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REVIEW

A review of agricultural drought assessment with remote sensing data: methods, issues, challenges and opportunities

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Abstract

Drought is a frequent hydrometeorological phenomenon that affects every individual, including animals. It causes significant economic and human losses. Various traditional methods are used to assess droughts in the early stages. However, conventional ways are time-consuming, expensive, and laborious. This has led to exploring remote sensing with recent methods for drought assessment. Therefore, the current paper gives a comprehensive overview of the recent studies on agricultural drought impact and its assessment using remote sensing datasets and various spectral index methods. The available satellite data sources have been provided with their sensors and spectral, spatial, and temporal information. Furthermore, we have also provided the general schema for agricultural drought assessment, essential indices, and drought severity methods with their importance and limitations. The normalized difference vegetation index (NDVI), standardized soil moisture index (SSMI), soil moisture percentile (SMP), normalized soil moisture (NSM), standardized precipitation index (SPI), vegetation health index (VHI), and soil moisture deficit index (SMDI) are the most used indices by researchers for drought detection and its assessment. Lastly, this review examines the challenges that need to be handled for the early detection of agricultural drought episodes. It is concluded that a long-term historical record of satellite images and meteorological data is required to calculate drought severity levels and identify drought-prone areas. This review can detect the hidden risks of agricultural drought and offer a theoretical foundation for decision-makers and mitigation agencies.

Keywords Agricultural drought assessment · Spectral indices · NDVI · Drought severity · Remote sensing

Introduction

Drought is a frequent hydrometeorological phenomenon that affects every individual, including animals. Drought episode occurs due to frequent weather conditions such as rising temperatures and unequal precipitation distributions. Therefore, drought surveillance is critical for surviving humans, the scientific community, and drought mitigation and management agencies. However, agricultural drought is directly related to human causes due to meteorological droughts (Gaikwad et al., 2022a). Thus, monitoring the risk of meteorological drought and agricultural droughts is needed. Due to the increased population, acquiring real-time ground observations and monitoring the vegetation conditions required for agricultural droughts are challenging. Recently, remote sensing technology has significantly impacted assessing and monitoring various droughts, especially agricultural droughts. Satellite imaging is utilized in agricultural areas to evaluate the severity of drought conditions (Gaikwad et al. 2019).

The macro-level decision-making is easy if crop yields are monitored precisely, especially in varied cropping patterns (Sruthi & Aslam 2015). Crop production can be increased using accurate analysis of variable weather conditions and agro-meteorological parameters (Amarnath et al. 2019). However, meteorological drought can affect

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agricultural productivity. As a result, it is crucial to look at the possibility of meteorological drought, including measures for drought preparation and response. Regular monitoring and evaluation of surface moisture conditions, precipitation quantities and patterns, and temperature in agricultural regions throughout the growing season are essential to continuously monitor agro-climatic factors like precipitation, temperatures, evaporation, and soil moisture.

Moreover, creating appropriate agricultural drought assessment indicators is also crucial in drought monitoring. This information is evaluated in drought reports, which scientifically, objectively, and correctly assess the severity, extent, or severity of drought conditions. Most of the time, this kind of integrated information assists in advising policymakers (i.e., government departments) and farmers regarding the current scenario (Narasimhan & Srinivasan 2005).

Regarding drought preparation activities, the emphasis is on raising knowledge and readiness among decision-makers. The focus is also on farmers, particularly during non-drought times, to react appropriately to the next drought crisis if it occurs. There are suitable methods to minimize drought effects on agricultural operations during and shortly after a drought event (Hazaymeh & Hassan 2016). Recently, remotely sensed images have provided a promising approach to crop categorization (Surase et al. 2019), crop condition monitoring (Guliyeva 2020), crop acreage estimation (Dhumal et al. 2017), and yield estimation (Vibhute & Gawali 2013). On the other hand, the field of remote sensing assists in reducing the amount of field data that must be collected and enhancing estimation accuracy (Shanmugapriya et al. 2019).

The evaluation of sustainable agriculture canopies has given important insights into the agronomic characteristics of crops. The surveillance of the agroecosystem shows substantial seasonal patterns concerning the observation of the agricultural production system. Such variables are highly changeable in terms of their spatial and temporal aspects. Thus, remote sensing technology is needed in agronomic research to identify soil, climate, environment, and physicochemical variations (Shanmugapriya et al. 2019).

There are several ways that remote sensing can be used to effectively monitor agronomic conditions, including monitoring vegetation conditions (Gaikwad et al. 2021a) using reflective remote sensing, monitoring environmental conditions using thermal remote sensing, monitoring soil moisture using microwave remote sensing, and monitoring environmental stress using thermal and reflective remote sensing (Subha et al. 2017).

Scholars have made significant efforts to develop drought-detecting indicators based on the format prescribed, and they have achieved essential findings as a consequence of their efforts. The fact that, even though many extensive drought indices have now been suggested, the study is still in its early stages should be noticed. In addition, multi-space–time remote weather indices are still necessary because holistic agricultural monitoring indices have their disadvantages. However, Zargar et al. (2011) listed six drought indicators that are commonly used in monitoring, forecasting, and preparing operations.

Additionally, remote sensing technology is a highly effective tool for data collection and detecting field drought. Multiple data sources and disparate temporal and geographical dimensions make it difficult to fully use the information (Liu et al. 2016). The two most challenging issues in agricultural drought regulation are the management of crops throughout the growing season and the objective evaluation of crop performance. Evaluation of the agricultural situation at various geographical and temporal dimensions is a severe concern for the administration of droughts. Field-level crop monitoring allows for prioritizing relief efforts based on the effect of drought on crops, allowing for the design of intelligent relief management systems. On a regional scale, routine monitoring of vegetative and drought calculation via coarse-resolution satellite pictures did not reveal spatial variations in drought effect within an area (Murthy et al. 2007).

Therefore, detecting and monitoring the agricultural drought is essential for better crop estimation and production. Several studies have been done on agricultural drought assessment using remote sensing datasets and spectral indices. However, the agricultural drought assessment is challenging due to unavoidable irregular environmental conditions. Additionally, it is still being determined when these conditions will occur, which strategy should be followed, and how. Therefore, the present study provides a comprehensive overview and challenges in assessing agricultural drought using recent approaches. The paper is organized into six sections. The second section briefly describes drought types, their impact, and the remote sensing technology used for drought monitoring. The general schema provided in section three consists of the availability of remote sensing datasets, their pre-processing, spectral indices, and drought severity classification strategy. Challenges in agricultural drought assessment are listed in the "Challenges in agricultural drought assessment" section. "Discussions" section discusses the synthesis of the study. The last section concludes the study.

Criteria for search

This is considered one of the most critical tasks in this survey. The flow of search is as follows:

Step 1: Find the sources from which we can retrieve the papers. This survey used all the science citation index journals, Scopus journals (national and international), and conference proceeding papers. In addition, all the online material, theses, and books were used to do the survey more effectively and efficiently. The sources used for retrieving the papers are listed in Table 1.

Step 2: 300 papers are identified based on the search keywords.
Step 3: Out of 300, 250 papers were shortlisted based on the title.
Step 4: Out of 250, 213 papers were scrutinized based on the abstract.
Step 5: Out of 213, 185 papers were shortlisted based on the citation.
Step 6: Relevant 77 papers were finalized for the survey.

Drought types and their impact

Drought is the least understood natural phenomenon induced by consequent hydrological imbalance and precipitation deficiency. Droughts drastically impact ordinary people, agriculture, and water resources. Over recent years, the frequencies of occurrence and intensities of droughts have continued to increase. The ever-growing requirement for water resources and the compound uncertainty of hydroclimatic factors aggravate the potential impacts. A decade ahead, the change in the climate would further exacerbate the droughts and their influences in many regions worldwide (Balti et al. 2020).

Table 1 Sources used for the survey

Springer (www.springer.com)
Google Scholar (www.scholar.google.com)
IEEE Xplore (www.ieee.org)
Wiley online library (www.onlinelibrary.wiley.com)
Taylor and Francis (www.taylorandfrancis.com)
Elsevier (www.elsevier.com)
ScienceDirect (www.sciencedirect.com)
Books and other online sources

Drought types

Droughts can be divided into four types: meteorological drought, agriculture drought, hydrological drought, and socioeconomic drought depicted in Fig. 1 (Van Loon & Van Lanen 2012).

Meteorological drought

Meteorological drought is frequently defined purely by the degree of dryness and the dry spell length. The lack of precipitation compared to average conditions over a specific location over but relatively period is known as meteorological drought (Van Loon & Van Lanen 2012), since the precipitation is region-specific and varies significantly from location to location (Hao et al. 2018). Several studies have evaluated droughts using monthly precipitation data, considering drought as a precipitation deficit relative to average values. Other parameters are also considered: how long a drought lasts and how severe it is. These concern total precipitation deficits (Mishra & Singh 2010). The monitoring and quantification of meteorological droughts are done using a variety of indices. The Palmer drought severity index

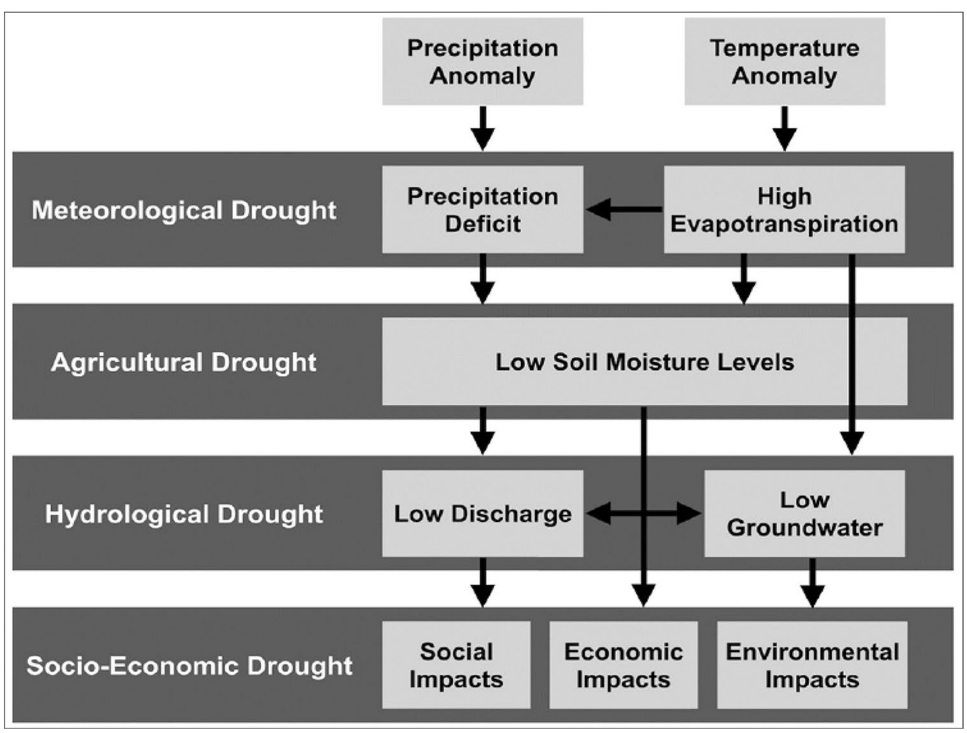

Fig. 1 Drought types and their impacts (Van Loon & Van Lanen 2012)

(PDSI), for example, is the most widely used indicator of meteorological drought in the USA and monitors moisture deficiency. The SPI is suited for any place because it is based on a long-term precipitation record for the desired duration. The rainfall data compares rainfall over the previous 3 months to a climatological record divided into ten quantiles or deciles (Zargar et al. 2011).

Agricultural drought

Agricultural or soil moisture droughts result from a meteorological drought paired with high-potential evapotranspiration (Hagenlocher et al. 2019). Agriculture drought is characterized by a lack of soil moisture far below the optimum amount needed for healthy plant growth at various stages of development, resulting in developmental stress and output loss (Van Loon & Van Lanen 2012). The effects of climatic and hydrological droughts and discrepancies in actual and prospective evapotranspiration have a role in soil moisture reduction (Mishra & Singh 2010). Agricultural drought forecasting frequently uses indices derived directly from soil moisture or other soil moisture-related indicators. The crop moisture index (CMI), SMP, NSM, SSMI, and SMDI are all commonly used agricultural drought indicators that are based on soil moisture simulations (SSI) (Hao et al. 2018).

Hydrological drought

The absence of natural and engineered surface or underground aquifer supplies is a hydrological drought (Van Loon & Van Lanen 2012). The effects of temperature anomalies, precipitation shortages, and anthropogenic demand pressures on the surface or subsurface water supplies, such as streams, reservoirs, lakes, or groundwater, cause hydrological droughts (Hagenlocher et al. 2019). A lack of precipitation causes droughts, but the transition from meteorological to hydrological (and agricultural) drought is not instantaneous and is governed by complex physical causes. As a result, not every meteorological drought will result in a hydrological drought. Though the primary cause is a lack of precipitation, other factors, such as low water storage, cold temperatures, and snow build-up, can contribute to hydrological drought (Van Loon & Van Lanen 2012). Palmer hydrologic drought index (PHDI) (Palmer 1965), runoff or streamflow percentile, and standardized runoff index (SRI) (Shukla & Wood 2008) are some of the most often used hydrologic drought indicators.

Socio-economic drought

The term "socioeconomic drought" refers to the close relationship between drought and human activities. When demand for an economic commodity exceeds supply due to a weather-related water shortage, socioeconomic drought arises (Mishra & Singh 2010). Limited studies have been done on socioeconomic drought prediction. Certain data types, such as water quality, wildfire occurrence, crop yield, and remotely sensed vegetation stress, are directly or indirectly relevant to drought impacts. Predicting these quantities can be regarded as approximations of socioeconomic drought prediction (Gudmundsson et al. 2014). Specific indicators (e.g., the social water stress index (SWSI)) have been established to assess water shortage while considering environmental and social factors affecting water consumption, supply, and vulnerability (Mishra & Singh 2010). The beginning of a meteorological drought is a crucial predictor of an agricultural or water-stress situation (Van Loon & Van Lanen 2012).

As illustrated in Fig. 1, the rise in evapotranspiration rates significantly contributes to meteorological and agricultural dryness. The surface soil moisture is susceptible to various environmental factors. The root zone soil moisture is essential for agricultural drought modeling. The root zone soil moisture is generally stable compared to the topsoil moisture (Gaikwad et al. 2021b). Nevertheless, drought indices have been developed from meteorology, oceanography, and agriculture perspectives due to the difficulties in predicting the commencement, magnitude, and simple sending of droughts. These indexes include those based on single variables such as precipitation and runoff, soil water warehouse, geostationary measures of crop production, and meteorological parameters (Liu et al. 2016).

Drought monitoring using remote sensing techniques

A single metric cannot adequately capture the drought's multi-scale, the multi-impact character in all its complexity. In light of this, all research on drought monitoring and assessments aim to create a composite index using the proper mixing strategies (Chandrasekar et al. 2018). Agricultural dryness is intimately linked to soil moisture and crop water deficit. In this regard, remotely sensed water elevation data of soil and plants is an efficient tool for intensive monitoring of land and crop water deficit (Kumar et al. 2019). Data assimilation techniques are often used to estimate soil moisture. Among these techniques, thermal inertia simulations of various soil textures have increased the effectiveness of groundwater inversion by including topographic and wind field characteristics.

Nevertheless, determining these values, in reality, has proven to be challenging. Since it solely considers precipitation and ignores the effect of evaporating on drought. The standardized precipitation-evapotranspiration index (SPEI) has emerged as one of the most effective methods for drought monitoring. Researchers have made significant efforts to develop drought monitoring indices based on the prescribed format and have achieved essential findings. In order to improve the effectiveness of drought monitoring systems, several studies have proposed hybrid approaches that use the fusion of several techniques (Inoubli et al. 2020).

The soil moisture is critical at various depths for agricultural drought monitoring. Hence, an accurate estimation of soil moisture at varying temperatures is essential. Thus, additional research is needed with remote sensing methods for agricultural monitoring. For example, a terrestrial surface model can be combined with microwave inversion results. Moreover, field survey data can also be frequently collected to improve the accuracy and depth of inversion (Liu et al. 2016).

Table 2 shows the standard SPI index used for short-term to long-term precipitation patterns and their applications for agricultural drought assessment.

A general schema for agricultural drought assessment

Agricultural drought assessment can be more effectively and accurately done through remote sensing. The general schema for the agricultural drought evaluation provides the factors such as (1) seasonal progression, (2) comparison of any selected indicator/indices with previous years by computing the relative deviation, and (3) weekly rainfall status.

The general schema for agricultural drought assessment consists of geospatial technology, including relevant data acquisition, essential pre-processing, spectral indices for feature extraction, and identification of drought severity.

Data sources

Numerous satellite data are available for agricultural drought research. Several studies have used datasets like Sentinel, Landsat, or Moderate Resolution Imaging Spectroradiometer (MODIS) for drought purposes. Various data sources and the relative methods used by several researchers are shown in Table 3. However, Landsat data is mainly used for drought assessment due to its high temporal and spatial resolution since MODIS, and Sentinel data are also freely available for monitoring the earth's observations with the high spatial and temporal resolution, which can be used for drought assessment.

Methods of soil moisture and surface roughness retrieval based on radar images

Numerous agricultural and hydrological applications use soil surface characteristics, particularly soil moisture. Benefits of SAR signal sensitivity to soil moisture include improved water management, forecasting floods and droughts, and sustainable agriculture (Mirsoleimani et al. 2019). For bare agricultural soils, the radar backscatter depends on the soil's moisture content, the surface's roughness, and the sensor's configuration (polarisation, incidence angle, and wavelength of the radar). Numerous remote sensing systems and hydrological models have been created to deliver SM on various geographical and temporal scales (Wagner et al. 2012). Soil moisture active and passive (SMAP), soil moisture and ocean salinity (SMOS), advanced SCATterometer (ASCAT), advanced microwave scanning radiometer-2 (AMSR2), European Reanalysis Interim (ERAinterim), and Global Land Data Assimilation System are the most notable missions now in operation (GLDAS) (Esch et al. 2018). More research needs to be done on the potential of obtaining these soil properties using C-band polarimetric SAR (synthetic aperture radar) data (Baghdadi et al. 2002). However, substantial research has been done to determine soil moisture.

Pre-processing

Pre-processing is the essential step after acquiring the data from relevant sources. Raw data always have some errors in geometry called geometric errors and registered amounts of pixels, known as radiometric errors. Irregularities and unwanted sensors, atmospheric noise, sensor-earth geometry changes, and other factors affect outcome

Table 2 Precipitation indices (SPI) and their application

SPI duration	Reflected phenomenon	Application
1 month	Short term	"Short-term soil moisture and crop stress"
3 months	Short-medium term	Precipitation forecasting for the season
6 months	Medium-term	Potential for efficiently portraying precipitation over different seasons. For example, the 6-month SPI in California can effectively indicate the quantity of precipitation from October to March
9 months	Precipitation pattern over a medium time scale	If SPI9 is less than – 1.5, significant repercussions may likely occur in agriculture (and probably other sectors)
12 months	Long-term precipitation patterns	Stream flows, reservoir levels, and groundwater levels may be all linked

Table 3 Data sources and relative methods used for agricultural drought assessment

Datasets	Methods/techniques	Period	References
MODIS and Tropical Rainfall Measuring Mission (TRMM)	Evaporative stress index (ESI), enhanced vegetation index (EVI), Vegetation health index (VHI), and standardized anomaly index (SAI)	2002–2019	Shahzaman et al. 2021
Landsat 8, MODIS	Principal component analysis (PCA)	2013–15	Hazaymeh and Hassan 2017
Landsat 8	Multi-criteria approach (MCA)-analytic hierarchy process (AHP)	2018	Ihinegbu and Ogunwumi 2021
MODIS	Vegetation condition index (VCI), TCI, VTCI	2015–16	Aswathi et al. 2017
Landsat TM, Landsat ETM +, and Landsat OLI/TIRS	Vegetation health index (VHI), temperature vegetation dryness index (TVDI), visible and shortwave infrared dryness index (VSDI)	1990–2018	Sultana et al. 2021
METEOSAT-5 thermal infrared (TIR)	NDVI	2000–2002	Nageswara Rao et al. 2005
MODIS, TRMM	Scaled drought condition index (SDCI)	2000–2009	Rhee et al. 2010
Sentinel-2	NDVI, SPI	2016–2018	Gaikwad et al., 2022a
MODIS	Evaporative stress index (ESI), enhanced vegetation index (EVI), vegetation health index (VHI), and standardized anomaly index (SAI)	2002–2019	Shahzaman et al. 2021
Modern-Era Retrospective analysis for Research and Applications (MERRA-2)	SPI	1983–2013	Agutu et al. 2017
eMODIS	SPI, NDVI, and VCI	2000–2016	Senamaw et al. 2021
MODIS, MEdium Resolution Imaging Spectrometer (MERIS) and Advanced Very-High-Resolution Radiometer (AVHRR)	Deep forwarded neural network (DFNN),	2001–2016	Prodhan et al. 2021
Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), MODIS	Normalized vegetation supply water index (NVSWI)	2000–2018	Sandeep et al. 2021
MODIS	NDVI and land surface temperature (LST)	2002–2012	Sruthi and Aslam 2015
MODIS, AVHRR	NDVI, VCI	1982–99	Thenkabail et al., 2004

accuracy. In this step, errors in the data are corrected. The earth's atmosphere's absorption and light dispersion cause image inaccuracy. Accordingly, atmospheric modification is a crucial pre-processing step of satellite images. Several algorithms are used for atmospheric corrections. For instance, the study conducted for agricultural drought assessment (Gaikwad & Kale 2015) used the ATCOR3 algorithm for atmospheric correction.

On the other hand, radiometric corrections include correcting the information for sensor irregularities and unwanted sensor or atmospheric noise and converting the information to accurately represent the reflected or emitted radiation measured by the sensor. Geometric corrections include correcting for geometric distortions due to sensor-earth geometry variations and converting the data to real-world coordinates (e.g., latitude and longitude) on the earth's surface (Vibhute et al. 2015).

Spectral indices

After improving the image quality through pre-processing, the data is ready for appropriate feature extraction. Various indices have been developed for remote sensing data as feature extraction methods for agricultural drought assessment. Researchers have used several indices in assessing droughts. The present paper details the most critical indices with their principle used for agricultural drought assessment.

It was found that the NDVI is one of the most popular vegetation indices used to identify and monitor vegetation health (Gaikwad et al., 2022b). The calculations of NDVI result in a number that ranges from minus one (-1) to plus one (+ 1). A zero value indicates the unavailability of vegetation, and approximately one, i.e., 0.8–0.9, shows the highest possibility of green vegetation. Values less than or equal to 0.1 are empty sand, rocks, or snow areas. Moderate values, i.e., 0.2 to 0.3, represent meadows and shrubs. Values from 0.6 to 0.8 demonstrate tropical forests and temperature. Especially in sparse vegetation, NDVI is sensitive to factors like soil background (Guliyeva 2020).

Additionally, the VCI is primarily used to compare the current NDVI to the values observed in previous years during the same period. Higher values of VCI indicate that the vegetation is in good condition, while lower values indicate that the vegetation is in bad condition. VCI has good spatial coverage and high resolution (Sierra-Soler et al. 2016). On the other hand, the TCI is used to find the stress on vegetation caused by excessive wetness and temperature. The range of TCI is from 0 to 100, where 0 indicates extremely unfavorable conditions and 100 means optimal conditions. The VCI and NDVI are used for agricultural droughts (Sultana et al. 2021).

The SPIE is designed to analyze the implications of evaporation and transpiration on drought. SPIE benefited from multi-scale SPI and perhaps even the virtue of incorporating PDSI evaporation, and it was suggested to include the impact of evaporation and perspiration on shortage. SPIE has emerged as one of the most effective methods for drought monitoring (Liu et al. 2016). In 1995, Kogan suggested that the VHI is an additive mixture of VCI and TCI (Karnieli et al. 2006). The plant water content is significantly connected to the NDWI (Gao 1996). The NDWI is a satellite-derived indicator based on the NIR and short-wave infrared (SWIR) channels. The NDWI product is dimensionless and ranges from − 1 to + 1, depending on the leaf water content and the kind and cover of vegetation. High NDWI readings indicate that there is much water in the vegetation and a lot of plant fraction cover. Poor NDWI values indicate low vegetation water content and fractional coverage (Gao 1996). Table 4 depicts the different indices used for agricultural drought assessment with their applications and limitations.

Identification of severity of drought

The severity of the drought can be identified based on parameters like extreme dry, dry, moderate, wet, and extremely wet. However, the drought severity is identified using severity indices. The comparison of drought severity indices and their concerning parameters for classification are shown in Table 5.

Challenges in agricultural drought assessment

Inconsistency in the data collected by various sensors

The discrepancy between values derived from multiple sensors results in uncertainty in multi-sensor integration attempts. Data synthesis is more complicated by geographical, temporal, spatial extent, spectral resolution, overpass time, and record duration. Recent advancements in new satellite data acquisition approaches and techniques highlight the need for more concentrated efforts on data fusion techniques (Jiao et al. 2021).

Sensor's spatial and spectral resolution

Datasets obtained from active and passive sensors have met resolution limits in agricultural drought monitoring. Researchers have frequently had to choose between spatial and spectral resolution when choosing data. Much of the research focuses on the trade-off between spatial resolution and temporal frequency: a compromise is frequently required, in which we can have one but not the other. Due to technical limitations, the possible detection of changes in critical environmental variables during drought circumstances has been limited (West et al. 2019).

Creating climate data archives

One of the primary drawbacks of many current accessible satellite datasets is their short record length relative to meteorological stations. Some relevant satellite missions and sensors (e.g., GRACE) give just a few years of data, which may need more for drought research from a climatological viewpoint. Still, they can provide helpful information on anomalies for drought effect assessment. Furthermore, some satellite sensors are research instruments, and there is no assurance that the same (or sufficiently equivalent) equipment will be released to replace them (Aghakouchak et al. 2015).

Limited area being monitored

The in-situ monitoring methods give regular data (i.e., daily measurements taken at ground stations) but are geographically limited to specific measuring locations. For agricultural drought monitoring, remote sensing satellites now collect pictures in the optical and thermal spectrum with varying spatial and temporal resolutions. Several remote sensing satellites, such as AVHRR, MODIS, and SPOT-VEG, can give high temporal resolution (daily) with low spatial data in the 250–1000 m range. Other satellites, such as Landsat, ASTER, and SPOT5, give data with a low temporal resolution but a high spatial resolution (e.g., 16–26-day intervals with spatial resolutions of 10–120 m). A similar problem exists with passive and active microwave remote sensing (Hazaymeh & Hassan 2016).

Droughts influence the ecology

Most existing multi-sensor drought monitoring techniques rely on data-driven models that lack processes that explain how shortages affect ecosystems. Few current drought indicators can directly represent vegetation water stress. Additional to drought, there are a variety of other causes that can create ecological abnormalities due to the complexity of the earth's system. The combination of risks (e.g., drought and heatwaves) needs additional cause-and-effect research to fully comprehend drought characteristics and their underlying aspects. Deficiencies cause the ecosystem to limit CO_2 absorption, raising CO_2 concentrations in the atmosphere,

Table 4 Significant indices/methods used for agricultural drought assessment

Index/method	Formulae	Applications	Limitations	References
NDVI	NDVI = (NIR-RED)/(NIR + RED)	Vegetation identification and their health monitoring with drought episodes	It has acoustic effects that build up. NDVI is not a structural feature for any land surface region. Since it is a ratio-based index, nonlinearity is a natural property. The NDVI makes much sense for any canopy background brightness	West et al. 2019, Thenkabail and Gamage 2004, Jayawardhana and Chathurange 2020, Dutta et al. 2015, Gandhi et al. 2015 Gaikwad et al., 2022a
VCI	$VHI = \propto \mathrm{VCI} + (1-\propto)\mathrm{TCI}$	Vegetation condition assessment for drought monitoring	High temporal data and real-time rainfall information are needed to monitor the vegetation condition	Singh et al. 2003; Dutta et al. 2015
TCI	$TCI = 100 * \frac{(BT\max - BT)}{(BT\max - BT\min)}$	It is utilised with the NDVI and the VCI to quantify the drought's effects on vegetation when agricultural implications are the main issue	Developing dependable inter-sensor interactions is challenging to continually monitor drought for as long as possible	Thenkabail and Gamage 2004, Singh et al. 2003
SPI	$\mathrm{SPI} = \mathrm{S}\frac{\mathrm{t}-(\mathrm{c2t}+\mathrm{c10})+\mathrm{c0}}{[(\mathrm{d3t}+\mathrm{d2})\mathrm{t}+\mathrm{d1}]\mathrm{t}+1.0}$	SPI readings for three months or less may be helpful for essential drought monitoring, values for six months or less may be useful for monitoring agricultural impacts, and values for 12 months or more may help monitor hydrological impacts	SPI, which assumes prior distribution, may only be appropriate for some contexts, mainly when we evaluate the onset or cessation of drought and short-duration events	Dutta et al. 2015; Liu et al. 2021
VHIs	$VHI = \propto \mathrm{VCI} + (1-\propto)\mathrm{TCI}$	VHI help assesses vegetation growth activity and monitors and quantifies dryness	The satellite data record period should be brief	Jiang et al. 2008, Sultana et al. 2021 Jiang et al. 2021
NDWI	$NDWI = \frac{(\mathrm{NIR}-\mathrm{SWIR})}{(\mathrm{NIR}+\mathrm{SWIR})}$	It is used as a way of stress detection to monitor how drought is affecting agriculture	Impacts other than drought can stress plant canopies, but it is challenging to identify them using simply NDWI	Jayawardhana and Chathurange 2020, Gao 1996
LST	$LST = (\mathrm{BT}/(1 + (0.00115 * \mathrm{BT}/(1{,}4388) * \mathrm{Ln}(\in))))$	It is used for VHI, soil moisture estimation, air temperature estimation evapotranspiration, and drought	The limitation of LST is the cloud cover effect	Jayawardhana and Chathurange 2020
SMDI	$SMDI_{\mathrm{i}} = 0.5 * \mathrm{SMDI}_{\mathrm{i}-1} + \frac{\mathrm{SD}_{\mathrm{SMOS}_1 1}}{50}$	ETDI and SMDI's acceptable spatial resolution paired with high temporal resolution will aid in gaining a better knowledge of agricultural drought and monitoring and planning to alleviate drought's effects	The output from the SWAT model is required to calculate SMDI. When all the depths are utilised, autocorrelation issues arise	Narasimhan and Srinivasan 2005
Soil Moisture Anamoly	$SMA = \frac{SMI_{\mathrm{t}} - \overline{SMI}}{\delta_{\mathrm{SMI}}}$	Developed and widely used to track the effects of drought on global agriculture and crop production	Calculations are complex because of the data needs. Estimates of potential evapotranspiration might vary significantly from region to region	Bergman Sabol, and Miskus 1988; Observatory 2019

Table 4 (continued)

Index/method	Formulae	Applications	Limitations	References
Soil Water Deficit Index	$SWDI_n = 10 * \left(\frac{SM_n - FC}{AWC}\right)$	It helps locate and track agricultural droughts	The output from the SWAT model is required to calculate SWDI. When all the depths are utilised, auto-correlation issues arise	Narasimhan and Srinivasan 2005; Saha et al. 2018; Pablos et al. 2018
Palmer drought Severity index	$X_i = 0.897X_{i-1} + \frac{Z_i}{3}$	It was created primarily to track droughts that impacted agriculture, but it has also been used to track and detect droughts with other kinds of impacts	The requirement for serially complete data could lead to issues. Due to the PDSI's nine-month time horizon and the computations' simplification of the soil moisture component, there is a delay in detecting drought conditions	Alley 1984
Soil Adjusted Vegetation Index	$SAVI = ((NIR - Red)/(NIR + Red + L)) * (1 + L)$	SAVI is helpful for monitoring vegetation and soil	Both are making calculations and acquiring data for operational use are challenging	Huete 1988; Zargar et al. 2011

and ecosystem structural and physiological responses to droughts may persist long after drought recovery and need to be better understood at broad scales. Drought coupled with less precipitation is usually followed by reduced cloud cover. Therefore, tremendous accessible energy for vegetation photosynthesis is required (Deng et al. 2021).

Discussions

Drought prediction is neither exact nor precise. Timely and trustworthy climate information, especially seasonal forecasts, is crucial for decision-making. If used correctly, this knowledge can help mitigate the effects of drought and other extreme weather occurrences. Drought early warning systems (EWS) can provide this information to decision-makers (Chandrasekar et al. 2018). Drought is classified into four types (Section “Drought Types”). Recent research has suggested additional drought types, such as ecological drought (episodic deficit of water availability that drives the ecosystem), environmental drought (water deficit and reduced ability for soil to support crops), and flash drought (rapid onset or intensification of drought) (Jiao et al. 2021). These droughts are linked, but this article focuses on agricultural droughts.

Agricultural drought assessment can be done more effectively and accurately using geospatial techniques and machine or deep learning methods (Khan et al. 2022). Geospatial technology allows the acquisition of high-resolution and high temporal real-time data via remote sensing, data management, GIS analysis, and geo-referencing ground truth data via GPS. Additionally, data is required to be integrated into an information system for a specific purpose (Choudhury 2005).

Many studies focus on the trade-off between spatial resolution and temporal frequency. We frequently need to compromise to have one but not the other (Jiao et al. 2021). Observations with high spatial resolution and temporal frequency are needed for various applications. However, preprocessing is essential in remote sensing datasets.

On the other hand, various indices are used for spectral feature extraction. The indices (Section “Spectral indices”) have their benefits and drawbacks, and their performance varies from application to application and area to area. Combining drought indices can effectively identify global and local droughts (Ali et al. 2019). One of the earliest and most frequently used integrated drought monitoring indicators, VegDRI (vegetation drought response index), was created by Brown et al. (2008) to use remote sensing and climate-based datasets. The VegDRI has been utilized to form new models and the assessment of drought on a national basis.

Table 5 Drought severity indices and their parameters concerning the classification

Index	Values	Classification	Source
PDSI	> 4.00	Extreme wet	Liu et al. 2016
	3.00–3.99	Severe wet	
	2.00–2.99	Moderate wet	
	1.00–1.99	Mild wet	
	0.50–0.99	Slight wet	
	− 0.49–0.49	Normal	
	− 0.99 to − 0.50	Slight drought	
	− 1.99 to − 1.00	Mild drought	
	− 2.99 to − 2.00	Moderate drought	
	− 3.99 to − 3.00	Severe drought	
	< − 4.00	Extreme drought	
SWSI (Surface Water Supply Index)	4.00 or more	Abundant water availability	Wambua et al. 2017
	3.99 to 1.99	Wet	
	2.00 to − 0.99	Near normal	
	− 1.00 to − 1.99	Incipient drought	
	− 2.00 to − 2.99	Moderate drought	
	− 3.00 to − 3.99	Severe drought	
	− 4.00 and less	Extreme drought	
NDVI	< 0	Extreme	Aziz et al. 2018
	0–0.2	Severe	
	0.2–0.4	Moderate	
	0.4–0.6	Mild	
	> = 0.6	No	
VCI	< 10	Extreme	Brema et al. 2019
	< 20	Severe	
	< 30	Moderate	
	< 40	Mild	
	> = 40	No	
TCI	< = 10	Extreme	Gaznayee and Al-Quraishi 2019
	10 and < = 20	Severe	
	20 and < = 30	Moderate	
	30 and < = 40	Mild	
	> = 40	No	

Previous agricultural drought studies have primarily focused on (i) drought ideas, (ii) data sets, and (iii) methods and tools for assessing and monitoring drought threats. However, in the present review, several research challenges in agricultural drought assessments have been detected, and several prerequisites have been highlighted to synthesize these gaps for future research.

Anthropogenic droughts will likely intensify due to the integrated impacts of environmental change and human action. At the same time, these models can be used to study a range of plausible policy responses and assess their outcomes. Significant uncertainties and assumptions are associated with the scenarios that may affect outcomes. Research in this direction may lead to policies and management strategies that mitigate the impact of artificial drought. However, currently available models are coarse in time and space and cannot study the effects of short-term and regional shocks (AghaKouchak et al. 2021).

Conclusions

The current paper presents an exhaustive review of agricultural drought characteristics, analysis, and assessment using remote sensing technology and advanced methods. This paper also provides a detailed description of standard and benchmark remote sensing datasets. Some of the datasets are available locally, and others are available globally. It was observed that the Landsat and MODIS datasets are the most used by the remote sensing community for drought assessment. The spectral indices are significant in detecting agricultural droughts. However, detecting and monitoring agricultural droughts are challenging due to inconsistency in data, variations in spatial and spectral resolutions, unavailability of climatic data, and limitations in area coverage. Therefore, it is necessary to use geospatial technology and machine learning methods in agricultural drought monitoring. In conclusion, launching additional satellites or sensors and creating new techniques and procedures are essential to detect and monitor droughts early. However, the high temporal and spatial resolution satellite information should be made freely available, which is needed in planning, management, and decision-making at the urban or village level to monitor drought episodes or climate change effectively. In the future, developing a novel method for automatically detecting early drought episodes would be essential for early drought monitoring for food production.

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Declarations

Ethics approval and consent to participate Not applicable.

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