Korean Journal of Remote Sensing, Vol.37, No.4, 2021, pp.815~831
https://doi.org/10.7780/kjrs.2021.37.4.11

ISSN 1225-6161 (Print)
ISSN 2287-9307 (Online)

Review

Satellite-based Drought Forecasting: Research Trends, Challenges, and Future Directions

Bokyung Son [1)*] · Jungho Im [2)*†] · Sumin Park [3)] · Jaese Lee [1)]

Abstract: Drought forecasting is crucial to minimize the damage to food security and water resources caused by drought. Satellite-based drought research has been conducted since 1980s, which includes drought monitoring, assessment, and prediction. Unlike numerous studies on drought monitoring and assessment for the past few decades, satellite-based drought forecasting has gained popularity in recent years. For successful drought forecasting, it is necessary to carefully identify the relationships between drought factors and drought conditions by drought type and lead time. This paper aims to provide an overview of recent research trends and challenges for satellite-based drought forecasts focusing on lead times. Based on the recent literature survey during the past decade, the satellite-based drought forecasting studies were divided into three groups by lead time (i.e., short-term, sub-seasonal, and seasonal) and reviewed with the characteristics of the predictors (i.e., drought factors) and predictands (i.e., drought indices). Then, three major challenges–difficulty in model generalization, model resolution and feature selection, and saturation of forecasting skill improvement–were discussed, which led to provide several future research directions of satellite-based drought forecasting.

Key Words: Drought forecasting, Drought prediction, remote sensing, Forecast lead time

1. Introduction

Drought is one of the natural disasters that can cause enormous damage to the society and economy (Alston and Kent, 2004; Martin-Ortega *et al.*, 2012). Drought typically occurs by a lack of precipitation. When it continues, drought can intensify through the regional and global hydrological cycles, resulting in the reduction of soil moisture and groundwater (Naumann *et al.*, 2015). Recently, the western US has experienced drought longer than six months since late 2020, and severe drought damage has been reported in many parts of the world (https://droughtmonitor.unl.edu/; Rao *et al.*, 2017; Zhang and Shen, 2019; Schuldt *et al.*, 2020; Marengo *et al.*, 2021). Documenting drought processes helps to understand the impact of climate change to

Received August 11, 2021; Revised August 18, 2021; Accepted August 23, 2021; Published online August 25, 2021

[1)] Combined MS/PhD Student, School of Urban and Environmental Engineering, Ulsan National Institute of Science and Technology
[2)] Professor, School of Urban and Environmental Engineering, Ulsan National Institute of Science and Technology
[3)] Postdoctoral Researcher, School of Urban and Environmental Engineering, Ulsan National Institute of Science and Technology

† Corresponding Author: Jungho Im (ersgis@unist.ac.kr)

* These authors contributed equally to this work.

water cycles (Mishra and Singh, 2010), and is useful for decision making processes closely related to human life such as food security and water resource management (Wilhite *et al*., 2014).

Due to the complex nature of drought, it is difficult to identify the causes, onset, and damage of drought. Drought is generally categorized into four types: meteorological, agricultural, hydrological, and socioeconomic drought based on different characteristics such as duration, triggers, and impacts (Wilhite and Glantz, 1985). Since there is no absolute quantitative measure of drought, various drought indices have been developed and typically used to indicate one or two types of drought (Zargar *et al*., 2011). Drought indices can be categorized into two groups: one is station-based indices such as Palmer Drought Severity Index (Palmer, 1965) and the other is satellite-based indices using satellite data and products such as Vegetation Condition Index (Kogan, 1990) and Scaled Drought Condition Index (Rhee *et al*., 2010). Station-based drought indices have limited spatial coverage due to the sparse distribution of stations. On the other hand, satellite-based drought indices can be derived over vast areas at a regular time interval. In addition, satellite data can be used to document useful information for identifying drought such as vegetation health and evapotranspiration (Peters *et al*., 2002; Park, 2004; Rhee *et al*., 2014; Kim and Shim, 2017). Thus, satellite-based drought monitoring and assessment have been widely studied since the late 20th century (West *et al*., 2019). As it is impossible to investigate all drought types and their spatiotemporal characteristics using one single drought index, a multitude of drought monitoring and assessment studies have been conducted locally, regionally, or even globally with various drought indices depending on data availability (Bhuiyan *et al*., 2017; Hao *et al*., 2017; Tran *et al*., 2017; Bayissa *et al*., 2019). There are also several review papers on satellite-based drought monitoring during the past decade (Zargar *et al*., 2011; AghaKouchak *et al*., 2015; Liu *et al*., 2016; West *et al*., 2019; Jiao *et al*., 2021).

In order to manage and respond to drought in a timely manner, it is important to forecast drought on the spatiotemporal domain as well as to monitor drought conditions based on drought indices or drought factors. In particular, it is crucial to increase the skill score of drought forecasting to minimize drought damage through an early warning system (Pozzi *et al*., 2013). Although satellite data provide information about current drought conditions, they can be used to predict future drought status based on the association between drought conditions and drought factors such as the lag-correlation between vegetation conditions and soil moisture (Bolten and Crow, 2012). In addition, spatiotemporal satellite data can be used for drought forecasting along with numerical weather prediction model data (Fung *et al*., 2020). While many satellite-based drought forecasting studies have been conducted in recent years, there is no review to summarize and discuss them focusing on satellite remote sensing. Fung *et al*. (2020) reviewed overall drought forecasting research, including some satellite-based ones, focusing on modeling methods (e.g., stochastic, dynamic, and artificial intelligence-based models). They concluded that the use of optimal input variables considering both time scales and lead times is crucial to improve drought forecasting skills. Drought factors (e.g., temperature and precipitation) used as input variables in drought forecasting models have different sensitivity by drought type and drought index (Hao *et al*., 2018). While several drought forecasting studies discussed how to select input variables to improve forecasting skills (Rhee and Im, 2017; Hao *et al*., 2018), no review of satellite-based drought forecasting from a lead time perspective has been conducted. Thus, it is necessary to discuss in detail the characteristics of drought factors that are selected as input variables of satellite-based forecasting models by lead time.

This paper focuses on reviewing satellite-based drought forecasting research with an emphasis on forecast lead times. First, we analyzed the papers published during the past decade (i.e., from 2010 to 2020) and categorized them into three by lead time (i.e., short-term, sub-seasonal, and seasonal). Then, the detailed discussion on the assumptions, variables, performance of forecasting models by lead time followed in section 2. Finally, overall challenges and future research directions were documented in section 3. This review can provide a basis for future satellite-based drought forecasting research.

2. Satellite-based drought forecasting reviews

This paper reviewed satellite-based drought forecasting research for the past decade according to lead times (i.e., short-term (<1 month), sub-seasonal (1-3 months), and seasonal (> 3 months)). Fig. 1 provides an overview of the papers reviewed in the present study focusing on predictor sources, lead times, and predictand types. A variety of predictor sources have been used in satellite-based drought forecasting research regardless of lead times. In particular, various numerical models or climate indices have been more commonly integrated in seasonal drought forecasting research other than satellite data. There is a trend of multi-source data

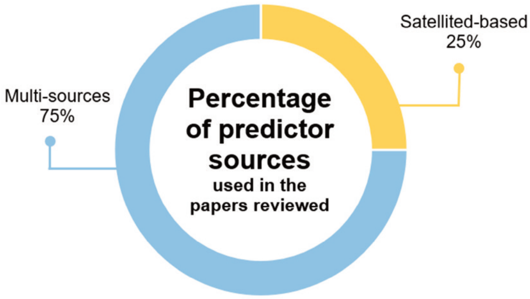

Fig. 2. The trend (with color by predictor source) of the papers reviewed.

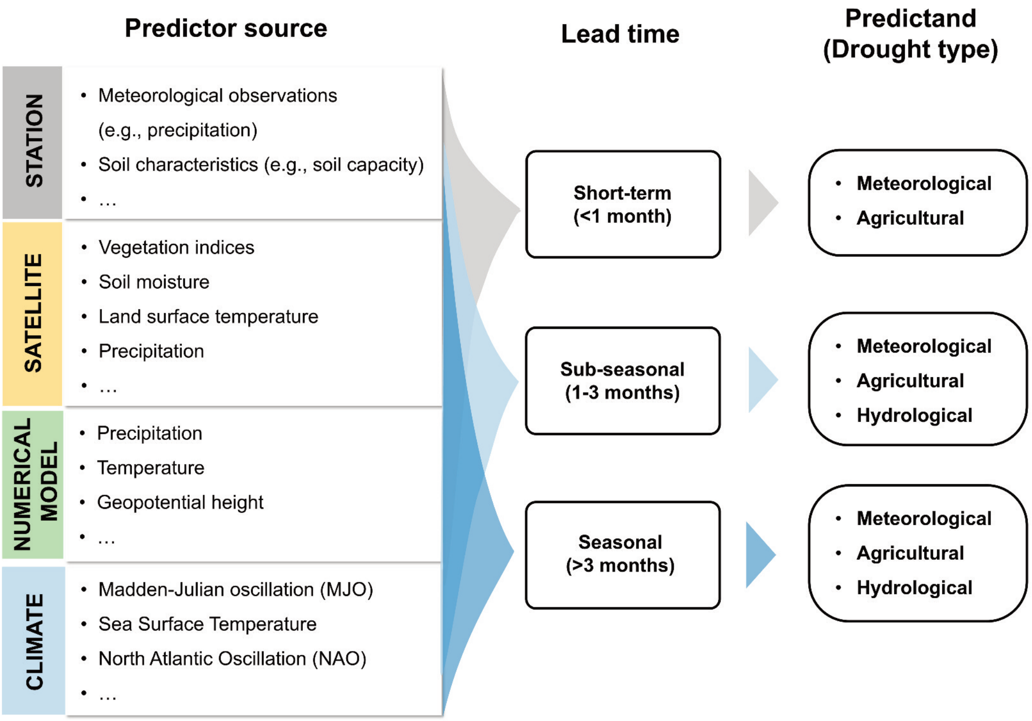

Fig. 1. Graphical overview of the satellite-based drought forecasting papers published during the past decade, which were reviewed in this study.

Table 1. Summary of the satellite-based drought forecasting papers reviewed in this study

Type of drought	Authors	Predictand	Spatial resolution	Lead time	Method	Predictor source (Fig. 1 and 2)
Agricultural	Han *et al.* (2010)	Vegetation Temperature Condition Index (VTCI)	–	10 days interval (up to 20 days)	Autoregressive model (AR)	Satellite
Agricultural	Tedesse *et al.* (2010)	A standardized seasonal greenness	1 km	2-6 weeks	Classification and Regression Tree	Multi-sources
Agricultural	Fernández-Manso *et al.* (2011)	Normalized Vegetation Difference Index (NDVI)	1 km	10 days interval (a 10-day lag)	Seasonal Autoregressive integrated moving average (SARIMA)	Satellite
Agricultural	Marj and Meijerink (2011)	NDVI	8 km	1 year	Artificial Neural Networks (ANN)	Multi-sources
Integrated drought (Meteorological and Agricultural)	Hao *et al.* (2014)	Multivariate Standardized Drought Index (MSDI)	2/3°×1/2°, 0.125°, 0.5x2.5°, 1°	monthly	Ensemble Streamflow Prediction	Multi-sources
Meteorological	Jalili *et al.* (2013)	Standardized Precipitation Index (SPI)	1.1 km	1 month	Neural Networks, and Autoregressive moving average model	Satellite
Agricultural	Shukla *et al.* (2014)	Soil moisture	0.5°	Monthly (up to 3 months)	Land surface model (LSM)	Multi-sources
Agricultural	Tadesse *et al.* (2014)	The standardized values of NDVI	8 km	Weeks to 3 months	Regression tree technique	Multi-sources
Agricultural	Asoka and Mishra (2015)	NDVI	0.25°	Monthly (up to 3 months)	Multiple linear regression	Multi-sources
Agricultural	Tan and Perkowski (2015)	SPI	point	1-3 months for SPI 12 and 1-6 months for SPI24	Wavelet transformed ANN and Wavelet transformed Support Vector Regression (SVR)	Multi-sources
Agricultural	Tian *et al.* (2016)	VTCI	1.1 km	10 days interval (up to 30 days)	SARIMA, AR	Satellite
Agricultural	Liu *et al.*, (2017)	Soil water deficit index (SWDI)	point	1-4 weeks	Support Vector Machine	Multi-sources
Meteorological	Rhee and Im (2017)	SPI, and Standardized Precipitation Evaportranspiration Index (SPEI)	0.05˚	1-6 months	Extremely Randomized Tree	Multi-sources
Hydrological	Yan *et al.* (2017)	Drought probability (defined by root-zone soil moisture)	0.125˚	3months	Hydrologic model, Data assimilation, and Copula-based probabilistic forecast model	Multi-sources
Agricultural	Zhang *et al.* (2017)	Soil moisture	0.25˚	1-3 months	LSM	Multi-sources
Agricultural	Nay *et al.* (2018)	Enhanced Vegetation Index (EVI)	250 m	16-days	Gradient boosted machine	Satellite

Table 1. Continued

Type of drought	Authors	Predictand	Spatial resolution	Lead time	Method	Predictor source (Fig. 1 and 2)
Agricultural	Park *et al.* (2018)	Each Scaled drought condition index (SDCI), microwave integrated drought index (MIDI), and very short-term drought index (VSDI)	0.05°	5-days	Random Forest (RF)	Multi-sources
Meteorological	Rhee and Yang (2018)	SPI6	0.01°	Monthly (up to 6 months)	Extra-Trees, and Adaboost	Multi-sources
Agricultural and hydrological	Arsenault *et al.* (2020)	Various	0.25°	1-5 months	LSM	Multi-sources
Meteorological, Agricultural	Park *et al.* (2020b)	Each SDCI, and SPI	0.05°	8-days	Convolutional Long Short Term Memory and RF	Multi-sources

fusion for drought forecasting especially focusing on satellite data in very recent years (Fig. 2 & Table 1). The publications reviewed in this paper are summarized in Table 1.

1) Short-term (< 1 month) lead times

The short-term lead times of drought forecasting in this paper refer to days to a few weeks (typically less than 1 month). In general, drought starts with a lack of precipitation causing meteorological drought, and then propagates to agricultural, hydrological, and socioeconomic drought in turn. Agricultural to socioeconomic drought tends to progress with a time lag from initial drought conditions, which starts from a deficit of precipitation (Fig. 3; Huang *et al.*, 2017; West *et al.*, 2019; Muhammad *et al.*, 2019). Drought indices generally tend to show less fluctuation on the temporal domain and longer duration for agricultural and hydrological drought events than meteorological one (Wong *et al.*, 2013; Karamuz *et al.*, 2021). Thus, short-

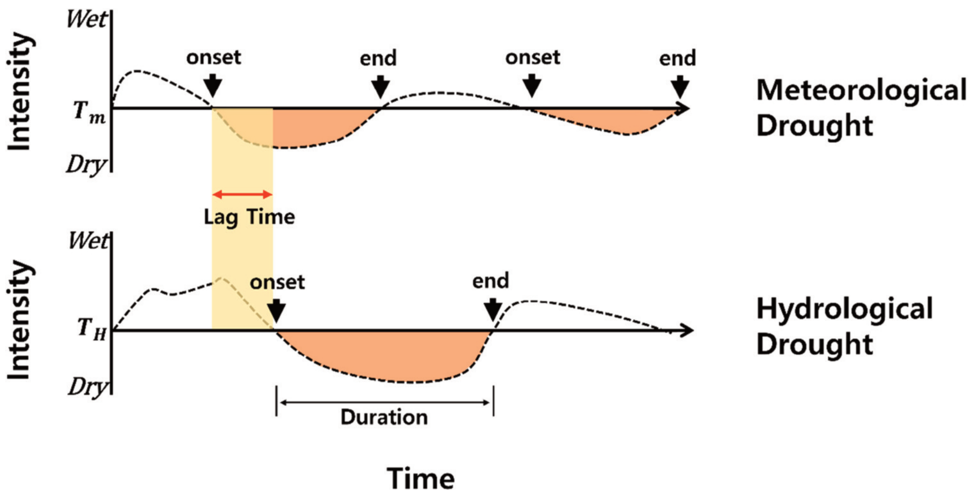

Fig. 3. Concept of lag time in drought propagation adapted from Muhammad *et al.* (2019). The x-axis indicates a time dimension, and the y-axis means intensity of drought indices for each drought type. The intensity below a specific threshold value (here, T_M and T_H, respectively) indicates a drought. The lower the intensity, the more severe drought it indicates. The onset and end of drought are determined when the intensity of drought indices reaches to the threshold.

term forecasting research reviewed here has focused on meteorological and agricultural drought to respond to the short time scale (<1 month) changes in drought conditions. In addition, in order to prevent unexpected damage in crop production caused by drought, many studies have been conducted to predict agricultural drought indices that are highly related to vegetation health (Table 1) (Tian *et al*., 2016; Nay *et al*., 2018; Park *et al*., 2018).

There are several studies that predicted drought using the pattern of drought indices in the past as predictor variables. Both Han *et al*. (2010) and Tian *et al*. (2016) predicted drought using Vegetation Temperature Condition Index (VTCI) based on Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) over Guanzhong Plain in China. VTCI timeseries with 10-day intervals were used in Auto-regressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA) to predict VTCI up to 30 days. Both studies reported that the skill scores of drought forecasting decreased with increasing lead times. In particular, the timeseries features selected for the SARIMA model in Tian *et al*. (2016) were different between the irrigated and rainfed farmlands. This is consistent with He *et al*. (2020) that the sensitivity of drought conditions varies depending on irrigation. Thus, drought forecasting in agricultural areas should take into account local characteristics such as irrigation.

Recent satellite-based drought forecasting studies have considered not only the sensitivity of drought indices to the short-term time scale as predictors, but also the ability of the predictors to respond to future drought conditions. Main predictors for short-term forecasting of drought are precipitation, temperature, and soil moisture (SM) (Liu *et al*., 2017; Park *et al*., 2018). Since agricultural drought often occurs with a decrease of SM availability to plants, Liu *et al*. (2017) predicted agricultural drought with the lead times of 1-4 weeks using soil water deficit index (SWDI), which is calculated based on soil parameters such as SM and field capacity. Meteorological variables such as air temperature and precipitation, and satellite-based products such as soil moisture and leaf area index were used as input variables to predict SWDI. In order to consider lag correlation between input variables and SWDI, the lagged time series of input variables were used for the prediction.

Otkin *et al*. (2015) and Park *et al*. (2018) pointed out that short-term forecasting of drought based solely on local historical information work less for sudden changes of drought when compared to long-term forecasting as drought factors tend to respond slowly to the sudden changes. In order to predict rapid drought changes for the short lead time (< 10 days), the historical pattern of the target drought index has been integrated with numerical meteorological forecast model output or teleconnection features. Park *et al*. (2018) reported that the use of Madden-Julian Oscillation (MJO), one of atmospheric variability indices at intra-seasonal timescale, could improve the short-term (i.e., pentad) prediction of drought over East Asia. Park *et al*. (2020b) used the forecast fields of Global Forecasts Systems (GFS) as input variables along with the historical pattern of the target drought index in the deep learning-based drought forecasting models. They also found that the use of additional input variables from numerical model output improved the forecasting skills of the deep learning models.

Many of satellite-based drought prediction studies at the short-term time scale have focused on the early warning of agricultural drought. Satellite-based vegetation indices and soil moisture indices that affect agricultural production loss at local or regional scale have been used as target variables. While only the historical data of drought factors were used to predict drought in the early 2010s, various predictor sources such as numerical models or climatic indices have been integrated in the drought forecasting models in the late 2010s (Table 1).

2) Sub-seasonal (1-3 months) lead times

The long-term deficiency of precipitation increases the stress of hydrological variables such as SM and ground water (Behrangi *et al*., 2016). In many drought forecasting studies with sub-seasonal lead times (i.e., 1 to 3 months), hydrological variables have been frequently used as drought factors or drought indices (Mishra and Singh, 2011; Hao *et al*., 2016; Sawada *et al*., 2019). Some of the studies improved the initial conditions of process-based models using satellite-derived hydrological products, resulting in the improvement of the drought forecasting skills. For example, Zhang *et al*. (2017) used the rainfall product of the Tropical Rainfall Measuring Mission (TRMM) as forcing in the Variable Infiltration Capacity (VIC) model to provide a reasonable estimate of forecast initial conditions (ICs) of SM in real-time mode. They showed that SM forecast performance was mostly controlled by ICs with one month lead time. Arsenault *et al*. (2020) improved forecast ICs of two Land Surface Models (LSM) (i.e., Noah-Multi-parameterization and Catchment-LSM) using Soil Moisture Active Passive (SMAP)-derived SM and terrestrial water storage generated from Gravity Recovery And Climate Experiment (GRACE) through data assimilation.

Satellite-derived vegetation products can improve the performance of drought forecasting especially at the sub-seasonal lead time scale. Tan and Perkowski (2015) predicted hydrological drought with the lead times from one to six months using station-based stream flow and satellite-derived NDVI and Normalized Difference Water Index (NDWI). The use of satellite-based vegetation information has improved the decrease in skill scores as lead times increased. Rhee and Im (2017) reported that NDVI was one of the important variables when predicting drought with the 3-month lead time.

Some studies used not only satellite data but also the forecast fields from numerical models to predict drought at the sub-seasonal lead time (Shukla *et al*., 2014; Zhang *et al*., 2017). However, as the lead time increases (from 1 month to 3 months), the accuracy of the forecast fields from numerical models decreases, resulting in the deteriorated performance of drought prediction (Rhee and Im 2017; Zhang *et al*., 2017; Esit *et al*., 2021).

3) Seasonal (> 3 months) lead times

Most drought forecasting studies with seasonal lead times have used meteorological variables, such as precipitation, provided by reanalysis models such as North American Land Data Assimilation System. Recently, such reanalysis data have been integrated with satellite-derived drought factors such as precipitation and soil moisture to improve the drought forecasting skills (Hao *et al*., 2014; Yan *et al*., 2017). Some studies indicate that it is crucial to consider climate indices with time scales over months for seasonal drought forecasting with long lead times (> 3 months), as they can remotely influence atmospheric circulation events (e.g., rainfall) in seasonal time scales (Kim *et al*., 2017; Lima and AghaKouchak, 2017; Merryfield *et al*., 2020).

Teleconnection patterns of various drought factors such as hydroclimatic anomalies, sea surface temperature (SST), and climate indices have been critical components for seasonal drought forecasts (Schubert *et al*., 2004; Mishra and Singh, 2011). In particular, the teleconnection patterns of SST anomaly affect atmospheric-oceanic circulations, resulting in different precipitation and temperature patterns by region or continent (Hao *et al*., 2018). Many seasonal drought forecasting studies have used large-scale climate indices such as El Nino-Southern Oscillation (ENSO) calculated from SST as a main predictor component. In addition, the forecast fields from numerical models have been integrated with reanalysis and/or satellite data for the seasonal prediction of drought in the studies (Hao *et al*., 2018). In satellite-based seasonal drought forecasting studies, meteorological drought indices such as SPI and Standard Precipitation Evapotranspiration Index (SPEI) have been often used as target variables (Rhee and Im, 2017; Rhee and Yang, 2018). For example, Rhee and Im (2017) predicted drought (i.e., SPI and SPEI) up to 6 months using satellite-based LST and NDVI, climate indices (i.e., the Multivariate ENSO Index and Arctic Oscillation Index), and long-rage forecast data of Global Climate Models as predictors. They concluded that the drought forecast skills could be further improved if the performance of the long-range forecast data was improved through various processes including bias correction. Hao *et al*. (2018) documented that satellite data had been used for seasonal drought forecasts through the integration with other data sources through data assimilation or machine learning, which provided promising results.

3. Current challenges and future research direction

Drought forecasts using satellite data have been widely studied during the past decade. Predictors used in the drought forecasting models were selected considering the characteristics of target variables and lead times. Forecasting skills have been gradually improved through the fusion of multiple predictor sources such as satellite data and numerical models. However, there are still several major challenges and limitations, including difficulty in model generalization, model resolution and feature selection, and saturation of forecasting skill improvement.

1) Model generalization

In order to quantify drought, a multitude of drought indices have been developed by drought type (Zargar *et al*., 2011). A drought index explains drought conditions from its own perspective. For example, SWDI documents how much SM is available within 50 cm soil layer depth based on the fact that SM is closely related to drought (Liu *et al*., 2017). Drought forecasting studies select specific drought indices as predictands considering research objectives and the characteristics of the study area under investigation. Thus, even though drought is predicted for the same drought type (e.g., agricultural drought), different predictands can be used (Table 1). This makes it difficult to directly compare multiple drought forecasting models proposed by different studies. A variety of drought indices also make it difficult to select an appropriate predictand that represents drought conditions in the areas under investigation.

The studies reviewed in this paper conducted drought forecasting at local or regional scale, showing relatively good performance over the areas under investigation. However, the models proposed in the studies were not evaluated over different areas, limiting their generalization. The generalization issue always remains for local or regional modeling studies (Liu *et al*., 2017). Since there exist numerous drought indices, it is often difficult to identify an optimum drought index (i.e., predictand) to develop drought forecasting models for a certain area. The predictand selected for a certain region might not work well to predict drought for areas with different environment conditions (e.g., climate zones or land cover) (Jiao *et al*., 2019b). Such a generalization problem may be improved if an adaptive approach for generating an integrated drought index is available (Son *et al*., 2021).

An “integrated” drought index should be able to explain various drought types and to be generalized across regions. Development of integrated drought indices has been challenged in the field of satellite-based drought monitoring, leading to a multitude of studies proposing new integrated approaches (West *et al*., 2019; Jiao *et al*., 2019a; Son *et al*., 2021). Such integrated approaches can provide less complex information of drought conditions for the end users such as water resource managers and a range of decision makers. Similar integrated approaches are necessary for drought forecasting to provide consistent information for the end users. However, research on integrated drought forecasting systems has yet had minimal exploration. Current satellite-based drought prediction studies focus more on improving forecasting skills with incorporating local and regional characteristics than generalization.

2) Model resolution and feature selection

The temporal resolution of drought forecasting models varies by drought type and lead time. The short-term lead time studies start with a pentad scale, while drought prediction with seasonal lead time has monthly intervals. The spatial resolution of drought forecasting models depends on predictor sources, study areas, and lead times. The longer the lead times, the coarser the spatial resolution of the drought forecasting model mainly due to data and model uncertainties. It is often necessary to have prior knowledge on the spatial scales (i.e., regional or continental) that climate indices affect when they are used in drought forecasting (Tadesse *et al*., 2010; Dahlin and Ault, 2018). In order to reflect local or regional variations of drought in drought forecasting models at fine scale, it is necessary to improve the spatiotemporal resolutions of the models, often requiring predictors and predictands at such resolutions (Asoka and Mishra, 2015). In particular, there is a need of high spatial resolution drought information for precision agriculture and water resource management from an end-user perspective. Advanced satellite data with higher spatiotemporal resolutions can improve the model resolution problem (Ghazaryan *et al*., 2020; Park *et al*., 2020a).

The range of lead times should be considered for drought forecasting along with the spatial and temporal resolutions. The sensitivity of predictand and predictors to a specific drought type was considered in the satellite-based drought prediction studies (Tan and Perkowski, 2015; Liu *et al*., 2017; Park *et al*., 2018). Such a sensitivity is related to lag correlation between drought conditions and predictors. As the lead time of drought forecasting increases, large time scale teleconnection factors such as ENSO are more frequently used to improve the forecasting skills of the models (Rhee and Yang, 2018). When various lead time predictions (from short-term to seasonal) were conducted for the same predictor set, there was a tendency of decreasing prediction skills with increasing lead times (Tan and Perkowski, 2015; Zhang *et al*., 2017). This implies that the careful selection of predictors by lead time is crucial even for targeting the same predictand.

3) Saturation of forecasting skill improvement

Researchers have put effort on improving drought forecasting skills. Such effort includes 1) selection of input predictors considering the lag correlation between predictand and predictors, 2) improvement of the initial conditions of forecasting models through data assimilation using satellite data, and 3) integration with local historical patterns of drought, climate indices, and the forecast fields of numerical models. In particular, many studies have adopted the third approach to improve drought forecasting skills (Table 1).

When only historical patterns of drought conditions were used for drought prediction, they often did not work well for abrupt changes of drought conditions, leading to the further integration with weather forecast data (Han *et al*., 2010; Park *et al*., 2020b). However, the use of multiple predictor sources still has some limitations. When multiple predictor sources were used, the forecasting skills has been improved, but tended to be saturated (Park *et al*., 2018; Park *et al*., 2020b; Rhee and Im, 2017). There are several possible reasons for the saturation of forecasting skill improvement. First is the accuracy of data sources such as numerical model output. Lorenz *et al*. (2018) predicted rapid drought intensification over the United States using numerical model data. They reported that not only the error inherent in the model itself, but also the error of the forecasting fields of numerical models affected the performance of the drought forecasting model. They concluded that if the accuracy of numerical models is improved, the forecasting skills of drought prediction models can be further improved. Second is the limited ability of drought factors and climate indices to fully explain drought occurrences due to the very complex mechanism of drought. Each drought factor has different temporal characteristics (e.g., persistency) in terms of drought occurrences (Manning *et al*., 2018). However, satellite-assist drought forecasting research considering such characteristics of predictors has had minimal exploration (Table 1). Third is climate change, which makes it difficult to forecast drought. Sudden changes or extreme cases of drought conditions have not been well predicted in the literature, which remains as a major limitation. Due to on-going climate change, the frequency and intensity of drought have increased (Trenberth *et al*., 2014; Dai, 2011; Mukherjee *et al*., 2018), which makes future drought forecasting more difficult. In addition, different drought indices have shown varied sensitivity even for the same level of continental warming (Mukherjee *et al*., 2018). Consequently, the models predicting existing drought indices might not work well for future climate conditions.

4) Possible future directions

Based on the careful review of the satellite-based drought forecasting studies during the past decade, the following three aspects are expected to be the main research themes in the next decade: 1) Integrated approaches for documenting drought conditions are necessary to mitigate the model generalization problem. 2) The drought propagation concept (i.e., propagation from meteorological to hydrological drought) should be carefully considered as various drought types are not independent, but closely related each other. 3) Advanced modeling techniques should be adopted to improve drought forecasting skills.

In order to predict drought, there should be quantitative reference data for drought. Since a single drought index cannot represent all drought types regardless of regions, there has been effort to develop an integrated approach for drought indices. For example, Son *et al*. (2021) adapted multiple drought indices and factors to merge them into one drought index to provide general applicability across diverse climate regions as well as both short- and long-term drought monitoring. The use of such integrated drought indices in forecasting models can further improve the model generalization, which in turn provides consistent and comprehensive drought prediction information for the end users such as decision makers.

Drought propagation processes (from meteorological to hydrological drought) have been recently studied to improve our skills for monitoring and mitigating drought events (Wang *et al*., 2016; Huang *et al*., 2017; Muhammad *et al*., 2019; Guo *et al*., 2020). The recent studies investigated not only drought propagation characteristics such as lag time and attenuation, but also propagation sensitivities in terms of the seasonal characteristics of propagation time and the response of hydrological drought to different meteorological drought conditions. Since there is a lag time between drought types in the drought propagation processes (Fig. 3), such a lagged relationship can be used to predict a hydrological (or agricultural) drought from a meteorological one (Shin *et al*., 2020; Zhang *et al*., 2021). A long-lasting meteorological drought is expected to result in the next levels of drought (i.e., agricultural or hydrological drought) (Van Loon, 2015). Although a meteorological drought index is used as a predictand, its forecasts not only provide future meteorological drought conditions but also may give potential information (e.g., a future prospect of a drought onset) for the other drought types. Drought forecasting with the drought propagation concept should consider both propagation characteristics and sensitivities, which are important to guide early drought warning for the sustainable management of drought. Thus, local or regional scale investigations on the sensitivities between drought types and forecasting models with various lead times (e.g., interval steps) would be required to extrapolate the next levels of drought conditions from meteorological drought forecast output timeseries. Most papers reviewed in this study independently predict a specific drought index without considering a drought propagation process. A drought forecasting model with a drought propagation concept is expected to provide a systematic drought prediction.

Deep learning models can be used to forecast drought with multiple lead times and drought types. Many of the papers reviewed in this study adopted relatively simple machine learning approaches such as random forest and support vector machines for drought forecasting (Table 1). The same trend was found in the previous review on drought studies (Fung *et al*., 2020). More advanced deep learning approaches such as convolutional neural networks (CNN) and long short term memory (LSTM) can be used to improve the drought forecasting skills. As deep learning techniques are good at dealing with non-linear relationships between input features, it is flexible to predict drought that has the non-linear characteristics between drought indices and factors (Feng *et al*., 2019; Liu *et al*., 2020; Prodhan *et al*., 2021). Furthermore, image-based deep learning can extract both spatial and temporal features from input variables (i.e., drought factors), which are also important to describe the spatiotemporal characteristics of drought. In fact, image-based deep learning has been widely used to improve classification and regression performance in various remote sensing fields (Park *et al*., 2020b; Kim *et al*., 2020; Muthukumar *et al*., 2020; Sothe *et al*., 2020). In particular, the fusion of multiple machine learning and deep learning models has recently shown powerful performance in predictive modeling. For example, Park *et al*. (2020b) integrated random forest and convolutional LSTM (ConvLSTM) for drought prediction, resulting in better performance than the case when ConvLSTM was solely used. Muthukumar *et al*. (2020) combined Graph convolutional networks (GCN) coupled with ConvLSTM for air pollution prediction with 69.5% of error reduction compared to the model with only ConvLSTM. The use of deep learning and their combinations should be further examined to improve drought forecasting. The improvement of the forecast fields of numerical models will also benefit drought forecasting using multi-source data along with advanced modeling techniques.

4. Conclusion

This paper examined the satellite-based drought forecasting studied during the past decade according to lead times (i.e., short-term, sub-seasonal, and seasonal). It is crucial to identify optimum predictors targeting a certain predictand considering forecast lead times. For longer lead times, teleconnection information at the larger time scale may help improve drought forecasting skills. Most reviewed papers have tried to improve drought forecasting skills by fusing multiple predictor sources regardless of lead times. However, they were conducted using different predictands at the regional scale, which had difficulty in model generalization. There is a need for drought information with higher spatiotemporal resolution, which advanced satellite remote sensing can benefit. In addition, Predictors for drought forecasting models need to be carefully determined considering lead times and predictands. Most satellite-based drought forecasting studies have used statistical and machine learning approaches to improve the forecasting skills. However, there was saturation in the improvement of the skills mainly due to data and model uncertainties. Based on these limitations and challenges, we provided three possible future directions to further improve satellite-based drought forecasting: 1) integrated drought monitoring approaches, 2) consideration of drought propagation processes, and 3) synergetic use of deep learning approaches. This paper is expected to provide a basis for developing comprehensive satellite-based drought forecasting systems.

Acknowledgements

This research was supported by the Ministry of Science and ICT (MSIT), Korea, under the Information Technology Research Center (ITRC) support program (IITP-2021-2018-0-01424) supervised by the Institute for Information & communications Technology Promotion (IITP). S. Park is partially supported by the National Research Foundation of Korea funded by the Ministry of Education of Korea (NRF-2021R1I1A1A01052823).

References

AghaKouchak, A., A. Farahmand, F.S. Melton, J. Teixeira, M.C. Anderson, B.D. Wardlow, and C.R. Hain, 2015. Remote sensing of drought: Progress, challenges and opportunities, *Reviews of Geophysics*, 53(2): 452-480.

Alston, M. and J. Kent, 2004. Social impacts of drought, *Centre for Rural Social Research*, Charles Sturt University, Wagga Wagga, AU.

Arsenault, K.R., S. Shukla, A. Hazra, A. Getirana, A. McNally, S.V. Kumar, K. Randal D, C.D. Peters-Lidard, B.J. Zaitchik, H. Badr, H.C. Jung, B. Narapusetty, M. Navari, W. Shugong, D.M. Mocko, C. Funk, L. Harrison, G.J. Husak, A. Alkhalil, and G. Galu, 2020. The NASA hydrological forecast system for food and water security applications, *Bulletin of the American Meteorological Society*, 101(7): E1007-E1025.

Asoka, A. and V. Mishra, 2015. Prediction of vegetation anomalies to improve food security and water management in India, *Geophysical Research Letters*, 42(13): 5290-5298.

Bayissa, Y.A., T. Tadesse, M. Svoboda, B. Wardlow, C. Poulsen, J. Swigart, and S.J. Van Andel, 2019. Developing a satellite-based combined drought indicator to monitor agricultural drought: A case study for Ethiopia, *GIScience & Remote Sensing*, 56(5): 718-748.

Behrangi, A., E.J. Fetzer, and S.L. Granger, 2016. Early detection of drought onset using near surface temperature and humidity observed from space, *International Journal of Remote Sensing*, 37(16): 3911-3923.

Bhuiyan, C., A.K. Saha, N. Bandyopadhyay, and F.N. Kogan, 2017. Analyzing the impact of thermal stress on vegetation health and agricultural drought–a case study from Gujarat, India, *GIScience & Remote Sensing*, 54(5): 678-699.

Bolten, J.D. and W.T. Crow, 2012. Improved prediction of quasi-global vegetation conditions using remotely-sensed surface soil moisture, *Geophysical Research Letters*, 39(19): L19406.

Dahlin, K.M. and T.R. Ault, 2018. Global linkages between teleconnection patterns and the terrestrial biosphere, *International Journal of Applied Earth Observation and Geoinformation*, 69: 56-63.

Dai, A., 2011. Drought under global warming: a review, *Wiley Interdisciplinary Reviews: Climate Change*, 2(1): 45-65.

Esit, M., S. Kumar, A. Pandey, D.M. Lawrence, I. Rangwala, and S. Yeager, 2021. Seasonal to multi-year soil moisture drought forecasting, *npj Climate and Atmospheric Science*, 4(1): 1-8.

Feng, P., B. Wang, D. Li Liu, and Q. Yu, 2019. Machine learning-based integration of remotely-sensed drought factors can improve the estimation of agricultural drought in South-Eastern Australia, *Agricultural Systems*, 173: 303-316.

Fernández-Manso, A., C. Quintano, and O. Fernández-

Manso, 2011. Forecast of NDVI in coniferous areas using temporal ARIMA analysis and climatic data at a regional scale, *International Journal of Remote Sensing*, 32(6): 1595-1617.

Fung, K.F., Y.F. Huang, C.H. Koo, and Y.W. Soh, 2020. Drought forecasting: A review of modelling approaches 2007-2017, *Journal of Water and Climate Change*, 11(3): 771-799.

Ghazaryan, G., O. Dubovyk, V. Graw, N. Kussul, and J. Schellberg, 2020. Local-scale agricultural drought monitoring with satellite-based multi-sensor time-series, *GIScience & Remote Sensing*, 57(5): 704-718.

Guo, Y., S. Huang, Q. Huang, G. Leng, W. Fang, L. Wang, and H. Wang, 2020. Propagation thresholds of meteorological drought for triggering hydrological drought at various levels, *Science of the Total Environment*, 712: 136502.

Han, P., P.X. Wang, and S.Y. Zhang, 2010. Drought forecasting based on the remote sensing data using ARIMA models, *Mathematical and Computer Modelling*, 51(11-12): 1398-1403.

Hao, Z., A. AghaKouchak, N. Nakhjiri, and A. Farahmand, 2014. Global integrated drought monitoring and prediction system, *Scientific Data*, 1(1): 1-10.

Hao, Z., F. Hao, and V.P. Singh, 2016. A general framework for multivariate multi-index drought prediction based on Multivariate Ensemble Streamflow Prediction (MESP), *Journal of Hydrology*, 539: 1-10.

Hao, Z., X. Yuan, Y. Xia, F. Hao, and V.P. Singh, 2017. An overview of drought monitoring and prediction systems at regional and global scales, *Bulletin of the American Meteorological Society*, 98(9): 1879-1896.

Hao, Z., V.P. Singh, and Y. Xia, 2018. Seasonal drought prediction: advances, challenges, and future prospects, *Reviews of Geophysics*, 56(1): 108-141.

He, Y., F. Chen, H. Jia, L. Wang, and V.G. Bondur, 2020. Different drought legacies of rain-fed and irrigated croplands in a typical Russian agricultural region, *Remote Sensing*, 12(11): 1700.

Huang, S., P. Li, Q. Huang, G. Leng, B. Hou, and L. Ma, 2017. The propagation from meteorological to hydrological drought and its potential influence factors, *Journal of Hydrology*, 547: 184-195.

Jiao, W., C. Tian, Q. Chang, K.A. Novick, and L. Wang, 2019a. A new multi-sensor integrated index for drought monitoring, *Agricultural and Forest Meteorology*, 268: 74-85.

Jiao, W., L. Wang, K.A. Novick, and Q. Chang, 2019b. A new station-enabled multi-sensor integrated index for drought monitoring, *Journal of hydrology*, 574: 169-180.

Jiao, W., L. Wang, and M.F. McCabe, 2021. Multi-sensor remote sensing for drought characterization: current status, opportunities and a roadmap for the future, *Remote Sensing of Environment*, 256: 112313.

Jalili, M., J. Gharibshah, S.M. Ghavami, M. Beheshtifar, and R. Farshi, 2013. Nationwide prediction of drought conditions in Iran based on remote sensing data, *IEEE Transactions on Computers*, 63(1): 90-101.

Karamuz, E., E. Bogdanowicz, T.B. Senbeta, J.J. Napiórkowski, and R.J. Romanowicz, 2021. Is It a Drought or Only a Fluctuation in Precipitation Patterns?–Drought Reconnaissance in Poland, *Water*, 13(6): 807.

Kim, J.S., G.S. Seo, H.W. Jang, and J.H. Lee, 2017. Correlation analysis between Korean spring drought and large-scale teleconnection patterns for drought forecasting, *KSCE Journal of Civil Engineering*, 21(1): 458-466.

Kim, Y.W.and C.S. Shim, 2017. Towards an Integrated Drought Monitoring with Multi-satellite Data Products Over Korean Peninsular, *Korean*

Journal of Remote Sensing, 33(6-1): 993-1001 (in Korean with English abstract).

Kim, Y.J., H.C. Kim, D.H. Han, S.G. Lee, and J.H. Im, 2020. Prediction of monthly Arctic sea ice concentrations using satellite and reanalysis data based on convolutional neural networks, *The Cryosphere*, 14(3): 1083-1104.

Kogan, F.N., 1990. Remote sensing of weather impacts on vegetation in non-homogeneous areas, *International Journal of Remote Sensing*, 11(8): 1405-1419.

Lima, C.H. and A. AghaKouchak, 2017. Droughts in Amazonia: spatiotemporal variability, teleconnections, and seasonal predictions, *Water Resources Research*, 53(12): 10824-10840.

Liu, X., X. Zhu, Y. Pan, S. Li, Y. Liu, and Y. Ma, 2016. Agricultural drought monitoring: Progress, challenges, and prospects, *Journal of Geographical Sciences*, 26(6): 750-767.

Liu, D., A.K. Mishra, Z. Yu, C. Yang, G. Konapala, and T. Vu, 2017. Performance of SMAP, AMSR-E and LAI for weekly agricultural drought forecasting over continental United States, *Journal of Hydrology*, 553: 88-104.

Liu, X., X. Zhu, Q. Zhang, T. Yang, Y. Pan, and P. Sun, 2020. A remote sensing and artificial neural network-based integrated agricultural drought index: Index development and applications, *Catena*, 186: 104394.

Lorenz, D.J., J.A. Otkin, M. Svoboda, C.R. Hain, and Y. Zhong, 2018. Forecasting rapid drought intensification using the Climate Forecast System (CFS), *Journal of Geophysical Research: Atmospheres*, 123(16): 8365-8373.

Manning, C., M. Widmann, E. Bevacqua, A.F. Van Loon, D. Maraun, and M. Vrac, 2018. Soil moisture drought in Europe: a compound event of precipitation and potential evapotranspiration on multiple time scales, *Journal of Hydrometeorology*, 19(8): 1255-1271.

Marengo, J.A., A.P. Cunha, L.A. Cuartas, K.R. Deusdará Leal, E. Broedel, M.E. Seluchi, C.M. Michelin , C.F. De Praga Baião, E.C. Ângulo, E.K. Almeida, M.L. Kazmierczak, N.P.A. Mateus, R.C. Silva, and F. Bender, 2021. Extreme Drought in the Brazilian Pantanal in 2019-2020: Characterization, Causes, and Impacts, *Frontiers in Water*, 3(13): 1-20.

Marj, A.F. and A.M. Meijerink, 2011. Agricultural drought forecasting using satellite images, climate indices and artificial neural network, *International Journal of Remote Sensing*, 32(24): 9707-9719.

Martin-Ortega, J., M. González-Eguino, and A. Markandya, 2012. The costs of drought: the 2007/2008 case of Barcelona, *Water Policy*, 14(3): 539-560.

Merryfield, W.J., J. Baehr, L. Batté, E.J. Becker, A.H. Butler, C.A.S. Coelho, G. Danabasoglu, P.A. Dirmeyer, F.J. Doblas-Reyes, D.V.I. Domeisen, L. Ferranti, T. Ilynia, A. Kumar, W.A. Müller, M. Rixen, A.W. Robertson, D.M. Smith, Y. Takaya, M. Tuma, F. Vitart, C.J. White, M.S. Alvarez, C. Ardilouze, H. Attard, C. Baggett, M.A. Balmaseda, A.F. Beraki, P.S. Bhattacharjee, R. Bilbao, F.M. de Andrade, M.J. DeFlorio, L.B. Díaz, M.A. Ehsan, G. Fragkoulidis, S. Grainger, B.W. Green, M.C. Hell, J.M. Infanti, K. Isensee, T. Kataoka, B.P. Kirtman, N.P. Klingaman, J.-Y. Lee, K. Mayer, R. McKay, J.V. Mecking, D.E. Miller, N. Neddermann, C.H. Justin Ng, A.t Ossó, K. Pankatz, S. Peatman, K. Pegion, J. Perlwitz, G.C. Recalde-Coronel, A. Reintges, C. Renkl, B. Solaraju-Murali, A. Spring, C. Stan, Y. Q. Sun, C.R. Tozer, N. Vigaud, S. Woolnough, and S. Yeager, 2020. Current and emerging developments in subseasonal to decadal prediction, *Bulletin of the American Meteorological Society*, 101(6): E869-E896.

Mishra, A.K. and V.P. Singh, 2010. A review of drought concepts, *Journal of Hydrology*, 391(1-2): 202-216.

Mishra, A.K. and V.P. Singh, 2011. Drought modeling– A review, *Journal of Hydrology*, 403(1-2): 157-175.

Muhammad, N.S., J.E. Kim, J.H. Lee, and T.W. Kim, 2019. Probabilistic analysis of drought propagation over the Han River Basin under climate change, *Journal of The Korean Society of Civil Engineers*, 39(1): 155-163.

Mukherjee, S., A. Mishra, and K.E. Trenberth, 2018. Climate change and drought: a perspective on drought indices, *Current Climate Change Reports*, 4(2): 145-163.

Muthukumar, P., E. Cocom, K. Nagrecha, J. Holm, D. Comer, A. Lyons, I. Burga, C.F. Calvert, and M. Pourhomayoun, 2020. Satellite Image Atmospheric Air Pollution Prediction through Meteorological Graph Convolutional Network with Deep Convolutional LSTM, *Proc. of in 2020 International Conference on Computational Science and Computational Intelligence (CSCI)*, Las Vegas, NV, US, Dec. 16-18, pp. 521-526.

Naumann, G., J. Spinoni, J.V. Vogt, and P. Barbosa, 2015. Assessment of drought damages and their uncertainties in Europe, *Environmental Research Letters*, 10(12): 124013.

Nay, J., E. Burchfield, and J. Gilligan, 2018. A machine-learning approach to forecasting remotely sensed vegetation health, *International Journal of Remote Sensing*, 39(6): 1800-1816.

Otkin, J.A., M.C. Anderson, C. Hain, and M. Svoboda, 2015. Using temporal changes in drought indices to generate probabilistic drought intensification forecasts, *Journal of Hydrometeorology*, 16(1): 88-105.

Palmer, W.C., 1965. *Meteorological drought: Research Paper 45*, Office of Climatology U.S. Weather Bureau, Washington DC, US.

Park, S.Y., 2004. Development of a Drought Detection Indicator using MODIS Thermal Infrared Data, *Korean Journal of Remote Sensing*, 20(1): 1-11 (in Korean with English Abstract).

Park, S., E. Seo, D. Kang, J. Im, and M.I. Lee, 2018. Prediction of drought on pentad scale using remote sensing data and MJO index through random forest over East Asia, *Remote Sensing*, 10(11): 1811.

Park, S., D. Kang, C. Yoo, J. Im, and M.I. Lee, 2020a. Recent ENSO influence on East African drought during rainy seasons through the synergistic use of satellite and reanalysis data, *ISPRS Journal of Photogrammetry and Remote Sensing*, 162: 17-26.

Park, S., J. Im, D. Han, and J. Rhee, 2020b. Short-Term Forecasting of Satellite-Based Drought Indices Using Their Temporal Patterns and Numerical Model Output, *Remote Sensing*, 12(21): 3499.

Peters, A.J., E.A. Walter-Shea, L. Ji, A. Vina, M. Hayes, and M.D. Svoboda, 2002. Drought monitoring with NDVI-based standardized vegetation index, *Photogrammetric Engineering and Remote Sensing*, 68(1): 71-75.

Pozzi, W., J. Sheffield, R. Stefanski, D. Cripe, R. Pulwarty, J.V. Vogt, Richard R. Heim Jr.7, M.J. Brewer, M, Svoboda, R. Westerhoff, A.I.J.M. van Dijk, B. Lloyd-Hughes, F. Pappenberger, M. Werner, E. Dutra, F. Wetterhall, W. Wagner, S. Schubert, K. Mo, M. Nicholson, L. Bettio, L. Nunez, R. van Beek, M. Bierkens, L.G.G. de Goncalves, J.G.Z. de Mattos, and R. Lawford, 2013. Toward global drought early warning capability: Expanding international cooperation for the development of a framework for monitoring and forecasting, *Bulletin of the American Meteorological Society*, 94(6): 776-785.

Prodhan, F.A., J. Zhang, F. Yao, L. Shi, T.P. Pangali Sharma, D. Zhang, D. Cao, M. Zheng, N.

Ahmed, and H.P. Mohana, 2021. Deep Learning for Monitoring Agricultural Drought in South Asia Using Remote Sensing Data, *Remote Sensing*, 13(9): 1715.

Rao, M., Z. Silber-Coats, S. Powers, L. Fox III, and A. Ghulam, 2017. Mapping drought-impacted vegetation stress in California using remote sensing, *GIScience & Remote Sensing*, 54(2): 185-201.

Rhee, J., J. Im, and G.J. Carbone, 2010. Monitoring agricultural drought for arid and humid regions using multi-sensor remote sensing data, *Remote Sensing of Environment*, 114(12): 2875-2887.

Rhee, J., J. Im, and J. Kim, 2014. Hydrological Drought Assessment and Monitoring Based on Remote Sensing for Ungauged Areas, *Korean Journal of Remote Sensing*, 30(4): 525-536 (in Korean with English abstract).

Rhee, J. and J. Im, 2017. Meteorological drought forecasting for ungauged areas based on machine learning: Using long-range climate forecast and remote sensing data, *Agricultural and Forest Meteorology*, 237: 105-122.

Rhee, J. and H. Yang, 2018. Drought prediction for areas with sparse monitoring networks: A case study for Fiji, *Water*, 10(6): 788.

Sawada, Y., T. Koike, E. Ikoma, and M. Kitsuregawa, 2019. Monitoring and predicting agricultural droughts for a water-limited subcontinental region by integrating a land surface model and microwave remote sensing, *IEEE Transactions on Geoscience and Remote Sensing*, 58(1): 14-33.

Schubert, S.D., M.J. Suarez, P.J. Pegion, R.D. Koster, and J.T. Bacmeister, 2004. Causes of long-term drought in the US Great Plains, *Journal of Climate*, 17(3): 485-503.

Schuldt, B., A. Buras, M. Arend, Y. Vitasse, C. Beierkuhnlein, A. Damm, M. Gharung, T.E.E. Gramsh, M. Haucki, P. Hajekj, H. Hartmannk, E. Hiltbrunnerc, G. Hochc, M. Holloway-Phillipsc, C. Körner, E. Laryschl, T. Lübbe, D.B. Nelsonc, A. Rammigb, A. Riglingd, L. Rosej, N.K. Ruehrn, K. Schumannm, F. Weisere, C. Wernero, T, Wohlgemuthd, C.S. Zangb, and A. Kahmen, 2020. A first assessment of the impact of the extreme 2018 summer drought on Central European forests, *Basic and Applied Ecology*, 45: 86-103.

Shin, J.Y., H.H. Kwon, J.H. Lee, and T.W. Kim, 2020. Probabilistic long-term hydrological drought forecast using Bayesian networks and drought propagation, *Meteorological Applications*, 27(1): e1827.

Shukla, S., A. McNally, G. Husak, and C. Funk, 2014. A seasonal agricultural drought forecast system for food-insecure regions of East Africa, *Hydrology and Earth System Sciences*, 18(10): 3907-3921.

Son, B., S. Park, J. Im, S. Park, Y. Ke, and L.J. Quackenbush, 2021. A new drought monitoring approach: Vector Projection Analysis (VPA), *Remote Sensing of Environment*, 252: 112145.

Sothe, C., C.M. De Almeida, M.B. Schimalski, L.E.C. La Rosa, J.D.B. Castro, R.Q. Feitosa, M. Dalponte, C.L. Lima, V. Liesenberg, and A.M.G. Tommaselli, 2020. Comparative performance of convolutional neural network, weighted and conventional support vector machine and random forest for classifying tree species using hyperspectral and photogrammetric data, *GIScience & Remote Sensing*, 57(3): 369-394.

Tadesse, T., B.D. Wardlow, M.J. Hayes, M.D. Svoboda, and J.F. Brown, 2010. The Vegetation Outlook (VegOut): A new method for predicting vegetation seasonal greenness, *GIScience & Remote Sensing*, 47(1): 25-52.

Tadesse, T., G.B. Demisse, B. Zaitchik, and T. Dinku, 2014. Satellite-based hybrid drought monitoring tool for prediction of vegetation condition in

Eastern Africa: A case study for Ethiopia, *Water Resources Research*, 50(3): 2176-2190.

Tan, R. and M. Perkowski, 2015. Wavelet-Coupled machine learning methods for drought forecast utilizing hybrid meteorological and remotely-sensed data, *Proc. of the International Conference on Data Mining (DMIN'15)*, Las Vegas, NV, Jul. 27, pp. 50-56.

Tian, M., P. Wang, and J. Khan, 2016. Drought forecasting with vegetation temperature condition index using ARIMA models in the Guanzhong Plain, *Remote Sensing*, 8(9): 690.

Trenberth, K.E., A. Dai, G. Van Der Schrier, P.D. Jones, J. Barichivich, K.R. Briffa, and J. Sheffield, 2014. Global warming and changes in drought, *Nature Climate Change*, 4(1): 17-22.

Tran, H.T., J.B. Campbell, T.D. Tran, and H.T. Tran, 2017. Monitoring drought vulnerability using multispectral indices observed from sequential remote sensing (Case Study: Tuy Phong, Binh Thuan, Vietnam), *GIScience & Remote Sensing*, 54(2): 167-184.

Van Loon, A.F., 2015. Hydrological drought explained, *Wiley Interdisciplinary Reviews: Water*, 2(4): 359-392.

Wang, W., M.W. Ertsen, M.D. Svoboda, and M. Hafeez, 2016. Propagation of drought: from meteorological drought to agricultural and hydrological drought, *Advances in Meteorology*, 2016(6547209): 1-6.

West, H., N. Quinn, and M. Horswell, 2019. Remote sensing for drought monitoring & impact assessment: Progress, past challenges and future opportunities, *Remote Sensing of Environment*, 232: 111291.

Wilhite, D.A. and M.H. Glantz, 1985. Understanding: the drought phenomenon: the role of definitions, *Water international*, 10(3): 111-120.

Wilhite, D.A., M.V. Sivakumar, and R. Pulwarty, 2014. Managing drought risk in a changing climate: The role of national drought policy, *Weather and Climate Extremes*, 3: 4-13.

Wong, G., H.A.J. Van Lanen, and P.J.J.F. Torfs, 2013. Probabilistic analysis of hydrological drought characteristics using meteorological drought, *Hydrological Sciences Journal*, 58(2): 253-270.

Yan, H., H. Moradkhani, and M. Zarekarizi, 2017. A probabilistic drought forecasting framework: A combined dynamical and statistical approach, *Journal of Hydrology*, 548: 291-304.

Zargar, A., R. Sadiq, B. Naser, and F.I. Khan, 2011. A review of drought indices, *Environmental Reviews*, 19(NA): 333-349.

Zhang, X., Q. Tang, X. Liu, G. Leng, and Z. Li, 2017. Soil moisture drought monitoring and forecasting using satellite and climate model data over southwestern China, *Journal of Hydrometeorology*, 18(1): 5-23.

Zhang, J. and Y. Shen, 2019. Spatio-temporal variations in extreme drought in China during 1961-2015, *Journal of Geographical Sciences*, 29(1): 67-83.

Zhang, Y., Z. Hao, S. Feng, X. Zhang, Y. Xu, and F. Hao, 2021. Agricultural drought prediction in China based on drought propagation and large-scale drivers, *Agricultural Water Management*, 255: 107028.