor and predict a suite of drought indices to facilitate drought characterization in multiple aspects. Moreover, drought conditions related to vegetation or evapotranspiration have also been monitored with drought indices from remote sensing products, such as NDVI or ESI.

Besides using drought indicators on a continuous scale to assess the magnitude, discrete drought categories (or classes based on certain triggers) have also been included in drought monitoring (Lawrimore et al. 2002; Svoboda et al. 2002; Sepulcre-Canto et al. 2012; Zink et al. 2016), which are useful to trigger responses in drought management (Steinemann and Cavalcanti 2006). The USDM drought category has been used as a benchmark for developing categorical DMAPS in the United States, either through optimizing drought area percentage (Xia et al. 2014b) or regressing drought categories with USDM as the initial condition (Hao et al. 2016b). For example, an automated approach was developed recently to objectively generate and reconstruct USDM-style drought maps with the objective blended NLDAS drought index (OBNDI) based on NLDAS-2 data by minimizing the differences with USDM drought area percentages (Xia et al. 2014b). This method was used to reconstruct the USDM drought categories for 1988 based on drought indices from NLDAS-2 (Fig. 4), which generally depicted the severe drought condition during the dry period of 1988 in the United States. Apart from monitoring the current status of drought, the drought tendency (e.g., persistence, improvement, or recovery) has also been used to monitor the evolution of drought conditions, as shown in the U.S. Monthly (Seasonal) Drought Outlook (www.cpc.ncep.noaa.gov/products/Drought/). However, common to all these drought information systems is that mostly physical indicators are used for drought characterization, while drought impacts are rarely incorporated into the system, except for a few drought information systems, such as USDM through the Drought Impact Reporter (DIR; Svoboda et al. 2015). Along with the progress in developments of drought information systems, the transition of advances in DMAPS into operations has been achieved and used operationally to aid decision-making. One of the recent advances in this regard is the transition of experimental hydrological prediction systems from Princeton University to the National Centers for Environmental Prediction (NCEP) of the National Oceanic and Atmospheric Administration (NOAA) as part of the NOAA Climate Test Bed (Huang et al. 2016; Wood et al. 2015).

GLOBAL DROUGHT INFORMATION SYSTEMS. The development of an experimental global drought information system (GDIS) with real-time monitoring and forecasts has recently been recommended and promoted (Heim and Brewer 2012; Pozzi et al. 2013).This is challenging mainly because of the lack of near-real-time forcing datasets of long-term historical records of the global coverage. Because satellite remote sensing precipitation provides the only practical way to measure precipitation on a

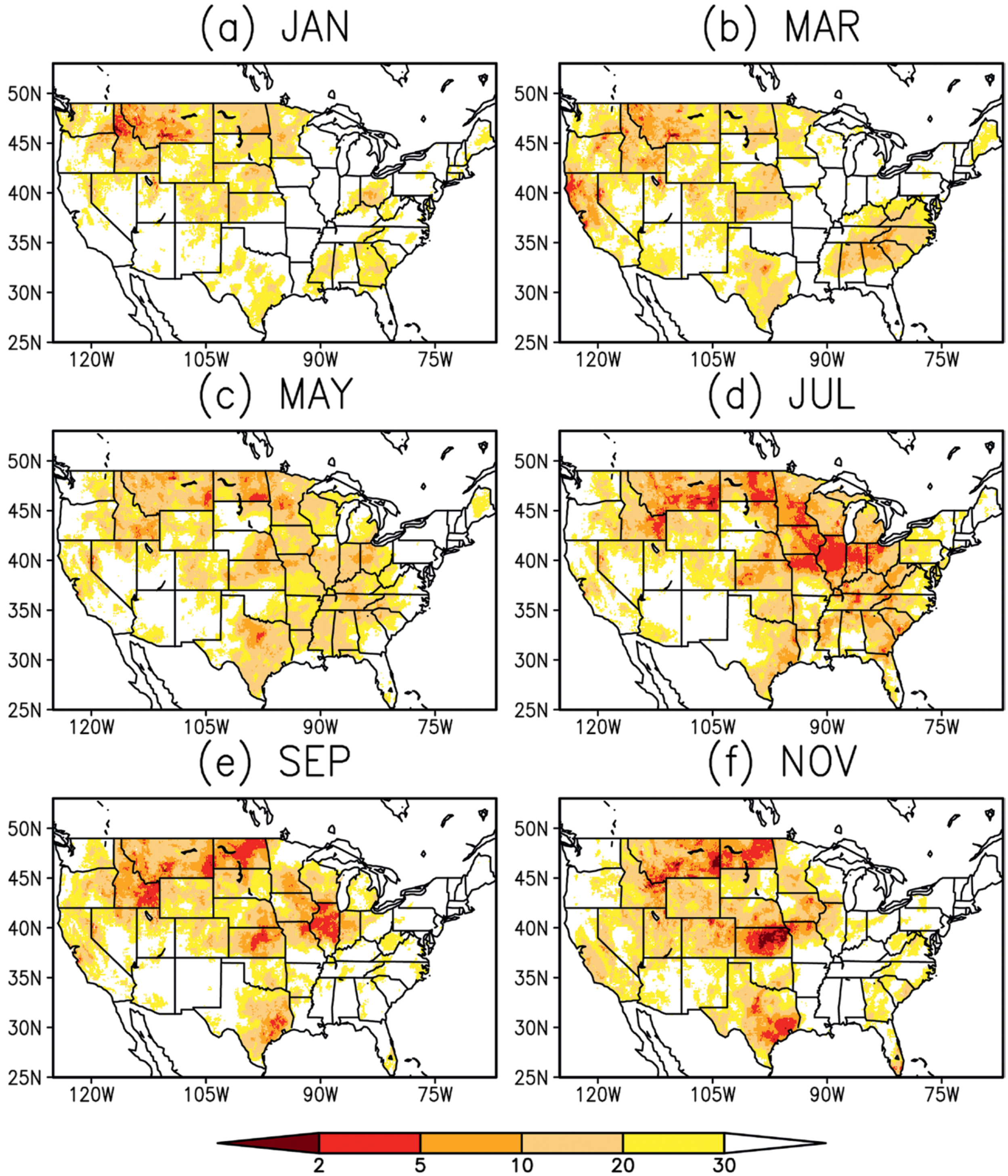

Fig. 4. Reconstructed drought categories from OBNDI for 1988 based on land surface model simulations from NLDAS-2 [modified from Xia et al. (2014b)].

global basis (Yong et al. 2015), the development of a comprehensive DMAPS of the global coverage can only be achieved by reconstructing long-term records through integrating remote sensing products with ground-based observations and land surface model simulations (Pozzi et al. 2013).

For illustrative purposes, Table 2 lists DMAPS at the global scale that are mostly updated consistently. Global drought monitoring is in its early stages and is mainly focused on the meteorological drought (or drought related to vegetation; Dutra et al. 2014a; Vicente-Serrano et al. 2010; Ziese et al.

TABLE 2. Examples of global drought monitoring and prediction systems. Abbreviations indicate the following: drought severity index (DSI), Global Precipitation Climatology Centre drought index (GPCC-DI), multivariate standardized drought index (MSDI), Palmer drought severity index (PDSI), standardized precipitation evapotranspiration index (SPEI), temperature condition index (TCI), vegetation condition index (VCI), and vegetation health indices (VHI). (Abbreviations *P*, *R*, *S*, *E*, SPI, SRI, SSI, SWE, and NDVI are explained in Table 1.)

System	Indicator	Time scale	Resolution	Reference and/or website
NOAA/NESDIS Global Vegetation Health products	VCI, TCI, VHI, NDVI	Weekly	4 and 16 km	www.star.nesdis.noaa.gov/smcd/emb/vci/VH/vh_browse.php
SPEI Global Drought Monitor	SPEI	Monthly	0.5°	Vicente-Serrano et al. (2010); http://sac.csic.es/spei/
Global terrestrial drought severity index	DSI	8 days, annual	0.05°, 0.5°	Mu et al. (2013); www.ntsg.umt.edu/project/dsi
Global Drought Monitoring Portal	SPI	Monthly	—	www.drought.gov/gdm/
Global Integrated Drought Monitoring and Prediction System	SPI, SSI, MSDI	Monthly	0.5°, 2/3° × 1/2°, 1°, 2.5°	Hao et al. (2014); http://drought.eng.uci.edu/
GPCC drought index product	GPCC-DI	Monthly	1°	Ziese et al. (2014); ftp://ftp.dwd.de/pub/data/gpcc/html/gpcc_di_doi_download.html
Multimodel GDIS	Percentile of *S*, SWE	Monthly	0.5°	Nijssen et al. (2014)
Princeton's Global Seasonal Hydrologic Forecast System	Percentile of *S* and *R*	Monthly	1°	Yuan et al. (2015a); http://hydrology.princeton.edu/

2014). Advances in remote sensing in recent decades have resulted in several global drought monitoring systems for monitoring drought conditions related to vegetation or evapotranspiration (Kogan 1997; Mu et al. 2013). Hydrological and agricultural droughts are more difficult to monitor at global scales as compared with those at regional scales because of the lack of long-term forcing datasets at the global scale to provide inputs to land surface models. Few DMAPS have been developed to monitor different components of the hydrological cycle at the global scale (Hao et al. 2014; Nijssen et al. 2014; Yuan et al. 2015a).

The advances of seasonal climate forecast, such as the NCEP Climate Forecast System (CFS), the North American Multimodel Ensemble (NMME), and the European Centre for Medium-Range Weather Forecasts (ECMWF) have enabled drought prediction at the global scale, and thus the development of global drought forecast/prediction component is feasible. As shown in Fig. 5, Princeton's Global Seasonal Hydrologic Forecast System (Yuan et al. 2015a) uses meteorological ensemble forecasts from NMME to drive the Variable Infiltration Capacity (VIC) land surface hydrologic model and forecast hydrologic extreme events. As compared with the ESP forecasts over global large river basins, the multimodel global seasonal forecast system provides better detection of soil moisture droughts, more reliable hydrologic drought forecast products, and a better real-time prediction for the 2012 North American extreme drought (Yuan et al. 2015a). Currently, drought prediction in the global systems is mainly focused on drought indices, such as SPI or the percentile of soil moisture/runoff, while drought tendency (e.g., onset, persistence, or recovery; Pan et al. 2013; Yuan and Wood 2013) and impacts need more investigation.

DISCUSSION.

Advances. INTEGRATED DROUGHT MONITORING. Reliable drought monitoring requires the integration of multiple hydroclimatic variables or indices from different sources to track multiple aspects of drought. Merging in situ observations, remote sensing products, land surface model simulations, and climate forecasts with methods such as data assimilation for drought monitoring (and prediction) is an important advance in the development of DMAPS. These data products for drought characterization are not only on a monthly basis but may also be available on a weekly or daily scale with refined spatial resolution (e.g., 4 km). With advances in data products and tools, the development of composite drought indicators for comprehensive drought characterization has been active in the past decade with substantial progress in approaches to combine multiple indicators. A variety of drought indicators have been continuously tracked and

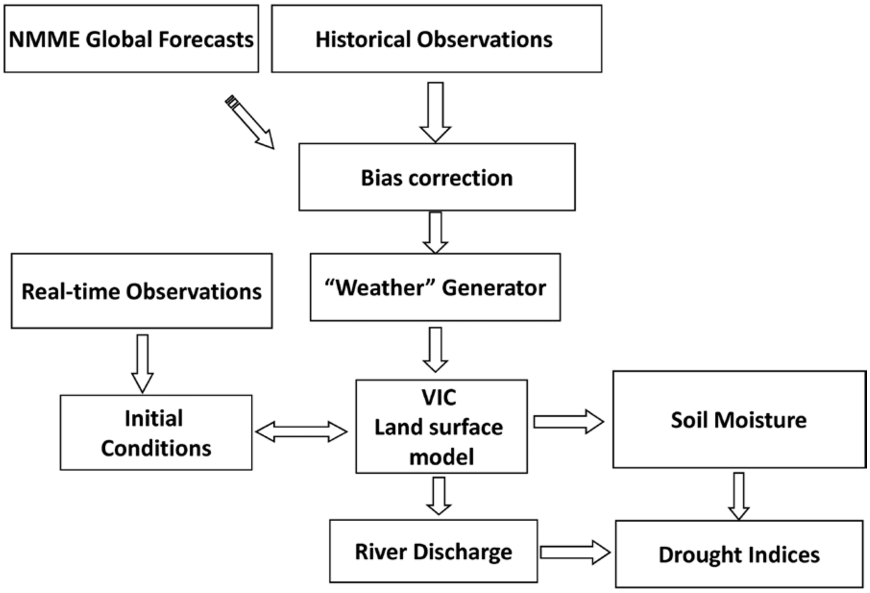

Fig. 5. Framework of the Princeton's Global Seasonal Hydrologic Forecast System. The system is based on a land surface hydrologic model and multiple global climate forecast models participating in the NMME project [revised from Yuan et al. (2015a)].

displayed in map or other forms to monitor various aspects of drought, including severity, duration, spatial extent, onset, development, recovery, and impacts as well. In addition, incorporating user preferences and feedback into the development (and evaluation) of drought indicators has also emerged to aid decision-making for operational drought management (Schubert et al. 2007; Steinemann et al. 2015; Bachmair et al. 2016).

Multimodel ensemble drought prediction. Significant advances have been achieved in developing better general circulation models for seasonal climate and drought prediction (Mariotti et al. 2013; Mishra and Singh 2011; Pozzi et al. 2013), for which the multimodel ensemble has been among the most recent advances, either through multiple GCMs or multiple LSMs. For example, phase 1 of the NMME projects (Kirtman et al. 2014) released three decades of seasonal hindcast datasets that are widely used for drought diagnosis from climate and hydrologic perspectives (Mo and Lyon 2015; Yuan et al. 2015a). As NMME is entering into the second stage, high-temporal-frequency datasets are being made available, and the process-based drought predictability studies (e.g., ocean–atmosphere and land–atmosphere interactions) by using NMME hindcasts become feasible.

Assessment of the drought prediction skill based on hindcasts from climate models generally shows the added value from the multimodel ensemble drought forecasting (Huang et al. 2016; Kirtman et al. 2014; Yuan and Wood 2013). Figure 6 shows real-time forecasting of a severe drought that occurred over southern China during the summer of 2013. NOAA/NCEP's operational seasonal climate forecast model CFS, version 2 (CFSv2), predicted a broad drought condition over eastern China but did not capture the center of the drought over the middle and lower reaches of the Yangtze River basin (Figs. 6a,b). It even provided a false alarm over northern China where drought did not occur (Fig. 6b). By averaging CFSv2 and five other NMME climate forecast models, the wet–dry dipole pattern over the northern and southern parts of China was captured well (Fig. 6c). The multimodel ensemble not only provides an improved forecast skill but also helps the uncertainty quantification of drought prediction. Considering the inherent uncertainties from difference sources, such as seasonal climate forecasting, land surface simulations, and model structure, it is important to enhance probabilistic drought forecast with multimodel ensemble techniques to aid decision-making, which is an important step to bridge the gaps between the hydroclimatic forecasts and needs of stakeholders/users.

Challenges and opportunities. Near-real-time and long-term data products. The reliability and accuracy of DMAPS largely depend on the availability and quality of hydroclimatic observations (or simulations) and impact data. Providing near-real-time and long-term data products of finer temporal resolution is desirable and challenging for the development of DMAPS, especially at the global scale. The consistency between historical drought conditions and real-time monitoring and prediction is a key issue faced by nearly all real-time regional and global DMAPS (Huang et al. 2016; Wood et al. 2015). This has been partly addressed in several drought information systems (Sheffield et al. 2014; Wood 2008) either based on merging historical records with near-real-time remote sensing precipitation estimation

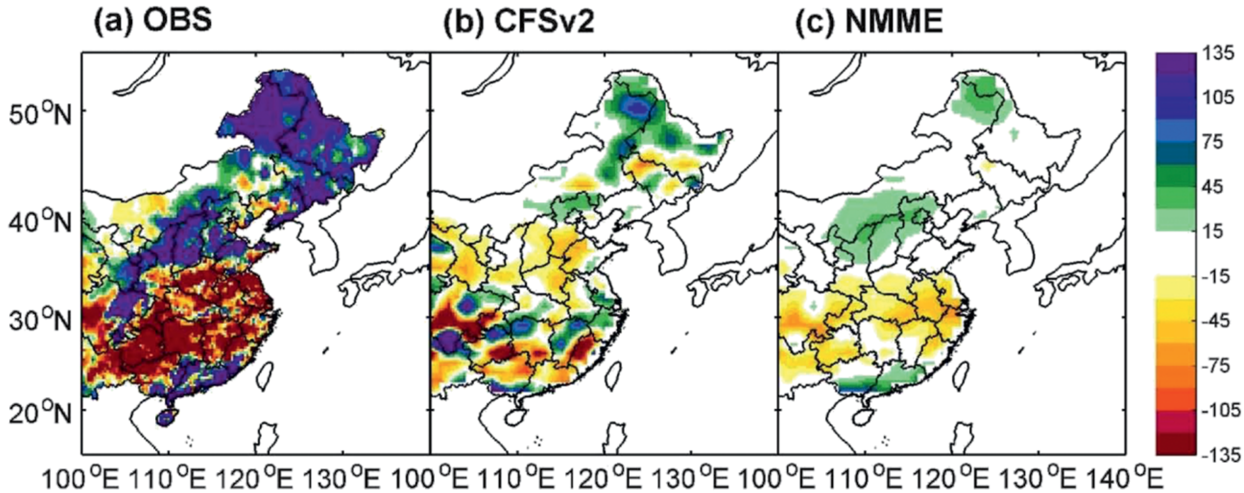

Fig. 6. (a) Observation and (b),(c) real-time forecasting of seasonal-mean precipitation anomaly (mm) over eastern China during June–August (JJA) 2013 based on seasonal CFSv2 and NMME.

(Nijssen et al. 2014) or short-range forecasts (Dutra et al. 2014a,b). For example, the multimodel GDIS developed at the University of Washington (Nijssen et al. 2014) is based on three separate datasets, including the Princeton forcing dataset (Sheffield et al. 2006; extended through 2008); the Tropical Rainfall Measuring Mission (TRMM) Multisatellite Precipitation Analysis, version 7, research quality product (Huffman et al. 2007; available with a time lag from a few weeks to months); and the TMPA real-time product. In addition, since drought is always defined in relative terms, an inherent and particular requirement of the dataset for drought monitoring is a relatively long record (generally 30 years of records are required) to facilitate retrospective analysis. To provide the long record of climatology (and/or to improve the accuracy), considerable efforts have been devoted to combining or merging different datasets of different temporal/spatial scales or lengths with methods such as data assimilation (AghaKouchak and Nakhjiri 2012; Dorigo et al. 2015; Dutra et al. 2014a; Kumar et al. 2014; Sheffield et al. 2006). Moreover, data products of higher spatial resolutions are increasingly required for the local-scale drought assessment (e.g., 1-km subcounty level or 100-m field level), which is primarily achieved through satellite imagery (Wardlow et al. 2012).

Currently, remote sensing products for drought monitoring are subject to few challenges, including short-record temporal inhomogeneity due to changes of observing platforms and inherent inaccuracies (Sheffield et al. 2014; Wardlow et al. 2012), while for the land surface model simulations, certain limitations still exist, such as different simulations from even the identical forcing datasets due to different hydrologic parameterizations (Mo et al. 2012a; Nijssen et al. 2014). How to merge different datasets (e.g., in situ observations, remote sensing, land surface model simulations, and weather and climate forecasts) with improved accuracy/resolution to develop near-real-time and long-term products and to maintain consistency with the historical condition needs to be explored.

Drought indicator development and linkage to impacts. The lack of an internationally accepted and agreed drought indicator for different types of drought is a sustained barrier in the development of operational DMAPS, especially for hydrological and agricultural droughts. In addition, certain limitations of currently used indicators, such as the statistical inconsistency across temporal and spatial scales, noncomparability with other indicators, and subjective metrics hinder the effectiveness for decision-making (Mishra and Singh 2010; Steinemann et al. 2015). While integrated drought monitoring with multiple indicators has been well recognized, the development of objective indicators and approaches to integrating multiple information sources that are directly linked to the particular need of users is required and still challenging (Schubert et al. 2007; Steinemann et al. 2015; Wood et al. 2015).

Most of the current DMAPS are based on physical indicators, while only few systems have been linked to socioeconomical or environmental impacts (Blauhut et al. 2015; Hannaford et al. 2015; Svoboda et al. 2015). Recently, drought indicator development integrating drought impacts and physical (or hydrometeorological) indicators for improved drought monitoring has been highlighted (Ferguson et al. 2016; Bachmair et al. 2016),

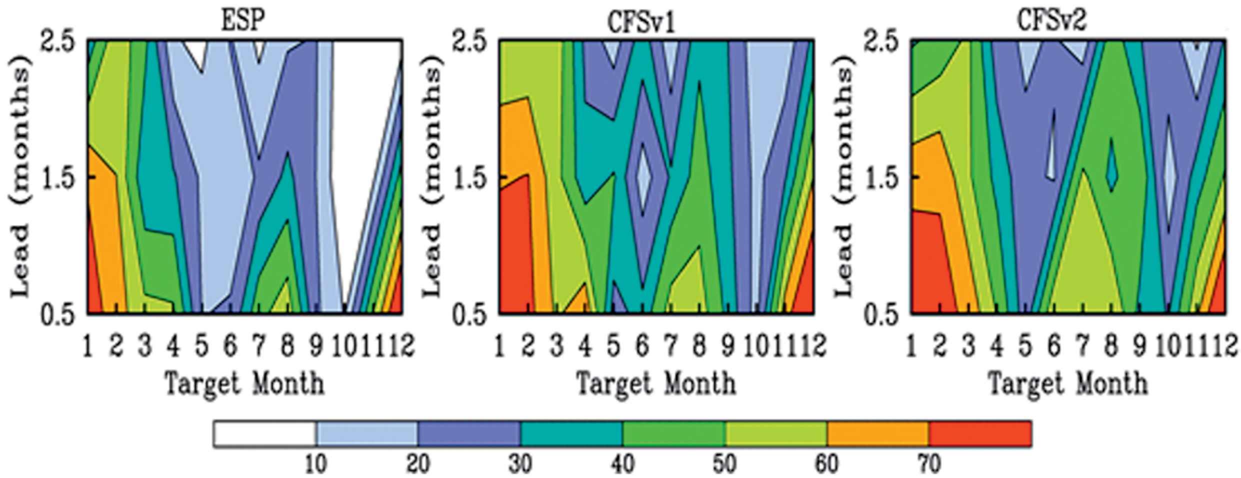

FIG. 7. The squared correlation of predicted seasonal soil moisture drought severity (3-month duration) from a climatological forecast (ESP) and dynamical forecasts (CFSv1 and CFSv2) accumulated over the conterminous United States as functions of target months and lead months [revised from Yuan et al. (2013)].

which would be an important opportunity to enhance the development of integrated DMAPS to consider the vulnerability of the society or ecosystem to drought impacts. For example, the multinational Drought Impacts: Vulnerability Thresholds in Monitoring and Early Warning Research (DrIVER) project aims to fill the gap of integrating physical and socioeconomic drought indicators through strengthening the link between natural drought characterizations and ecological/socioeconomic impacts on North America, Europe, and Australia (Hannaford et al. 2015). Though certain challenges exist in measuring or quantifying drought impacts, crop yield statistics, vegetation stress from remote sensing, and sources of the drought impacts database, such as the European Drought Impact Report Inventory (EDII; www.geo.uio.no/edc/droughtdb/; Stahl et al. 2016) and DIR (http://droughtreporter.unl.edu/map/), may aid drought research along this line (Bachmair et al. 2016). How to better use datasets from different sources to develop indicators that are directly linked to users' needs and drought impacts across different sectors/scales for enhanced DMAPS remains a challenge.

DROUGHT PREDICTION SKILL EVALUATION AND IMPROVEMENT. The drought prediction skill, based on hydroclimatic forecast, varies with seasons, regions, and lead time. Thus, a systematic evaluation of the forecast skill (and uncertainty) is of particular importance for the use of drought forecast products. Decades of seasonal climate hindcast products facilitate the model-based drought predictability analysis. For example, seasonal hindcasts from the CFSv2 and its previous version CFSv1 have been used to force a well-calibrated land surface hydrologic model to carry out 27-yr soil moisture seasonal hindcasts over the conterminous United States, and the performance of the forecast with respect to different lead times and target months is shown in Fig. 7 (Yuan et al. 2013). Figure 7 shows that the dynamical forecast generally offers added values compared with the ESP forecast with advantages at longer-lead forecast (fewer impacts from the initial condition). The predictive skill is generally higher in winter due to the strong initial soil moisture control and/or better precipitation prediction from climate models, but it is relatively low in other seasons (and for long-lead forecast; Yuan et al. 2013). These results highlight the fact that the challenge still remains in improving the performance of seasonal drought (or precipitation) prediction for certain seasons (e.g., summer), regions, and beyond the 1-month lead time (or beyond lead times with negligible control by the initial condition; Wood et al. 2015).

Improved understanding of the drought mechanism and predictability sources has great implications for drought prediction (Hoerling et al. 2014; Roundy et al. 2015; Schubert et al. 2009; Yuan et al. 2016). For example, the relationship between large-scale teleconnection patterns [e.g., El Niño–Southern Oscillation (ENSO)] and drought has been established at different regions and used for improving drought prediction (Hoerling and Kumar 2003; Schubert et al. 2007, 2016; Wood et al. 2015). Though drought is generally defined over an extended period of time (e.g., months), drought onset and termination may occur at the subseasonal scale (e.g., flash drought). Thus, the improvement of drought (or hydrologic) forecast may be achieved through seamless (or subseasonal to seasonal) prediction to integrate weather and climate prediction, which considers drought propagation or development within these time scales (Brown et al. 2012; Mo and Lettenmaier 2015; Wang et al. 2016; Yuan et al. 2014). Multi-model ensemble forecasts also have the potential to improve drought prediction capability. How to create reliable ensembles that retain sharpness, how to combine different climate forecast models with the largest model diversity and less overconfidence, and how to integrate dynamical and statistical ensemble forecasting approaches are needed for the forecast skill enhancement. Last, assessing current drought prediction (and monitoring) capability and incorporating the latest advances are essential for the improvement of drought information systems at the regional and global scales. The NOAA Drought Task Force (DTF) Drought Capability Assessment Protocol, which helps quantify the capabilities of drought monitoring/prediction with several elements, such as assessment metrics, verification datasets, case studies, and baselines (Wood et al. 2015), would be particularly useful in improving DMAPS in the United States and other regions.

Information dissemination and communication. An essential element of a drought information system is the dissemination of tailored drought information to end users and decision-makers of different sectors. Effective dissemination of drought information that is timely and easy to understand for end users is needed to make informed decisions for operational drought management. This is of particular importance for the research-to-operation (R2O) transitions, which require not only effective distribution or delivery tools (e.g., user-friendly web interface, location-aware applications on smartphones and mobile devices) but also building of added values into DMAPS products with a deeper understanding of the needs of different user communities. Specifically, drought information from DMAPS should be disseminated by incorporating the needs of users (e.g., temporal and spatial scales, indicators) and tailored to specific applications or regions. A recent survey of state drought managers in the 19 Western Governors' Association (WGA) states highlights the need to communicate with the decision-makers the information that drought managers actually use and need (Steinemann 2014; Steinemann et al. 2015). Improved services of the provision of drought information to users should involve appropriate engagement and feedback between drought information providers and end users to aid dissemination of drought information for decision-making (Otkin et al. 2015; Rhee et al. 2015; Schubert et al. 2007; Tadesse et al. 2016).

CONCLUSIONS. The current drought monitoring and prediction capacities and needs in the development of DMAPS at regional and global scales are reviewed in this study. Land surface model simulations, remote sensing products, and seasonal climate forecasts have been among the important advances toward enhanced and integrated drought monitoring and prediction capabilities. A common feature of most DMAPS is that multiple drought indicators are continuously tracked to characterize the climatic and hydrologic aspects of drought and the vegetation condition as well. The development of DMAPS at the global scale is still in its infancy with focus on meteorological drought or drought related to vegetation. Efforts are needed for the generation of near-real-time and long-term datasets at a finer temporal and spatial resolution to aid the development of DMAPS, especially for the global coverage. Enhancing integrated drought monitoring to combine multiple indicators (or with impacts) and improving (probabilistic) drought prediction skills with multimodel climatic/hydrological forecasting, which are disseminated effectively with associated uncertainties and incorporating the needs of different users, are also desirable to develop DMAPS for informed decision-making.

This study mainly focuses on scientific and technical aspects of the development of DMAPS without considering other related aspects, such as institutional challenges. A locally relevant DMAPS with global coverage will be invaluable both for large-scale assessment and local-scale planning, which can be built through regional and global partnerships. The development of the drought information system necessitates participation and collaboration of local authorities and research institutions (Heim and Brewer 2012; Sivakumar et al. 2014; Schubert et al. 2007), but there might be many issues regarding data sharing policy, coordination of participants with different backgrounds and purposes, and the sources of stable funding that can sustain continuous monitoring and forecasting efforts.

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