Agricultural Drought Assessment and Monitoring - A Review

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Abstract— Agricultural drought refers to circumstances when rainfall and soil moisture is insufficient and results in the unhealthy crop growth and reduction in crop production. The main consequence of agricultural drought is the reduction in crop yield, which is too small for farmers to neither feed their families nor their livestock. The prolonged food deficit will force farmers to sell livestock as the decline in production may reduce food supplies. The overall effect of fall in crop production and fall in fodder reduces the draft capacity of farming sector. Therefore timely assessment of Agricultural drought assessment would have greater significance in reducing regional disaster and Agricultural losses. The spatial assessment of Agricultural drought provides the information required for decision makers to make decisions on drought resistance. This paper reviews how agricultural drought assessment and monitoring is being carried out on geospatial basis. This paper reviews various indexes that are used for agricultural drought assessment, parameters considered under each of the indexes and the difficulties encountered with each. This paper also reviews different drought monitoring systems across globe.

I. INTRODUCTION

Agricultural drought occurs when the insufficient soil moisture fails to meet the needs of a particular crop at a particular time. A deficit of rainfall over cropped areas during critical periods of the growth cycle can result in destroyed or underdeveloped crops with greatly depleted yields. A threshold value (percentage reduction from the mean yield) is selected and drought is considered to have occurred if crop yield is below the threshold. Thus agricultural drought links characteristics of meteorological and hydrological droughts to agricultural impacts, focusing on precipitation shortages, differences between actual and potential evapotranspiration, soil water deficits.Thereby, Agricultural drought leads to the decline in the productivity of crops as a result of irregularities in rainfall as well as decrease in the soil moisture, which in turn affects the economy of the nation.

II. GEOSPATIAL APPROACH FOR AGRICULTURAL DROUGHT ASSESSMENT

There are several ways in which remote sensing can effectively be used for monitoring agronomic conditions, this may include

- Vegetation condition monitoring through reflective remote sensing
- Environmental condition monitoring through thermal remote sensing
- Soil moisture monitoring through microwave remote sensing
- Environmental stress monitoring by combining thermal and reflective remote sensing

Indexes used in drought assessment

Palmer Drought Severity Index (PDSI)

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Palmer Drought Severity Index (PDSI) uses readily available temperature and precipitation data to estimate relative dryness. It is a standardized index that spans -10 (dry) to +10 (wet). It has been reasonably successful at quantifying long-term drought. As it uses temperature data and a physical water balance model, it can capture the basic effect of global warming on drought through changes in potential evapotranspiration.

Monthly PDSI values do not capture droughts on time scales less than about 12 months; more pros and cons are discussed in the Expert Guidance Palmer took the water demand of crops into consideration and developed CMI, which was broadly applied for agricultural drought monitoring (Palmer, 1968). Scholars gradually understood the limitations of PDSI (Alley, 1984; Heddinghaus et al., 1991), and Wells (2004) reported self-calibrated PDSI to overcome the limitations. The biggest advantage of this improved index is that it decides different calibration parameters according to the local climate characteristics and therefore improves the ability of PDSI.

Surface water supply index (SWSI)

Shafer (1982) and Jackson (1988) proposed the surface water supply index (SWSI) which is a predictive indicator of the surface water available in a basin compared to historic supply. The SWSI is calculated by summing the two major sources of irrigation water supply; reservoir carryover and spring and summer stream flow runoff. These two sources are analyzed together when determining the total surface water supply available for the season

Crop water stress index (CWSI)

Crop water stress index (CWSI) is the most often used index to quantify crop water stress based on canopy surface temperature) after comprehensive consideration of surface water supply and crop water demand. Much research has been done to evaluate the application of the CWSI in irrigation scheduling for different crops in different places (Garrot et al., 1990; Ben-Asher et al., 1992; Barnes et al., 2000; Alderfasi and Nielsen, 2001). In 1993, McKee (1993) found that the observed precipitation has a skewed distribution rather than a normal distribution and proposed SPI

Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index (**NDVI**) is a numerical indicator that uses the visible and near-infrared bands of the electromagnetic spectrum, and is adopted to analyze remote sensing measurements and assess whether the target being observed contains live green vegetation or not.

NDVI is calculated from these individual measurements as follows:

NDVI = (NIR –VIS) / (NIR + VIS)

where VIS and NIR stand for the spectral reflectance measurements acquired in the visible (red) and near-infrared regions,

Concept behind NDVI

Researchers observe the distinct colors (wavelengths) of visible and near-infrared sunlight reflected by the plants to determine the density of green on a patch of land. When sunlight strikes objects, certain wavelengths of this spectrum are absorbed and other wavelengths are reflected. The pigment in plant leaves, chlorophyll, strongly absorbs visible light (from 0.4 to 0.7 µm) for use in photosynthesis. The cell structure of the leaves, on the other hand, strongly reflects near-infrared light (from 0.7 to 1.1 µm). The more leaves a plant has, the more these wavelengths of light are affected, respectively.

The NOAA AHVRR instrument has five detectors, two of which are sensitive to the wavelengths of light ranging from 0.55–0.70 and 0.73–1.0 micrometers. With AHVRR’s detectors, researchers can measure the intensity of light coming off the Earth in visible and near-infrared wavelengths and quantify the photosynthetic capacity of the vegetation in a given pixel (an AVHRR pixel is 1 square km) of land surface. In general, if there is much more reflected radiation in near-infrared wavelengths than in visible wavelengths, then the vegetation in that pixel is likely to be dense and may contain some type of forest. If there is very little difference in the intensity of visible and near-infrared wavelengths reflected, then the vegetation is probably sparse and may consist of grassland, tundra, or desert.

NDVI is calculated from the visible and near-infrared light reflected by vegetation. Healthy vegetation (left) absorbs most of the visible light that hits it, and reflects a large portion of the near-infrared light. Unhealthy or sparse vegetation (right) reflects more visible light and less near-infrared light. Thus The Normalized Difference Vegetation Index (NDVI) is an index of plant “greenness” or photosynthetic activity, and is one of the most commonly used vegetation indices.

Vegetation indices are based on the observation that different surfaces reflect different types of light differently. Photo synthetically active vegetation, in particular, absorbs most of the red light that hits it while reflecting much of the near infrared light. Vegetation that is dead or stressed reflects more red light and less near infrared light. Likewise, non-vegetated surfaces have a much more even reflectance across the light spectrum.

Vegetation Condition Index (VCI)

The Vegetation Condition Index (VCI) proposed by Kogan(1990) compares the current NDVI to the range of values observed in the same period in previous years. The VCI is expressed in % and gives an idea where the observed value is situated between the extreme values (minimum and maximum) in the previous years. Lower and higher values indicate bad and good vegetation state conditions, respectively.

VCI has proven to be a useful means for measuring the drought intensity, duration, and impacts (Ji and Peters 2003; Kogan 1995).VCI separates the effect of ecology and weather on vegetation growth, while VCIT adjusted also separates the effect of production technology.

During the assessment of agricultural drought in Rajasthan State of India,Time series of 16-day maximum value composite NOAA-AVHRR GIMMS normalized difference vegetation index (NDVI) dataset from 1982 to 2006 was used. The crop phenology parameters such as start of the season (SOS), end of early season (EOES), time for the mid of season (MOS), start of late season (SOLS), end of the season (EOS), and length of the season (LOS) were computed for agricultural area using TIMESAT.Using pixel-wise phenology parameters, NDVI was integrated for early, mid, late, and whole kharif seasons and was used for the computation of VCIT adj for corresponding season over the 24 years (Sehgal & Dhakar, 2016).

Vegetation temperature condition index (VTCI)

Vegetation temperature condition index (VTCI) is a near-real-time drought monitoring approach which is derived from normalized difference vegetation index (NDVI) changes in a given region to land surface temperature (LST) changes of pixels with a given NDVI values . The index can be used to monitor drought occurrences at a regional level for a special period (e.g. 10 days) of a year, and can be also used to study the spatial distribution of drought within the region.

VTCI is not only related to NDVI changes in the region, but also related to land surface temperature changes of pixels with the same NDVI value. A pilot study was carried out for drought monitoring in the Guanzhong Plain area of the Loess Plateau in the Northwest China. The results showed that VTCI had better performances in classifying the relative drought occurrence levels and in studying the distribution of drought occurrences.The drought stress effects are closed linked to actual evapotranspiration, vegetation temperature condition index (VTCI) which is more closely related to crop water status and holds a key place in real-time drought monitoring and assessment. In this study, NDVI and land surface temperature (Ts) from MODIS 8-day composite data during cloud-free period (September–October) were adopted to construct an NDVI–Ts space, from which the VTCI was computed.

The crop moisture index (based on estimates of potential evapotranspiration and soil moisture depletion) was calculated to represent soil moisture stress on weekly basis for 20 weather monitoring stations. Correlation and regression analysis were attempted to relate VTCI with crop moisture status and crop performance. VTCI was found to accurately access the degree and spatial extent of drought stress in all years (2000, 2002, and 2004). The temporal variation of VTCI also provides drought pattern changes over space and time. (Patel, Parida, Venus, Saha, & Dadhwal, 2012).

Standardized Precipitation Index (SPI)

Standardized Precipitation Index (SPI) (McKee et al. 1993) was chosen to quantify precipitation deficit for different time scales because SPI substantially outranked among 14 indices of precipitation anomaly for their robustness, tractability, transparency, sophistication, extendibility, and dimensionality as reviewed by Keyantash and Dracup (2002). Mathematically, SPI for period i is calculated based on equation:

SPI= Xi–X mean / σ

where Xi is transformed rainfall of station for period i, and X mean and σ are long-term mean and standard deviation of transformed rainfall for the same period.

Precipitation is not normally distributed;therefore the long-term precipitation record was first fitted to an incomplete gamma probability distribution, which is then transformed into a normal distribution. The study used gridded monthly precipitation time series data constructed by Climatic Research Unit (CRU TS 3.0) at a spatial resolution 0.5×0.5° for 1951–2006 time period (New et al. 2000; Mitchell and Jones 2005). SPI was computed spatially (grid wise) at four time scales during the main kharif season, namely, tri-monthly SPI_JJA (June, July, August), bi-monthly SPI_AS (August, September), bi-monthly SPI_SO (September, October), and penta-monthly SPI_JJASO (June to October) corresponding to early, mid, late, and whole crop periods.

A drought hazard assessment model is developed based on SPI in a GIS environment. In this model, the annual occurrences of drought are categorized into two levels including extreme wet to near normal defined as near normal and moderate to extreme drought as severe drought . Then, each drought severity theme was given a particular weight (0 and1) to compute drought hazard index map. Drought hazard index (DHI) is the drought hazard index produced by sum overlaying of the drought thematic maps (xi), for a time period of n030 years. This DHI integrates the annual drought theme severity for assigned drought occurrences in the long-term time period

Standardized Precipitation Evapotranspiration Index (SPEI)

The Standardized Precipitation Evapotranspiration Index (SPEI) is an extension of the widely used Standardized Precipitation Index (SPI). The SPEI is designed to take into account both precipitation and potential evapotranspiration (PET) in determining drought. SPEI captures the main impact of increased temperatures on water demand.

Like the SPI, the SPEI can be calculated on a range of timescales from 1-48 months. At longer timescales (>~18 months), the SPEI has been shown to correlate with the self-calibrating PDSI (sc-PDSI). If only limited data are available, say temperature and precipitation, PET can be estimated with the simple Thornthwaite method. In this simplified approach, variables that can affect PET such as wind speed, surface humidity and solar radiation are not accounted for. In cases where more data are available, a more sophisticated method to calculate PET is often preferred in order to make a more complete accounting of drought variability. However, these additional variables can have large uncertainties.

In SPEI values, the climatic water balance (D) compares the available water with the atmospheric evaporative demand, and therefore provides a more reliable measure of drought severity than only considering precipitation. In this study, the steps followed for the SPEI calculation were (i) the parameterization of potential evapotranspiration based on the monthly minimum and maximum air temperature, and extra-terrestrial radiation; (ii) a simple monthly water balance, calculated as the difference between monthly precipitation (P) and potential evapotranspiration (PET), and (iii) normalization of the climatic water balance into a log-logistic probability distribution to transform the original values to standardized units that are comparable in space and time . (Beguería, S., Vicente-Serrano, S.M., Reig, F., Latorre, B., 2013).

SPEI has become one of the ideal drought monitoring tools. Then, Vicente-Serrano (2012) compared the performances of SPI, SPEI, and PDSI with respect to global drought monitoring and found that SPI and SPEI were better than PDSI for hydrological and agricultural drought monitoring and that SPEI was excellent for monitoring summer drought. A recent study established the standardized relative humidity index (SRHI) by applying relative humidity data, and this index can detect the on- set start of a drought earlier than SPI and is considered an ideal index for drought warning (Farahmand ,2015)

Comprehensive index (CI)

In China, scholars made considerable efforts to build drought monitoring indices continuously and have tried to integrate various meteorological indices to improve monitoring ability. Zhang (1998) proposed the comprehensive index (CI), which made weighted summation of the standardized precipitation index and relative humidity index, and this index is widely used for drought monitoring in meteorological departments of China. Wang (2007) proposed the K index, which is defined as the ratio of the relative variability in seasonal precipitation and the relative variability in evaporation; it is suitable for monitoring meteorological and agricultural droughts.

Available water holding capacity of soils (AWHC)

Available water holding capacity of soils (AWHC) of soil is computed for each depth of the horizon in a particular soil series by the formula:

AWHC = (FC−PWP) X BD X L X10

where AWHC is available water holding capacity (mm/ m) for depth L, FC is percent water retention by mass at 33 kPa equivalent to field capacity, PWP is percent water retention by mass at 1500 kPa equivalent to permanent wilting point, BD is bulk density of soil (g/cm3), and L is depth of soil horizon (m).

The soil maps of Rajasthan at 1:500,000 scale published by National Bureau of Soil Survey & Land Use Planning (NBSS&LUP) were digitized, cleaned, mosaicked, and geocoded using ArcGIS 10.0. Soil mapping units were assigned unique ids and were linked to attributes of landform, texture, depth, etc.AWHC values were computed for depth up to 1m by summation of AWHC values computed for different depths and those soil series having depth less than 100 cm, AWHC value was computed up to available depth in that series. Finally, AWHC map was converted to raster format and classified (Sehgal & Dhakar, 2016)

III. DROUGHT MONITORING

Droughts develop gradually; they are referred to as slow-onset natural hazards. Droughts often do not get any global attention until they trigger a famine or cause wildfires. Unfortunately, response to droughts is too often reactive in terms of crisis management. According to WMO droughts are by far the most damaging of all natural disasters because of their long-term socio-economic impacts. Early detection of droughts is important for managing emerging crop losses to prevent or mitigate possible related famines, and for dealing with increased fire risk.

Satellite imagery helps to monitor precipitation, soil moisture, and vegetation health to support drought early warning systems. It is used to feed monthly drought bulletins and to issue warnings.

Several institutions worldwide are processing satellite data to provide useful information for drought monitoring to support drought early warning. They provide interactive webmaps, static maps in near-real-time, or monthly drought bulletins to be used by decision makers. See below how to access this information.

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Famine Early Warning Systems (FEWS)

The U.S. Agency for International Development (USAID) Famine Early Warning Systems Network (FEWS NET) with the USGS FEWS NET data portal provides free of charge and publicly available near-real-time and archived information via its global data portal as well as via its regional data portals for Africa, Central America/Caribbean/Mexico, South Asia, and. Central Asia. The information includes NDVI (temporally smoothed NDVI, mean anomaly, previous year difference, and percent of average) based on eMODIS 10-day composites in near-real-time and archived data for up to two years; different indices based on pentadal TRMM satellite rainfall estimates and ancillary data, e.g. the Water Requirement Satisfaction Index (WRSI) for the growing season, which is an indicator of crop performance based on the availability of water to the crop during a growing season for crops; the onset of rains/start of growing season and its anomaly; the crop soil water index (SWI); rainfall estimate and precipitation forecast; seasonal rainfall accumulation anomaly; and number of consecutive dry days.

The NDVI data are available as geotiff while all other information is only available as png graphics. In addition, an early warning explorer is provided for interactive visualization and download of data for parameters like NDVI and rainfall for Africa. An experimental decision support interface (DSI) with crop zones and current and archived drought conditions for Africa complements the FEWS NET services.

Agricultural Stress Index System (ASIS, FAO)

The Food and Agriculture Organization (FAO) provides wit ASIS free of charge and publicly available global web maps for near real time (10 days) information on seasonal indicators like the Agricultural Stress Index (ASI), progress of season, and mean vegetation health index (VHI), as well as an annual summary of ASI, mean VHI, and maps of the start and the end of season. ASIS also provides near-real-time information and monthly summaries of vegetation indices (NDVI anomaly, VCI, VHI) and precipitation indicators (estimated precipitation, precipitation anomaly, and long term average estimated precipitation). The global web maps are also available as archived maps from 1984 onwards. Additionally, seasonal indicators, vegetation indicators, and precipitation indicators as well as NDVI and precipitation graphs are provided at country level for the latest 12-months period.

Crop monitoring (GEOGLAM)

With its Global Agricultural Monitoring (GEOGLAM) initiative the Group on Earth observation (GEO) is delivering within its Agriculture Societal Benefit Area monthly global crop outlooks for wheat, maize, rice, and soy to support FAO's Agricultural Market Information System (AMIS). GEOGLAM provides an interactive monthly assessment tool for AMIS countries. Available layers in the assessment tool include anomalies of rainfall, temperature, and NDVI (since August 2013) as well as crop masks and associated crop calendars for the four crop types. The assessment results in the visualization of four different crop stages (planting-early vegetative, vegetative-reproductive, ripening through harvest, and out of season) and crop conditions (exceptional, favorable, watch, and poor). GEOGLAM satellite data are available via Earth Explorer (Landsat) and via the University of Maryland (MODIS).

Global Agricultural Drought Monitoring and Forecasting System (GADMFS - CSISS)

The Center for Spatial Information Science and Systems (CSISS) provides a the Global Agricultural Drought Monitoring and Forecasting System (GADMFS), a webtool for drought monitoring including the Vegetation Condition Index (VCI), Normalized difference vegetation index(NDVI), and a drought index layer showing six levels of drought (no drought, abnormally dry, moderate drought, severe drought, extreme drought, exceptional drought).

Global Drought Information System (NIDIS)

With its Global Drought Information System (GDIS), the U.S. National Integrated Drought Information (NIDIS) together with international partners provides a platform with non-prescriptive drought information from local providers with the objective to make drought conditions around the world comparable. The platform offers an interactive map with the following layers: global station-based SPI (from 1-24 months) and remotely sensed GPCC based SPI (1-24 months); soil moisture for Africa; rainfall percentiles and soil moisture for Australia; soil moisture, monthly rainfall, SPI, vegetation water content (NDWI), vegetation productivity (fAPAR), and combined drought indicator for Europe; and SPI, Palmer drought indices, percent of average precipitation, North American drought monitor for North America. An overview of current conditions of the standard precipitation index (SPI), the vegetation health index (VHI), and global drought monitor is also provided. Furthermore, the platform provides links to the regional drought monitoring platforms of the international partners: Monitor of the Australian Department of Agriculture, the African Flood and Drought Monitor (AFDM), the European Drought Observatory, and the North American Drought Portal.

Drought Monitoring (EOSDIS Worldview - NASA)

NASA's Earth Observing System Data and Information System (EOSDIS) provides access to near-real-time satellite data that are potentially useful for drought observation: MODIS Corrected Reflectance True Color and Bands 7-2-1, MODIS Land Surface Reflectance bands 1-2-1, MODIS Snow Cover, and AIRS precipitation. The satellite data can be visualized in NASA's interactive web mapping tool Worldview, where it can also be overlaid with the following layers from the Socio Economic Data and Applications Center (SEDAC): drought economic risk (2000) and drought hazard frequency and distribution (1980-2000).The latter is also available for visualization and download in the web interface provided by Database.

Access regional drought monitoring information

Besides global drought observation platforms, many regions in the world have implemented their own regional platforms and some global platforms also provide regional information, for example the below:

- European Drought Observation (EDO - JRC)
- Drought Monitor-US Only (NDMS)
- U.S. drought reports (NOAA)
- Drought Index Map for Vegetation-US Only (VegDRI - USGS)
- Enhanced Combined Drought Index in Southeast Asia - experimental version (TU Vienna)
- Famine Early Warning Systems (FEWS NET - USGS)

Site based drought monitoring

Research on drought monitoring initiated in the US in the early 20th century, and most early indices only took precipitation into consideration (Gibbs, 1967; Henry, 1906; Kincer, 1919; Marcovitch, 1930; McGuire et al., 1957; McQuigg, 1954; Munger, 1916; Van Rooy, 1965) .Palmer raised the concept of the current climate suitable precipitation (Palmer, 1965) and proposed PDSI in 1965. This index became a milestone for drought monitoring and was used both in America and other parts of the world and by governments and scholars as a drought monitoringtool.

IV. SUMMARY

The above review indicated that site-based drought monitoring indices have been developed over a long period, and it has become the main method for drought monitoring. In terms of data source, site-based indices mainly rely on the data records of meteorological stations. However, uncertainties still exist with respect to observed datasets, including uneven distribution in space and inconformity in

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time-series induced by site migration. Although a series of methods have been implemented to enhance observation station network density, such as addition of automatic weather stations, and develop data homogenization methods to correct abnormal sequences caused by non-climatic factors, there are few data records of new time series data and a shortage of stations.

REFERENCES

1. Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). Crop evapotranspiration: Guidelines for computing crop requirements. *Irrigation and Drainage Paper No. 56, FAO*, (56), 300. ht
2. Chandrasekar, K., & Sesha Sai, M. V. R. (2014). Monitoring of late-season agricultural drought in cotton-growing districts of Andhra Pradesh state, India, using vegetation, water and soil moisture indices. *Natural Hazards*.
3. Hossain, M. N., Chowdhury, S., & Paul, S. K. (2016). Farmer-level adaptation to climate change and agricultural drought: empirical evidences from the Barind region of Bangladesh. *Natural Hazards*.
4. Jayanthi, H. (2015). Prepared for the 2015 Global Assessment Report on Disaster Risk Reduction Assessing the agricultural rought risks for principal rainfed crops due to changing climate scenarios using satellite estimated rainfall
5. Li, R., Tsunekawa, A., & Tsubo, M. (2014). Index-based assessment of agricultural drought in a semi-arid region of Inner Mongolia, China. *Journal of Arid Land*.
6. Liu, X., Zhu, X., Pan, Y., Li, S., Liu, Y., & Ma, Y. (2016). Agricultural drought monitoring: Progress, challenges, and prospects. *Journal of Geographical Sciences*, *26*(6), 750–767.
7. Mahmoud, S. H., Adamowski, Alazba, & El-Gindy (n.d.). Rainwater harvesting for the management of agricultural droughts in arid and semi-arid regions. *Paddy and Water Environment*.
8. Mannocchi, F., & Todisco, F. (2004). Agricultural drought : indices , definition and analysis, (December 2003).
9. Mansouri Daneshvar, M. R., Bagherzadeh, A., & Khosravi, M. (2013). Assessment of drought hazard impact on wheat cultivation using standardized precipitation index in Iran. *Arabian Journal of Geosciences*.
10. Moeletsi, M. E., & Walker, S. (2012). Assessment of agricultural drought using a simple water balance model in the Free State Province of South Africa. *Theoretical and Applied Climatology*, *108*(3-4), 425–450.
11. Mokhtari, M. H., Adnan, R., & Busu, I. (2013). A new approach for developing comprehensive agricultural drought index using satellite-derived biophysical parameters and factor analysis method. *Natural Hazards*.
12. Nandintsetseg, B., & Shinoda, M. (2013). Assessment of drought frequency, duration, and severity and its impact on pasture production in Mongolia. *Natural Hazards*.
13. Patel, N. R., Parida, B. R., Venus, V., Saha, S. K., & Dadhwal, V. K. (2012). Analysis of agricultural drought using vegetation temperature condition index (VTCI) from Terra/MODIS satellite data. *Environmental Monitoring and Assessment*.
14. Potopov, V., Torkott, L.& Soukup, J. (2015). Performance of the standardised precipitation evapotranspiration index at various lags for agricultural drought risk assessment in the Czech Republic. *Agricultural and Forest Meteorology*.
15. Sehgal, V. K., & Dhakar, R. (2016). Geospatial approach for assessment of biophysical vulnerability to agricultural drought and its intra-seasonal variations. *Environmental Monitoring and Assessment*, *188*(3).

16. Sensing, R., Sciences, S. I., Patel, N. R., Sarkar, M., & Kumar, S. (2011). Use of earth observation for geospatial crop water accounting of rain-fed agro-ecosystem in india,
17. Sivapragasam, C., Kannabiran, K., Karthik, G., & Raja, S. (2015). Assessing Suitability of GP Modeling for Groundwater Level. *Aquatic Procedia*, *4*(Icwrcoe), 693–699.
18. Sun, Z., Zhang, J., Yan, D., Wu, @bullet Lan, & Guo, E. (2015). The impact of irrigation water supply rate on agricultural drought disaster risk: a case about maize based on EPIC in Baicheng City, China. *Natural Hazards*, *78*, 23–40.
19. Swathandran, S., & Aslam, M. A. M. (2016). Food productivity trend analysis of Raichur district for the management of agricultural drought. *Environmental Monitoring and Assessment*.
20. Thavorntam, W., Tantemsapya, N., & Armstrong, L. (2015). A combination of meteorological and satellite-based drought indices in a better drought assessment and forecasting in Northeast Thailand. *Natural Hazards*, *77*(3), 1453–1474.
21. Thomas, T., Jaiswal, R. K., Galkate, R., Nayak, P. C., & Ghosh, N. C. (2016). Drought indicators-based integrated assessment of drought vulnerability: a case study of Bundelkhand droughts in central India. *Natural Hazards*.
22. Todisco, F., Mannocchi, F., & Vergni, L. (2013). Severity-duration-frequency curves in the mitigation of drought impact: An agricultural case study. *Natural Hazards*, *65*(3), 1863–1881.
23. Waseem, M., Ajmal, M., Lee, J. H., & Kim, T.-W. (n.d.). Multivariate Drought Assessment Considering the Antecedent Drought Conditions. *Water Resources Management*.
24. Water, C., Satisfaction, R., Description, M., Senay, G., Wrsi, F. A. O., Africa, S., & America, C.(2004). (1) The water requirement of the crop (PETc) at a given time in the growing season is calculated by multiplying standard reference crop PET by the crop coefficient (Kc)., *i*(July).
25. Water, E. U., & Directive, F. (n.d.). Guidelines for preparation of the Drought Management Plans Guidelines for preparation of the Drought Management Plans.