Modern Civil Engineering (ISSN 2470-4180)
December 2022, Volume 2, No. 4, pp. 30-44
Doi: 10.15341/mce(2470-4180)/04.02.2022/004
Academic Star Publishing Company, 2022
www.academicstar.us

Recent Advancement in Drought Index Using Remote Sensing Techniques: A Review

Dahiru M. Z.[1,2,3], Mazlan Hashim[1, 2], and Noor Dyana Hassan[1,2]

1. Geoscience & Digital Earth Centre (INSTEG), Research Institute for Sustainable Environment (RISE), Universiti Teknologi Malaysia, Johor Bahru, Malaysia

2. Faculty of Geoinformation & Real Estate, Universiti Teknologi Malaysia, Johor Bahru, Malaysia

3. Adamawa State Polytechnic, Nigeria

Abstract: Drought monitoring is a key element of current drought preparedness approaches, providing critical information on recent conditions that can be used to trigger mitigation actions to lessen the impact of this natural threat. Drought can be both complex and challenging to monitor since it lacks a single universal definition, which makes findings intricate. Three effective and significantly grounded explanations were developed to differentiate and categorise drought types; namely, meteorological, agricultural, and hydrologic drought. Quite a lot of satellite-based drought indices have so far been suggested for regional and national levels. Meteorological and satellite-based indices are used to find diverse drought phenomena, including meteorological, agricultural and hydrological drought. The current remote sensing advancements have both confirmed useful for drought monitoring and prediction where some indicators provide a limited view of drought conditions, concentrating on vegetation health and agricultural drought. Several satellite-based remote sensing instruments have been advanced for drought monitoring and early warning. The numerous meteorological variables (indicators) such as precipitation, temperature, humidity and evapotranspiration are required to calculate drought severity level. The long-term historical records of satellite imagery and climatic data are essential to calculate drought severity levels and to determine drought risk-prone ranges. Recently quite a lot of satellite imagery has proven useful in agricultural drought assessment. Thus, the significance of new developed remote sensing-derived based drought indices will come to reality if researchers and experts for drought monitoring can come out with a new approach to integrating indices that will address both long-term and short-term drought effects concerning in-situ and satellite data to support the actualization of the SDG targets 2.4 by 2030 and 13.1, 13.2.

Key words: remote sensing, drought index, meteorological, agricultural, hydrological, socioeconomic droughts

1. Introduction

Drought is a complex, natural recurring hazard with slow onset affecting large zones with major wide-ranging impacts on many sections of society, including the environment, society, agriculture, energy, health, hydropower generation, water supply, economic and other natural phenomena [1, 2]. In quite a lot of areas in the world, drought is a common, recurring natural event that has significant, detrimental, economic and environmental shocks. Drought has added more widespread effects than any other natural tragedies (floods, landslides, strong wind etc.) and slows down over periods that are impressed by short-term measures, and difficult to be detected and determine its impact extent [3-5]. The U.S estimated annual drought impact to be over $6-8 billion [6]. The drought is well thought-out as the most complex phenomenon globally and is grouped into four classes into four [7] are; meteorological droughts (lack of precipitation), which resulted in the shortage of accessible soil water for plant growth [8, 9]; agricultural droughts (shortage in soil moisture, and

Corresponding author: Mazlan Hashim, E-mail: mazlanhashim@utm.my.

vegetation response), it causes deficit of soil water that lead to significant damage of agricultural ecosystems (e.g., Crop produce) [10-12]; hydrological droughts (deficit in the runoff, streamflow, or groundwater storage), denotes to groundwater decrease and absence of surface water which affect water resources distribution; socioeconomic droughts (community responses to water supply and demand) [13, 14].

Consequently, the remote sensing-based drought techniques remained the most efficient base for analysis and prediction of hydrometeorological perspective using data like precipitation, vegetation, ground surface temperature, soil moisture, and evapotranspiration for monitoring and application. However, these drought indices are useful depending on the data collection limitations, topography, weather condition, and water facilities source. The numerous drought indicators related to precipitation, soil moisture, vegetation health, and surface and groundwater have been analysed to define specific cases of drought together in efforts with another package like U.S. Drought Monitor (USDM) [15].

Remote-sensing imagery has been active from different facial terms of weather and climatology studies. The Television Infrared Observation Satellite (TRIOS-1) was the first meteorological satellite launched in the 1960s, since from that period the new epoch of land monitoring, opened the means to new development of other satellites such as the Advanced Very High-Resolution Radiometer (AVHRR), Landsat, and the Geostationary Operational Environmental Satellites (GOES). which overcome the limitations of gauge-based meteorological observation and drought monitoring purposes. The Satellite-based drought indices are capable of describing the spatial unpredictability of drought, they became the most reliable tools for drought monitoring and prediction at regional scales [16]. To reduce the ambiguity of satellites, drought monitoring has been tried using the combination of satellite and ground data for integration [1, 17].

More often than not, the application of satellite data in drought studies can be classified into two categories: an atmospheric perspective, which concentrates on obtaining drought-related atmospheric variables (e.g., Precipitation or relative humidity) from satellites as well as a land surface perspective, which related with earth surface. Different drought indices have been technologically advanced to measure a drought strength, magnitude and weakness from a different continent, which is often used in an effective approach in various fields to analyse sectoral drought attributes like frequency, harshness, and duration. To exemplify the contests, during the last two decades, drought indices (IDs) have been divided into Climatic or Satellite-derived (IDs), from regional to global scale assessment, and monitoring has been advanced and implemented. For example, the single index cannot describe the drought complication fully, but different drought indices are combined to develop for success [18].

Through modification of the normalized difference vegetation index (NDVI) by normalizing NDVI after seeing the possible maximum and minimum of an ecosystem the vegetation index VCI was developed [19]. The vegetation health index VHI and soil wetness shortage index SWDI were developed using NDVI and land surface temperature (LST) (VHI; [16] (SWDI; [20]). However, the scaled drought condition index was generated from LST, NDVI, and Tropical Rainfall Measuring Mission (TRMM) precipitation (SDCI) [21, 22]. The SDCI detects meteorological and agricultural droughts index in both humid and arid regions when compared to the U.S. Drought Monitor (USDM) data. The microwave integrated drought index is a short-term drought index that combines LST, NDVI, and soil moisture (MIDI) [23, 24]. Temperature Condition Index (TCI), Enhanced Vegetation Index (EVI), was organized to measure the drought effect on the Soil and or natural vegetation covered. To evaluate the severity of drought, the previous studies participate in deliberate various indices, of which the PDSI

(Palmer Drought Severity Index) and SPI (Standardized Precipitation Index) indexes are the most widely used [25]. Where PDSI designs require many parameters, including precipitation, air temperature, air pressure, soil moisture, etc. While the SPI is a physically-based drought index, the higher density of data needed in the calculating process limits the extensive use of PDSI because the majority of the research extents cannot contain the data and parameter requirements [26]. The purpose of this research is to identify the recent advancements in drought indices using remote sensing satellite-based techniques. Which will eventually be performed by conducting a spatiotemporal comparative review of myriad drought indices to identify the most accepted use.

1.1 Need for Drought Research

Looking at the complex nature of drought on precipitation levels for planning and management, studying drought has a significant role in freshwater assessment. There is a need for a critical understanding of historical droughts' nature in a particular area or the region as well as its behavioural occurrences. Therefore, different ideas about droughts will be of outstanding significance for the model's development for investigating the diverse drought nature as well as the current argument. Due to its advances in global drought changes in recent years [13]. Therefore, this review paper necessitated highlighting recent improvements in the drought index using remote sensing techniques based on meteorological, agricultural or hydrological drought features, and the necessary indices used to describe its reality. In improver, the review will provide an overview of indices applied to describe water accessibility in the ecosystem from the arenas of application mentioned above. Nevertheless, more than 50 publications, mostly related to remote sensing-derived based and climate drought indices were critically reviewed and cited in this clause Fig. 1. So, sometimes indices are reported as "physiologically-based" as the upshot of the associated literature and further questions whether some indices can be considered more appropriate than each of the above applications mentioned [27]. Thus, the early warning drought system (EWDS) is well projected to handle any drought event, lack of adequate planning and readiness, the foreseeing danger of drought is more alarming to the ecosystem [28, 29].

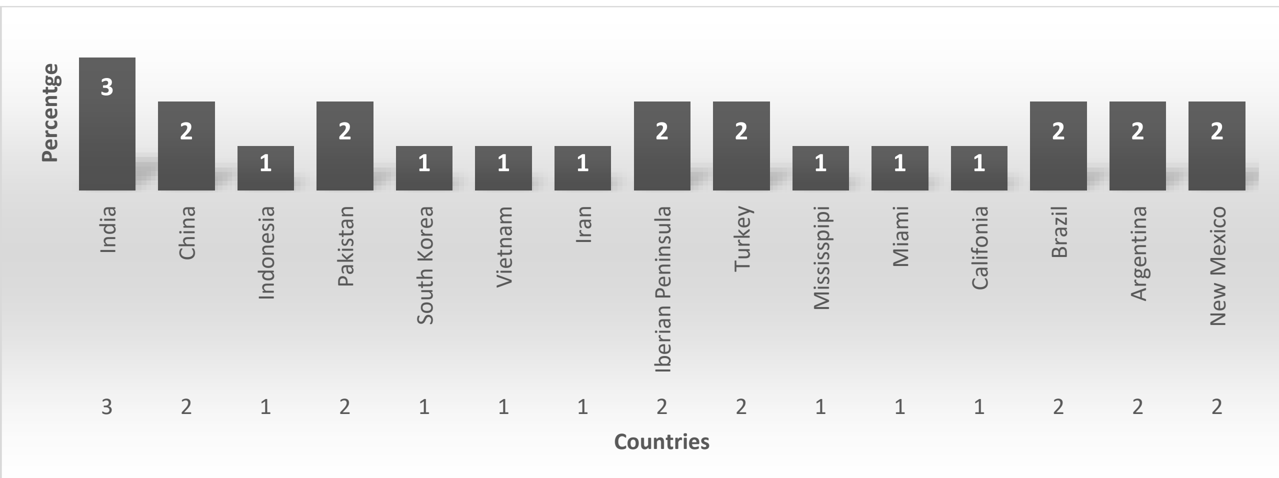

Fig. 1 Show the percentage of the reviewed article based on countries.

2. Methods

At the moment, several methods for drought monitoring are on the frontline; (In-situ, remote sensing, and synergy-based indices), theca methods are mathematically represented by integrating different variables of studying drought in either quantitative or qualitative means to overcome the use of field data directly [30]. Thus, many countries of the world come out the modern framework for drought monitoring and mitigation based on the social, economic, and environment at large [31], in which most of the studies depends on the use of a single data sources [31], this result to limited spatial and temporal resolution. In fact base, the single data sources used by many countries of the world resulted in the development and application so many methods that link the data from various sources for better and improved high spatial and temporal data quality for research [32].

2.1 Drought Monitoring Tools

Drought is described as the limitation or deficiency of precipitation over a stipulated period, causing stress to bodily processes, groups and the environment [13]. The in-situ can provide accurate results if properly applied during the measurement, and having shortcomings in spatial dynamics over a big area [33], to address this problem, the remote sensing approach is the best option because the program holds the ability to traverse large regions at a near temporal frequency. Nevertheless, it depends fully on the reflected/emitted energy of the objects, so the answer might change when compared with the in-situ derived results. Nevertheless, the even with the research carried on using remote sensing-based drought indices, there are still several challenges ahead that need to be addressed, few among; Monitoring small areas with limited in-situ data during the observation, consistency on the historic datasets to improve remote sensing-based forecasting techniques, mixing the past satellite sensors from a different platform, and developing comprehensive/standard validating scheme.

The in-situ observations are a representation of the ground measured conditioned point based on discrete geographic location, most of the traditional drought monitoring indicators fully depend on; meteorological (temperature and precipitation data), hydrologic parameters (e.g., soil moisture, groundwater, flow and reservoir levels) are capable to provide quantitative and quantitative derived information over an area. Thus, the estimation [34] provide by the indices are accurate during data acquisition in the field some example is; (i) Palmer drought severity index (PSDI) applied to precipitation and temperature [35]; (ii) Crop Mixture

Table 1 Some common selected remote sensing-based drought indices conducted in research publication.

Citation	Subject area	Indices/ Model	Data/Sensors	Strength	Restriction	Region
Abiodun et al., 2018; Anand et al., 2018; Ari et al., 2018; Brema et al., 2019; De Sousa et al., 2015; Elhag & Zhang, 2018; Jiao et al., 2019a; Parajuli et al., 2018; Park et al., 2018; Roodposhti et al., 2019; Nilda Sánchez et al., 2018; Seonyoung Parka et al., 2016; Serrano et al., 2018; Q. Zhao et al., 2018; Zhao et al., 2017	To monitor the impact of drought on soil moisture; the Impact of climate and land-use changes; Water availability to quantify the agricultural domain	SWAT; NDVI; TCI; SPI; VCI; VHI; ET	MODI; Landsat-8 OLI; NOAA-AVHRR; TRMM	A surface energy balance algorithm for land (SEBAL), which utilized Moderate Resolution Imaging Spectro-radiometer (MODIS) to generate monthly ET time series data, images were estimated by the SWAT model; The prediction drought model map shows a similar spatial distribution to the actual drought map; Apply hydrological factors (Precipitation, surface temperature evapotranspiration) & applied remote sensing data from various detectors	Because of low spatial resolution, it is difficult to analyze the small vegetation area; Highly depends on the soil types, ground moisture and level of fertilization and also weakly performs on a dominant temperature over the precipitation	Chimel, Asia; China; N/S Carolina, New Mexico; South Korea; Vietnam; California; Iran; India; Argentina; Iberian Peninsula; Indonesia; North West Mississippi Brazil; Northern India; Ethiopia; East Asia; Sudan

Table 2 Some common selected used in-situ-based drought indices conducted in research publication.

Citation	Subject area	Indices/ Models	Strength	Restriction	Region
Havrylenko et al., 2016; Fiaz et al., 2019; Sonam et al., 2019; Emeka, 2019; Tássia et al., 2019; David et al., 2019; Fiaz Hussain et al., 2019; Sabin Shrestha et al., 2019; Lei et al., 2017; Ismail, et al., 2017	To monitor the impact of drought on soil moisture; Evaluate soil erosion using semi distribution scale; Effective drought prediction using SWAT couple with the multivariate copulas	SWAT, SPI, NDVI, SWC; SPI, PDSI SSI, SPEI; GCM, PDSI_SWAT PCA	The reliability of this model was constructed with the temporal variation of SPI and NDVI to characteristics of drought episode; Flows simulation by SWAT in response to the majority of climate model projection show a consistent increase in low flow pattern	Not suitable for the large-scale region, especially with great elevation variation; Changes in hydrological component concerning changes in LULC underground rapid commercialization	Argentina; Pakistan India; Nigeria; Southern Brazil Iberian Peninsula; Miami the USA China; Turkey, Western Europe

index (CMI), in cooperating soil moisture, precipitation and Temperature [36]; (iii) Crop Water Stress Index (CSDI) applied on actual and potential [37]; (iv) Crop Specific Drought Index(CSDI) Incorporate soil moisture, precipitation and temperature (ISMPTI); Crop Water Stress Index (CWSI); Standardized precipitation Evapotranspiration Index (SPEI) [38]; (v) Standardized Precipitation Index (SPI) uses precipitation regimes. In addition, some of these indices would be used for meteorological drought, in fact, based on the world meteorological organization (WMO) recommended for SPI should be applied for the drought classes mention above [39], with the value ranges of drought classes (Near, normal, Moderate, Severe and Extreme drought) for a stipulated period as (1, 3, 6, 9, 12- and 24-month interval) as shown in Table 3.

Table 3 Most commonly used Climate drought monitoring indices.

Citation	Index	Description	Strengths	Weaknesses
Palmer, 1965; Haddinghaus and Sabol, 1991; Ashok et al., 2010; Dai et al., 2011; Sheriza et al., 2015; Majid et al., 2017; Mashe Rao et al., 2017; Lei Zou et al., 2017; Ismail Dabanli et al., 2017; Qi *Zhao* et al., 2018; Seou et al., 2018	Palmer Drought Severity Index (*PDSI*)	Calculated using precipitation, temperature, and soil moisture data. The soil moisture algorithm has been calibrated for relatively homogeneous regions	Worked out for flexible multiple time scales, provides early warning of drought and helps assess drought severity.	Is very weak for short-term detection, and also depends on soil moisture and its property which have been simplified to one value in each climate division.
Mckee et al., 1993; Sonmez et al., 2005; Zhang et al., 2009; Ashok et al., 2010; Zambrano et al., 2012; Sheriza et al., 2015; Zarch M. A. A. et al., 2015; Cui et al., 2015; Anderson et al., 2016; Schroeder et al., 2016; Majid et al., 2017; Ravinesh et al., 2017; Seon-yeoh Park et al., 2018; Nilda Sanchez et al., 2018	Standardized Precipitation Index (*SPI*)	A simple calculation based on the concept that precipitation deficits over varying periods scale influence groundwater, reservoir storage, ground moisture, snowpack, and stream flow	Worked out for flexible multiple time scales, provides early warning of drought and helps assess drought severity.	Precipitation is the only input data. SPI values based on long-term precipitation may change. The long time scale up to 24 months is not dependable.
Palmer, 1965; Quesney et al., 2000; KeyanTash & Drcup, 2002; Ashok et al., 2010; Sheriza et al., 2015; Majid et al., 2017	Crop Moisture Index (*CMI*)	A derivative of PDSI. CMI reflects moisture supply in the short term	Effective for the detection of short-term agricultural drought sooner than PDSI.	CMI cannot monitor long-term droughts well.
Shefer & Dezman, 1982; Ashok et al., 2010; Son et al., 2012; Sheriza et al., 2015; Majd et al., 2017; Suk Hwan Jang et al., 2019	Surface Water Supply Index (*SWSI*)	Developed from the Palmer index by combining hydrological and climatic features.	SWSI takes into account reservoir storage, streamflow, snowpack, and hurry. Effective under	SWSI is difficult to compare between different basins. SWSI cannot detect extreme events

			snowpack conditions.	effectively. Not a suitable indicator for agricultural drought.
Sheriza et al., 2015; Ainundin & Ampun, 2008; M. Taufik et al. 2019; B. Baniya et al., 2019	Keetch -Byram Drought Index *(KBDI)*		Is used as the national forest fire danger point forecasting tool, precipitation and soil moisture used in water balance?	
Meyer & Hullinger et al., 1993; Ashok et al., 2010	Crop Specification Drought Index (*CSDI*)	Temperature, precipitation, evapotranspiration	Provide daily Estimate of Soil water availability for different zones and ground layer	Too many requirements including soil types, crop phenology, and climatology data
Bhame & Mooly, 1980; Ashok et al., 2010; Aremu et al., 2012; Sheriza et al., 2015	Bhaimer, and Mooley Drought Index (BMDI)	Similar to SPI based on precipitation and PET	Very good standards of the current condition of drought, all the same, its take care of the short weather drought period.	Uncertainties in input data for the calculation of PET.
Tsakiris and Vangelis, 2005; Tsakiris et al., 2007	Reclamation Drought Index *(RDI)*			RDI at different basins cannot be compared with each other and has been computed seasonally.
Shafer & Desman, 1982; Hollinger et al., 1993; Ashok et al., 2010; Martinex-Fernandez et al., 2016; S. B. Havry Lenka, J. M. Bado gue et al., 2016; Aadhar and Mishra, 2017; Lei Zou, Jun Xia et al., 2017; Sanchez et al., 2018; Villamizar, Sergio M. et al., 2019; Jatin et al., 2019	Soil moisture drought index (*SMDI*)	Soil moisture, evapotranspiration	Weekly soil moisture and evapotranspiration values simulated by SWAT to address PDSI weakness	In several of the soil properties across different climate conditions.
Svoboda et al., 2002	U.S Drought Monitoring (*USDM*)	Based on several key physical indicators, such as PDSI, SPI, PNP, soil moisture model percentiles, daily streamflow percentiles, remotely sensed satellite vegetation health index and many supplementary indicators	Integrating remotely sensed satellite vegetation health index together with other drought indices (see text for details).	USDM is weighted to precipitation and soil moisture in the short term. USDM inherits the weaknesses of the other indices it uses (see text for details)
Palmer, 1965	*PHDI*	PHDI is derived from PDSI to quantify the long-term impact of hydrological drought	Same as PDSI, but more effective to determine when a drought ends.	So, is it a gradual change PHDI may change more slowly than PDSI
Gibbs and Maher, 1967; Smith et al., 1993; White and O'Meagher, 1995	Deciles	Foundation of the precipitation group, the deciles have been distributed from 1 to 10 showing the drier condition indicating the lowest value while the wetter condition indicating higher values than normal.	It establishes a uniform drought classification as an effect of accurate statistical measurement of responses to precipitation.	For better analysis, there is a need for a long-term climatology record of precipitation

2.2 Impact of Climate Change on Drought

For the past two decades, the most challenging issue for drought monitoring has been short-term drought prediction, the long-term drought prediction is more reliable than the short-term due to sudden slow signal responses by the drought condition [40, 41]. Even though the long-term drought predictions have occurred as a result of insufficient or limited precipitation data, the short-term period is highly based on factors such as temperature, and evapotranspiration rather than precipitation. While long to short-term prediction is still very difficult to be addressed as a result of the complexity of sufficient trends to measure meaningful drought anomalies of the phenomenon. However, short-term drought prediction has always been affected by an atmospheric variation on an intra-seasonal time scale [42].

Nevertheless, on that point are several factors that influence drought condition, namely; hydrological parameter (evapotranspiration, soil moisture, groundwater, and precipitation) is needed to offer a comprehensive depiction of drought condition to estimate the hydrological variable operationally from satellite sensors. Drought monitoring and prediction have been defined as a termination of the inability of the satellite sensors to observe and retrieve some valuable information which lacks [43]. Grounded on this fact, in the early 2000s new revolution satellite-based sensor was launched to trash these challenging with high temporal frequency (1 to 2 days revisit). The Moderate Resolution Imaging Spectroradiometer (MODIS), Advanced Microwave Scanning Radiometer-Earth Observing System (EOS) (AMSR-E) are used for water content assessment from the plant as well as thermal-based tools for evapotranspiration estimation, and the Quick Scatterometer (QuickSCAT) [44, 45]. Pair with this revolution in applied science, the environmental models and algorithms, and computing capabilities, have contributed to the speedy emergence of many new remote sensing tools like sentinel data to monitor several aspects of drought conditions [46, 47].

2.3 Classification of Droughts

With the frequent occurrences of drought, the world will never be safe as a result of its impact and severity, the deficit in precipitations to the ecosystem and environment at large [29, 48]. However, based on the related review, droughts have been classified into four major types (Meteorological, agricultural, hydrological, and socio-economic drought) [49, 50] (i) The Meteorological drought; causes as a result of a precipitation shortage or deficiency for a certain period over a geographical location, it could be a week, months or year. (ii) Agricultural drought emanated as a result of a deficiency in the soil moisture far below the expected vegetation growth requirement at different stages resulting in growth stress and low yield production [29]. (iii) Hydrological drought; occurred as a result of the shortage of natural, artificial or groundwater resources (Reservoir, Dam, Streams) [29]. (iv) Socioeconomic drought; effects of the above-named classes of drought cause havoc to human actions, and the ecosystem, therefore the effect of drought has social stability, food protection and economic loss of a country [3, 51]. Shot-term precipitation deficiency, soil moisture level and increase in evapotranspiration lead to rises in temperature [52, 53].

3. Remote Sensing Methods for Drought Monitoring

The overall spatial context of drought based in-situ is highly challenging, in the last two-decade, remote sensing-based drought indices are seen as one of the most comprehensive and significant tools used approach to speaking, integrating multi-criteria drought indices to support drought assessment [54]. Therefore, the unitary of the significant roles is the provision of spatial continuous spectral reflectance of pixel values across the areas ranging from several meters to kilometres, where the missing data from the in-situ will be overcome by the satellite imagery. The remote sensing-based drought indices are completely depending on the unique spectral signature (Red, Near, Infrared, shortwave and thermal spectral band) of reflected/emitted signal of electromagnetic radiation from multiregional countries. In some cases, the entire ecosystem and soil composition have a gradual effect on the sensors through physical phenomenon, where thermal and spectral responses will assist as a drought occurrence indicator. It refers to as the most potential indicator for investigating various classes of the drought [55, 56]. The drought-related environment phenomenon (soil moisture, organic matter, chlorophyll, vegetation biomass and ground temperature) can be assessed through respective spectral responses from electromagnetic radiation from different environmental parameters that lead to valuable source drought monitoring. Therefore, remote sensing-derived based operational drought monitoring methods can only be categorized based on methods and applications such as: Optical remote sensing method, Thermal remote sensing methods, Microwave remote sensing methods, and Combined remote sensing methods. All these depend on diverse factors such as availability of satellite information, quality and data Cost, and pre-processing and post-processing requirements. Lately, the remote sensing satellite provides advanced data for drought monitoring and prediction; (Vegetation indices, precipitation information, evapotranspiration, and soil moisture measurement) [57] for synoptic view with continuous data [58].

4. The Optical Remote Sensing Approach

The main environmental phenomenon such as natural flora (vegetation greenness and vegetation wetness conditions) and soil moisture are found in an electromagnetic range from 0.4 to 2.5 spectral bands being the primary input for meteorological, agricultural hydrological drought indices [59]. These spectral bands comprise (red, near-infrared [NIR], and short infrared [SWIR]) The red spectrum tends to occupy most of the incident rays as determining factors for healthy vegetation and reflects a significant sum of money in the NIR spectrum in contrast meaning unhealthy vegetation reflect more visible spectrum and reflect less in the NIR spectrum [60]. The SWIR is more sensitive to vegetation wetness (Vegetation, water content) [61] while the NIR shows signs of diminishing response to the vegetation wetness, thus the SWIR, the surface reflectance is progressively increasing as a result of water content deficiency level, [62]. The significant role of optical remote sensing-based drought indices have described based on the applications and demand of monitoring depends on soil moisture monitoring, responses on the bare soil rather than vegetation surfaces since multiple reactions from vegetation on leaves and roots could resist drought [63], this will eventually delay the drought identification in densely vegetated areas, and lead to uncertainty on the index (PDI) result [64]. The vegetation drought index was used to move positively in a thickly vegetated area than sparsely vegetation areas based on bare soil reflectance that lead to uncertainty in drought monitoring, such indices are; (NDVI; LWCI; NDWI; NDVI anomaly, VCI; SVI, SWIR; SPSI, and VWSI). Thus, vegetation drought indices nor the soil, drought indices, were applied to semi-arid areas (sparsely vegetated areas) [65], which would lead to uncertainty and inaccurate the effect of the drought monitoring result. Thusly, this required a better approach by performing land cover classification and assigning suitable index for each class [66] or in the other hand, the challenges will lead to addressing the newly developed approach for drought indices that match both the vegetation and bare soil at the same time such as; (SIWI; NMDI; VSDI) Table 4. Microwave remote sensing described both, passive or active sensors base index to detect and estimate Soil moisture and vegetation and serves as the most significant drought index for monitoring across the world, where the microwave sensors remain the only tool used to detect dielectric constants between water, soil and vegetation [67], however, the passive microwave remote sensors (Scanning Multichannel Microwave Radiometer (SMMR); Special Sensor

Microwave/Imager (SSM/I); Soil Moisture and Ocean Salinity (SMOS); and Soil Active and Passive Moisture) are extensively used for surface water contend detection through the measurement of microwave intensity from the soil and vegetation which directly related to water content [67, 68]. Nevertheless, when an optical remote sensing domain combines in one index, it indicates different sensitivity to drought conditions. For instance, (the Normalized Difference Drought Index [NDDI]; and Normalized Moisture Index (NMI) are computed as a function of NDWI and NDVI [69, 70]. However, some studies revealed that Optical and Thermal based indices have been combined; examples, (i) Microwave Integrated Drought Index (MIDI); Integrated the precipitation Condition Index (PCI), Soil Moisture Condition Index (SMCI), Temperature Condition Index (TCI), obtain from Precipitation based TRMM data and soil moisture and land surface temperature and data from Advanced Microwave Scanning Radiometer-EOS (AMSR); and used for monitoring short-term drought over the semi-arid region [23] (ii) Scaled Drought Condition Index (SDCI) employed TRMM-based precipitation data in Conjunction with MODIS-based Ts and NDVI data for agricultural drought monitoring over arid and semiarid and humid regions [71] (Table 5).

Table 4 Most commonly used optical remote sensing-based drought monitoring indices.

Citation	Index	Description	Strengths	Weaknesses	Type
Ghulam A., Li Z. L., Qin Q. et al., 2008	Precipitation Drought Index (PDI)	Soil Moisture	Effective in drought condition calculation	Weak in providing better accuracy on variable land cover types like bare soil and densely vegetated area	Soil drought index
Tucker C. J., Choudhury B. J., 1987; Majid et al., 2017; Khalid M., Elhag et al., 2018; Kogan, 1990; Nilda Sanchez et al., 2018; Zhang et al., 2017; Toulios et al., 2012	NDVI	For better measures of vegetation health or greenness condition in the moderate vegetation zone	On and natural vegetation index	In the sparsely vegetated area, the land would have an effect on reflectance which might cause doubts about the estimated values for the drought monitoring.	Vegetation drought Index
Hunt E. R., Rock B. N., 1989; Zanko-Tejada et al., 2003; Geo B., 1996; Hardisky K. V., Smart R. M., 1983; Xiao et al., et al., 2004	Moisture Stress Index (MSI), Simple Water Ratio Index (SRWI), Normalized Difference Water Index (NDWI), Normalized Difference Infrared Index (NDII), Shortwave infrared Water Stress index (SIWSI) Land Surface-water Index (LEWI) Vegetation condition Index (VCI)	For the efficient monitoring of vegetation conditions concerning water contend for long periods.	Botany variable, surface temperature, ground moisture, precipitation, develop impact Basically, are significantly on the sensibility of the dense vegetation condition rather than a bit of leaf grade.	Only applicable for a thickly vegetated area rather than a sparsely vegetated area, the presence of soil or bare surface might lead to affect the last outcome.	Vegetation drought Index
Ghulam A., Li Z. L., Qin Q. et al., 2008	Modified perpendicular Drought Index (MPDI) Normalized Multiband Drought Index (NMDI) Visible and Shortwave Drought Index (VSDI)	Is mostly marked by diverse topography, soil and ecosystem and builds a better estimation Vegetation, Soil and water fight	More effective on soil types and ground moisture.	Highly depends on the soil types, ground moisture and level off.	Soil and Water drought Index
Kogan F. N., 1995; McVicar T. R., Jupp D. L., 1998	Temperature Condition Index (TCI), Normalized Difference Temperature Index (NTDI)	Have better reflectance of Spatio-temporal variability of ground moisture	Other variables like solar radiation, wind speed, and leaf area index are too utilized.	Fertilization also weakly performs on a dominant temperature over the precipitation	Soil Moisture

Table 5 Some common selected Optical and active satellite-based drought indices for monitoring indices analysis.

Citations	Index	Sensors	Description	Strengths	Weaknesses	Type
Seon-young Park, Eunkyo et al., 2018a, 2018b; Seddon et al., 2016; Qi Zhao, Qianyun Chen et al., 2018; Brema et al., 2019; Kogan, 1990	NDVI, NDDI, NDWI, ET	MODIS, TRMM	Evapotranspiration is highly sensible and related to drought conditions as a result of reflected energy and water exchange within the vegetations, soil, and atmosphere which reposes to soil moisture characteristics.	Effective in monitoring vegetation, and water content, and providing vegetation greenness conditions.	Unable to provide higher accuracy over a variable land cover types, especially bare soils moisture and density vegetation field, also uncertainty increases considerable in the presence of soil and sparsely vegetation or bare surface.	Soil Moisture, Vegetation Cover.
Zhao T. B., 2014; Qi Zhao et al., 2018; Jiang S. H. et al., 2017	NDVI, LST, SDCI	MODIS, TRMM	These are satellite platforms with higher spatial resolution and precision of precipitation product, and currently, the most widely used precipitation product.	TRMM data have comparatively high accuracy in the different climatic regions, and the most widely used data in numerous applications, it works under all-weather conditions.	Low spatial resolution and unable to acquire images at high elevation	Precipitation
Kogan, 1990; Nilda Sanchez et al., 2018; Zhang et al., 2017; Toulios et al., 2012; Majid, shadman, Rood post, 2017	NDVI, ET LST, VHI	AVHRR, MODDIS	Botany variable, surface temperature, ground moisture, precipitation.	Develop impact on and natural vegetation index	Because of low spatial resolution, it is difficult to analyze the small vegetation area.	Precipitation
Khalid M., Elhag et al., 2018; Sandholt et al., 2002; Enenkel et al., 2016; Sanchez et al., 2008, 2016	MIDI (NDVI, LST)	EOS (AMSR-E)	The relationship between soil temperature (LST) and Vegetation responses (NDVI), Is used on a worldwide scale for drought assessment.	Scalable over space and time, it integrates remote sensing data set on (LST, Soil surface Moisture SSM and vegetation index NDVI)	Indirect application for the recovery of soil moisture status.	Soil Moisture

5. Recants Advance in Remote Sensing

Remote sensing techniques are an advanced approach that holds the potential to relieve time and view wider areas at a temporal resolution (daily data required for large regions or regions) [72] to identify the drought impact with efficiency and reliability for a long period [73, 74]. Monitoring and mapping drought extend is an alternative to control the present and the future occurrences [75]. In the final two decades satellites, and sensors have shown to be the most significant tools that supply data for global drought monitoring and assessment [18].

Therefore, recants advancement in remote sensing techniques for addressing not only drought index, but fused multiple satellites for enhancement and assisted in mitigating these limitations [76], this review tries to consent with a synthetic approach to monitor drought index using the recent progress in remote sensing sensors (low; NOAA AVHRR), (medium; Landsat TM, Landsat MSS, and ETM+), and (high; MODIS and

TRMM). Therefore, these sensors provide satellite pictures with better resolutions that come up to the current drought-related product issues which support different drought indices like Land Surface Temperature (LST), Normalized Difference Index (NDVI), and evapotranspiration (ET) [40]. The combined integrated indices have been developed such as the Vegetation Health Index VHI [77] and Soil Witness Deficits Index [78] were developed using LST and NDVI from Moderate Resolution Imaging Spectroradiometer (MODIS). The microwave integrated Drought Index (MIDI) [23] was developed using precipitation from Tropical Rainfall Measuring Mission TRMM [79, 80], soil moisture and LST from Advanced Microwave Scanning Radiometer for EO (AMSR-E) to address the meteorological drought. According to J. Rhee and J. Im (2017) [81], LST and NDVI were used from MODIS and precipitation from TRMM to study Agricultural drought through linear integration of the ware. In addition, some indices use both satellite data and Climate data for high accuracy monitoring; Vegetation Drought Response Index VegDRI [82]; Vegetation Outlook VegOut [83]; North American Drought Monitor NADM [18]; and U.S. Drought Monitor USDM [84]; also, Seonyoung Parka et al. (2016) [18] used seven types of satellite derive indices to monitor and investigate the impact of drought on meteorological and agricultural drought for 12 years; LST, NDVI, Normalized Difference drought Index NDDI [85]; Normalized Multi-band Drought Index NMDI [67]; Normalized Difference Water Index NDWI [86]; and actual ET from MODDIS and precipitation from TRMM, LST.

Based on this fact, in the early 2000s new satellite-based sensor (The Moderate Resolution Imagine Spectroradiometer (MODIS), Advanced Microwave Scanning Radiometer-Earth Observing System (EOS) (AMSR-E) was used for water content assessment from the plant as well as thermal-based tools for evapotranspiration estimation, and Quick Scatterometer (QuickSCAT) [46, 47, 87] was launched into orbit for addressing these challenges with high temporal frequency (1 to 2 days revisit) and over a board spectral extend to monitor various component of hydrological parameters to ease the drought effect globally. Currently, drought monitoring and assessment have been expended as a result of the ongoing development by the remote sensing community, example the development of solar-induced fluorescence (SIF) to address the presence of emitted radiation from chlorophyll pigment in the vegetations serves as an early stage indicator of stress (productivity reduction) for plant photosynthesis [88, 89]. Thus, remotely sense solar-induced fluorenones, as the potential and significant early drought indicator.

6. Conclusion

Over the past decade, the satellite remote sensing application for drought monitoring and early warning has changed with the development of new technology. These changes occur as a consequence of numerous various categories of Earth observations developed by several space-borne sensors that have been set up into orbit in the last two decades. Yet, with this development the satellite-derived (MODIS and TRMM) drought, provide global data (50N-50S) that is suited to any region with limited in-situ data. Evapotranspiration is highly sensible and related to drought conditions, therefore, reflected energy and water exchange within the vegetations, soil, and atmosphere reposes to soil moisture characteristics. The MODIS utilized to generate monthly ET time series data, and images and apply the SWAT model for evaluation [18, 81, 90]. Thus, drought monitoring and assessment have been expanded as a result of the ongoing development by the remote sensing community, example the development of solar-induced fluorescence (SIF) to address the presence of emitted radiation from chlorophyll pigment in the vegetations serves as an early-stage indicator of stress (productivity reduction) for plant photosynthesis [88, 89]. So, remotely sensing solar-induced fluorenones, serves equally the potential and meaning for the early drought indicator. Therefore, the meaning of new developed remote sensing-derived based drought indices will come to reality if researchers and experts for drought monitoring can come out with a new glide path to integrate indices that will address both long-term and short-term drought effects concerning in-situ and satellite information to support the realization of the SDG goal 2 and 13.

Acknowledgements

The author acknowledges the Adamawa State Polytechnic, Nigeria for providing the support and facilities to study at Universiti Teknologi Malaysia through the Tertiary Education Trust Fund (TET fund) I also express my sincere appreciation to Prof. Dr Sr. Mazlam Hashim and Dr NoorDyana Binti Hasan for their useful and constructive guide, comments and suggestions for the improvement of this paper.

References

[1] A. Ahmadalipour and H. Moradkhani, Analyzing the uncertainty of ensemble-based gridded observations in land surface simulations and drought assessment, *J. Hydrol.* 555 (2017) 557-568.

[2] B. D. Wardlow et al., Advancements in satellite remote sensing for drought monitoring, October 2017.

[3] A. K. Mishra and V. R. Desai, Drought forecasting using stochastic models, *Stoch. Environ. Res. Risk Assess.* 19 (2005) (5) 326-339.

[4] H. Takeda et al., Acetate-mediated novel survival strategy against drought in plants, *Nat. Plants* 3 (2017) (7) 17097.

[5] D. A. Wilhite, M. H. Glantz and M. H. And Glantz, Understanding the Drought Phenomenon: The Role of Definitions, 1985.

[6] A. M. Society, The Extraordinar, September 2014.

[7] J. Polania, C. Poschenrieder, I. Rao and S. Beebe, Root traits and their potential links to plant ideotypes to improve drought resistance in common bean, *Theor. Exp. Plant Physiol.* 29 (2017) (3) 143-154.

[8] F. K. Muriithi, D. Yu and S. Robila, Vegetation response to intensive commercial horticulture and environmental changes within watersheds in central highlands, Kenya, using AVHRR NDVI data, Vol. 1603, October, 2015.

[9] L. Zhang, W. Jiao, H. Zhang, C. Huang and Q. Tong, Studying drought phenomena in the Continental United States in 2011 and 2012 using various drought indices, *Remote Sens. Environ.* 190 (Mar. 2017) 96-106.

[10] N. Sánchez and A. Gumuzzio, Remote Sensing of Environment Satellite soil moisture for agricultural drought monitoring: Assessment of the SMOS derived Soil Water De fi cit Index, *Remote Sens. Environ.* 177 (2016) 277-286.

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

[12] C. S. A. Wallace, P. Thenkabail, J. R. Rodriguez and K. Melinda, Fallow-land Algorithm based on Neighborhood and Temporal Anomalies (FANTA) to map planted versus fallowed croplands using MODIS data to assist in drought studies leading to water and food security assessments, *GIScience Remote Sens.* 54 (2017) (2) 258-282.

[13] A. K. Mishra and V. P. Singh, A review of drought concepts, *J. Hydrol.* 391 (Sep. 2010) (1-2) 202-216.

[14] L. H. Yu et al., Arabidopsis EDT1/HDG11 improves drought and salt tolerance in cotton and poplar and increases cotton yield in the field, *Plant Biotechnol. J.* 14 (2016) (1) 72-84.

[15] A. J. Peters, E. A. Walter-Shea, L. Ji, A. Vina, M. Hayes, and M. D. Svoboda, Drought monitoring with NDVI-based standardized vegetation index, *Am. Soc. Photogramm. Remote Sens.* 68 (2002) (1) 71-75.

[16] L. S. Unganai and F. N. Kogan, Drought monitoring and corn yield estimation in Southern Africa, *AVHRR Data*, vol. 4257 (1993) (97).

[17] Z. Hao, A. AghaKouchak, N. Nakhjiri and A. Farahmand, Global integrated drought monitoring and prediction system, *Sci. Data* 1 (2014) 140001.

[18] Seonyoung Parka, J. Ima, E. Janga and J. Rhee, Peer review report 1 on "drought assessment and monitoring through blending of multi-sensor indices using machine learning approaches for different climate regions", *Agric. for. Meteorol.* 217 (2016) (50).

[19] F. N. Kogan, Droughts of the Late 1980s in the United States, *NOAA Polar-Orbiting Satellite Data*, 1993, pp. 655-668.

[20] M. R. Keshavarz, M. Vazifedoust and A. Alizadeh, Drought monitoring using a Soil Wetness Deficit Index (SWDI) derived from MODIS satellite data, *Agric. Water Manag.* 132 (2014) 37-45.

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

[22] S. Park, J. Im, E. Jang and J. Rhee, Drought assessment and monitoring through blending of multi-sensor indices using machine learning approaches for different climate regions, *Agricultural and Forest Meteorology* 216 (2016) 157-169.

[23] A. Zhang and G. Jia, Monitoring meteorological drought in semiarid regions using multi-sensor microwave remote sensing data, *Remote Sens. Environ.* 134 (2013) 12-23.

[24] X. Fang et al., Monitoring and estimating drought-induced impacts on forest structure, growth, function, and ecosystem services using remote-sensing data: Recent progress and future challenges, *Environ. Rev.* 21 (2013) (2) 103-115.

[25] Y. Bayarjargal, A. Karnieli, M. Bayasgalan, S. Khudulmur, C. Gandush and C. J. Tucker, A comparative study of NOAA-AVHRR derived drought indices using change vector analysis, *Remote Sens. Environ.* 105 (2006) (1) 9-22.

[26] J. Kangasjärvi et al., Reactive oxygen species signaling and stomatal movement in plant responses to drought stress and pathogen attack, *J. Integr. Plant Biol.* 60 (2018) (9) 805-826.

[27] M. J. R. Speich, M. Zappa and H. Lischke, Sensitivity of forest water balance and physiological drought predictions to soil and vegetation parameters — A model-based study, *Environ. Model. Softw.* 102 (2018) 213-232.

[28] D. Coumou and A. Robinson, Historic and future increase in the global land area affected by monthly heat extremes, *Environ. Res. Lett.* 8 (2013) (3).

[29] M. Valipour and S. Eslamian, Analysis of potential evapotranspiration using 11 modified temperature-based models, *Int. J. Hydrol. Sci. Technol.* 4 (2015) (3) 192.

[30] J. A. Otun and J. K. Adewumi, Using precipitation effectiveness variables in indexing drought in semi-arid regions, *Clim. Res.* 5 (2009) (14) 1784-1793.

[31] T. D. Delbiso, J. M. Rodriguez-Llanes, A. F. Donneau, N. Speybroeck and D. Guha-Sapir, Drought, conflict and children's undernutrition in Ethiopia 2000-2013: A meta-analysis, *Bull. World Health Organ.* 95 (2017) (2) 94-102.

[32] M. C. Anderson, C. A. Zolin, C. R. Hain, K. Semmens, M. Tugrul Yilmaz and F. Gao, Comparison of satellite-derived LAI and precipitation anomalies over Brazil with a thermal infrared-based Evaporative Stress Index for 2003-2013, *J. Hydrol.* 526 (2015) 287-302.

[33] K. Hazaymeh and Q. K. Hassan, Remote sensing of agricultural drought monitoring: A state of art review, *AIMS Environ. Sci.* 3 (2016) (4) 604-630.

[34] M. Shadman, T. Safarrad and H. Shahabi, Drought sensitivity mapping using two one-class support vector machine algorithms, *Atmos. Res.* 193 (2017) 73–82.

[35] T. R. Heddinghaus and P. Sabol, A review of the palmer drought severity index and where do we go from here?, in: *Proc. 7th Conf. Appl. Climatol. Am. Meteorol. Soc.*, 1991, pp. 242-246.

[36] E. Kanellou, C. Domenikiotis, E. Tsiros and N. R. Dalezios, *Satellite-based Drought Estimation in Thessaly*, 2008, pp. 111-122.

[37] E. S. P. B. V and P. L. Kircher, The Use of Canopy Temperature As an Indicator of drought stress in humid regions", *Agricultural Meteorology* 28 (1983) (9111).

[38] S. J. Meyer, K. G. Hubbard and D. A. Wilhite, A crop-specific drought index for corn: I. model development and validation, *Agron. J.* 85 (1993) (2) 388.

[39] C. Bonadonna, A. Folch, S. Loughlin and H. Puempel, Future developments in modelling and monitoring of volcanic ash clouds: Outcomes, in: *The First IAVCEI-WMO workshop on Ash Dispersal Forecast and Civil Aviation, Bull. Volcanol.* 74 (2012) (1) 1-10.

[40] M. C. Anderson et al., The Evaporative Stress Index as an indicator of agricultural drought in Brazil: An assessment based on crop yield impacts, *Remote Sens. Environ.* 174 (2016) 82-99.

[41] J. A. Otkin, M. C. Anderson, C. Hain and M. Svoboda, Using temporal changes in drought indices to generate probabilistic drought intensification forecasts, *J. Hydrometeorol.* 16 (2014) (1) 88-105.

[42] P. R. Julian, Arlance spectra of synoptic SC wino components in midlatitudes and in T, *Weather* 99 (1957) (12) 954-965.

[43] D. J. McEvoy, J. L. Huntington, J. F. Mejia and M. T. Hobbins, Improved seasonal drought forecasts using reference evapotranspiration anomalies, *Geophys. Res. Lett.* 43 (2016) (1) 377-385.

[44] D. King, A. Apan, D. Keogh and M. Thomas, Natural disasters and adaptation to climate change, *Nat. Disasters Adapt. to Clim. Chang.*, 2013, pp. 95-106.

[45] S. C. Swenson and J. S. Famiglietti, Future water security of the Colorado River Basin, *Geophys. Res. Lett.* 41 (2014) 5904-5911.

[46] A. AghaKouchak et al., Reviews of Geophysics Remote sensing of drought: Progress , challenges, *Rev. Geophys.*, 53 (2015) 1-29.

[47] F. Zambrano, B. Wardlow, T. Tadesse, M. Lillo-Saavedra and O. Lagos, Evaluating satellite-derived long-term historical precipitation datasets for drought monitoring in Chile, *Atmos. Res.*186 (2017) 26-42.

[48] R. A. Al-Weshah and Y. Yihdego, Flow modelling of strategically vital freshwater aquifers in Kuwait, *Environ. Earth Sci.* 75 (2016) (19) 1-13.

[49] A. Zargar, R. Sadiq, B. Naser and F. I. Khan, A review of drought indices, *Int. J. Constr. Res. Civ. Eng.* 3 (2017) (4) 333-349.

[50] Y. Yihdego, B. Vaheddoost and R. A. Al-Weshah, Drought indices and indicators revisited, *Arab. J. Geosci.* 12 (2019) (3).

[51] K. Nakashima, K. Yamaguchi-Shinozaki and K. Shinozaki, The transcriptional regulatory network in the drought response and its crosstalk in abiotic stress responses including drought, cold, and heat, *Front. Plant Sci.* 5 (2014) 1-7.

[52] D. A. Wilhite, M. D. Svoboda and M. J. Hayes, Understanding the complex impacts of drought: A key to enhancing drought mitigation and preparedness, *Water Resour. Manag.* 21 (2007) (5) 763-774.

[53] M. Lagi, Y. Bar-Yam and Y. Bar-Yam, *The Food Crises: The US Drought*, July 2012, pp. 1-6.

[54] W. Jiao, C. Tian, Q. Chang, K. A. Novick and L. Wang, A new multi-sensor integrated index for drought monitoring, *Agric. For. Meteorol.* 268 (2019) 74-85.

[55] S. Shafiq, N. A. Akram and M. Ashraf, Assessment of physio-biochemical indicators for drought tolerance in different cultivars of maize (ZEA MAYS L.)", *Pakistan Journal of Botany* 51 (2019) (4) 1241-1247.

[56] S. Skakun, N. Kussul, A. Shelestov and O. Kussul, The use of satellite data for agriculture drought risk quantification in Ukraine, *Geomatics, Nat. Hazards Risk* 7 (2016) (3) 901-917.

[57] A. P. Williams, R. Seager, J. Abatzoglou, B. Cook, J. Smerdon and E. Cook, Contribution to California drought during 2012-2014, *Geophys. Res. Lett.* (2015) 1-10.

[58] N. R. Dalezios, A. Blanta and N. V. Spyropoulos, Assessment of remotely sensed drought features in vulnerable agriculture, *Nat. Hazards Earth Syst. Sci.* 12 (2012) (10) 3139-3150.

[59] A. Ajith, *Research Collection* 10 (2019) (3).

[60] T. Leeuw and E. Boss, The HydroColor app: Above water measurements of remote sensing reflectance and turbidity using a smartphone camera, *Sensors (Switzerland)* 18 (2018) (1).

[61] J. Tian and W. D. Philpot, Relationship between surface soil water content, evaporation rate, and water absorption band depths in SWIR reflectance spectra, *Remote Sens. Environ.* 169 (2015) 280-289.

[62] M. Farooq, A. Wahid, N. Kobayashi and D. B. S. M. A. Fujita, Plant drought stress: Effects, mechanisms and management to cite this version: Review article," *Agron. Sustain. Dev.* 29 (2009) (1) 185-212.

[63] A. Ghulam, Z. L. Li, Q. Qin, H. Yimit and J. Wang, Estimating crop water stress with ETM+NIR and SWIR data, *Agric. For. Meteorol.* 148 (2008) (11) 1679-1695.

[64] H. P. Ritzema et al., Review of the methodologies used to derive groundwater characteristics for a specific area in the Netherlands, *Geoderma Reg.* 14 (2018) e00182.

[65] X. Wu et al., Differentiating drought legacy effects on vegetation growth over the temperate Northern Hemisphere, *Glob. Chang. Biol.* 24 (2018) (1) 504-516.

[66] L. Wang and J. J. Qu, NMDI: A normalized multi-band drought index for monitoring soil and vegetation moisture with satellite remote sensing, *Geophys. Res. Lett.* 34 (2007), (20) 1-5.

[67] S. D. Wilson et al., Functional group, biomass, and climate change effects on ecological drought in semiarid grasslands, *J. Geophys. Res. Biogeosciences* 123 (2018) (3) 1072-1085.

[68] T. W. Ford and S. M. Quiring, Comparison of contemporary in situ, model, and satellite remote sensing soil moisture with a focus on drought monitoring, *Water Resour. Res.* (2019) 1565-1582.

[69] C. Dong, G. M. MacDonald, K. Willis, T. W. Gillespie, G. S. Okin and A. P. Williams, Vegetation Responses to 2012-2016 drought in northern and southern California, *Geophys. Res. Lett.* (2019) 0-2.

[70] S. A. Romshoo, M. Rafiq and I. Rashid, Spatio-temporal variation of land surface temperature and temperature lapse rate over mountainous Kashmir Himalaya, *J. Mt. Sci.* 15 (2018) (3) 563-576.

[71] P. J. Hardin and R. R. Jensen, Small-scale unmanned aerial vehicles in environmental remote sensing: Challenges and opportunities, *GIScience Remote Sens.* 48 (2011) (1) 99-111.

[72] L. W. Lass, T. S. Prather, N. F. Glenn, K. T. Weber, J. T. Mundt and Lass et al., Review remote sensing for early detection of invasive plants, *Haefner* (2005) 242-251.

[73] P. B. Parajuli, P. Jayakody and Y. Ouyang, Evaluation of using remote sensing evapotranspiration data in SWAT, *Water Resour. Manag.* 32 (2018) (3) 985-996.

[74] C. Hartl-Meier et al., Priority questions in multidisciplinary drought research, *Clim. Res.* 75 (2018) (3) 241-260.

[75] J. Walker, K. de Beurs and R. H. Wynne, Phenological response of an Arizona dryland forest to short-term climatic extremes, *Remote Sens.* 7 (2015) (8) 10832-10855.

[76] S. Ali, M. Henchiri, F. Yao and J. Zhang, Analysis of vegetation dynamics, drought in relation with climate over South Asia from 1990 to 2011, *Environ. Sci. Pollut. Res.* (2019) 11470-11481.

[77] J. Baik, M. Zohaib, U. Kim, M. Aadil and M. Choi, Agricultural drought assessment based on multiple soil moisture products, *J. Arid Environ.* (2019) 1-13.

[78] Z. He, L. Yang, F. Tian, G. Ni, A. Hou and H. Lu, "Intercomparisons of Rainfall Estimates from TRMM and GPM multisatellite products over the Upper Mekong River Basin, *J. Hydrometeorol.* 18 (2016) (2) 413-430.

[79] M. L. Tan, V. P. Chua, K. C. Tan and K. Brindha, Evaluation of TMPA 3B43 and NCEP-CFSR precipitation products in drought monitoring over Singapore, *Int. J. Remote Sens.* 39 (2018) (8) 2089-2104.

[80] J. Rhee and J. Im, Meteorological drought forecasting for ungauged areas based on machine learning: Using

long-range climate forecast and remote sensing data, *Agric. for. Meteorol.* 237-238 (2017) 105-122.

[81] T. Tadesse et al., Building the vegetation drought response index for Canada (VegDRI-Canada) to monitor agricultural drought: first results, *GIScience Remote Sens.* 54 (2017) (2) 230-257.

[82] Y. Bayissa, T. Tadesse and G. Demisse, Building a high-resolution vegetation outlook model to monitor agricultural drought for the Upper Blue Nile Basin, Ethiopia, *Remote Sens.* 11 (2019) (4) 371.

[83] J. A. Otkin et al., Assessing the evolution of soil moisture and vegetation conditions during the 2012 United States flash drought, *Agric. For. Meteorol.* 218-219 (2016) 230-242.

[84] G. J. Huffman et al., The TRMM Multisatellite Precipitation Analysis (TMPA): Quasi-Global, Multiyear, Combined-Sensor Precipitation Estimates at Fine Scales, *J. Hydrometeorol.* 8 (2007) (1) 38-55.

[85] K. Rokni, A. Ahmad, A. Selamat and S. Hazini, Water feature extraction and change detection using multitemporal landsat imagery, *Remote Sens.* 6 (2014) (5) 4173-4189.

[86] J. W. Crowley, J. X. Mitrovica, R. C. Bailey, M. E. Tamisiea and J. L. Davis, Annual variations in water storage and precipitation in the Amazon Basin, *J. Geod.* 82 (2007) (1) 9-13.

[87] Z. Ding et al., Identification of photosynthesis-associated C4 candidate genes through comparative leaf gradient transcriptome in multiple lineages of C3 and C4 species, *PLoS One* 10 (2015) (10) 1-19.

[88] A. Damm et al., Far-red sun-induced chlorophyll fluorescence shows ecosystem-specific relationships to gross primary production: An assessment based on observational and modeling approaches, *Remote Sens. Environ.* 166 (2015) 91-105.

[89] R. G. Allen, L. S. Pereira, T. A. Howell and M. E. Jensen, Evapotranspiration information reporting: II. Recommended documentation, *Agric. Water Manag.* 98 (2011) (6) 921-929.