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Review

Agricultural Drought Monitoring: A Comparative Review of Conventional and Satellite-Based Indices

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Abstract: Drought is a natural hazard that causes significant economic and human losses by creating a persistent lack of precipitation that impacts agriculture and hydrology. It has various characteristics, such as delayed effects and variability across dimensions like severity, spatial extent, and duration, making it difficult to characterize. The agricultural sector is especially susceptible to drought, which is a primary cause of crop failures and poses a significant threat to global food security. To address these risks, it is crucial to develop effective methods for identifying, classifying, and monitoring agricultural drought, thereby aiding in planning and mitigation efforts. Researchers have developed various tools, including agricultural drought indices, to quantify severity levels and determine the onset and evolution of droughts. These tools help in early-stage forecasting and ongoing monitoring of drought conditions. The field has been significantly advanced by remote sensing technology, which now offers high-resolution spatial and temporal data, improving our capacity to monitor and assess agricultural drought. Despite these technological advancements, the unpredictable nature of environmental conditions continues to pose challenges in drought assessment. It remains essential to provide an overview of agricultural drought indices, incorporating both conventional methods and modern remote sensing-based indices used in drought monitoring and assessment.

Keywords: drought; drought indices; agricultural drought; conventional indices; satellite-based indices

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1. Introduction

Climate variability affects all regions, but drought is one of its most significant impacts. This natural phenomenon, characterized by its complex physical mechanisms, has far-reaching consequences for human populations and economic stability [1,2]. As the planet warms, we see more frequent and severe weather events like drought. Recent years have seen a surge in both the occurrence and the severity of extreme drought events, leading to significant environmental degradation, ecosystem disruption, and reduced agricultural output [3,4].

Drought, a complex environmental phenomenon, is typically categorized into four distinct types based on its impacts. These classifications include meteorological, agricultural, hydrological, and socioeconomic droughts, each with its own unique characteristics and consequences [1,5]. These drought types are interconnected and often follow a sequential pattern in their occurrence. The process typically begins with meteorological drought, characterized by a significant reduction in precipitation compared to normal levels for a specific area and time period. This initial phase can lead to agricultural drought, where soil moisture becomes depleted, negatively impacting plant growth and potentially reducing crop yields. As the drought persists, it may evolve into a hydrological drought, marked by diminished water levels in surface and groundwater sources due to reduced recharge from soil moisture. Finally, socioeconomic drought can emerge when water scarcity begins to affect human activities and hinder regional development. This study focuses primarily on examining various indices used to measure and assess agricultural drought.

Agriculture is the major sector to be affected by drought. Although overall agricultural production has risen in recent years, agricultural drought constitutes the primary cause of crop failure, resulting in global food price instability and threatening global food security [6]. Therefore, assessing and monitoring droughts, especially agricultural drought, are of primary importance.

Effective early warning systems for agricultural drought are essential for planning and mitigating its impacts [7]. Numerous methods have been devised to identify, classify, and monitor agricultural drought, commonly referred to as agricultural drought indices [8]. These indices facilitate the quantitative evaluation of drought intensity, duration, and spatial extent, and can sometimes aid in decision-making processes [9]. Various frameworks exist for monitoring and mitigating the effects of agricultural drought. Traditional drought monitoring and assessment methods typically rely on single data sources and in situ measurements, which are resource-intensive and time-consuming, thus limiting their spatial and temporal resolution. However, advancements in remote sensing technology have revolutionized the assessment and monitoring of agricultural drought. By integrating data from multiple sources, remote sensing provides high spatial and temporal resolution data crucial for agricultural drought research [10,11]. Satellite imagery, for instance, can be used to gather information on crop phenology, offering valuable insights into crop development and productivity [12].

Despite numerous studies on agricultural drought assessment, significant challenges remain due to the variability of environmental conditions. This study aims to offer a comprehensive overview of the importance of agricultural drought and examines both traditional and remote-sensing-based drought indices commonly employed to monitor these conditions. The analysis includes a discussion of the strengths and limitations of these indices, as well as a summary of relevant studies that have utilized them in their assessments.

A critical aspect of writing this review was establishing a robust research strategy to identify relevant papers and reports. The process began by identifying and retrieving sources based on specific keywords related to agricultural drought and drought indices. Next, these sources were shortlisted by evaluating their titles and abstracts to ensure relevance. In the final step, citation analysis was employed to refine the selection, focusing on highly cited and influential papers pertinent to the current survey. The search encompassed a wide range of resources, including all Science Citation Index journals and international Scopus-indexed journals, as well as books and other reputable online sources.

2. Drought Characterization Concepts

Drought is a multifaceted phenomenon arising from the interplay of natural factors and human water consumption patterns. Rather than simply being a lack of water, drought represents a deficit relative to specific needs in a given context. Due to its different impacts across sectors and widespread occurrence, there is no universally accepted definition of drought. However, it can generally be characterized as a prolonged imbalance between water supply and demand in a particular region over a specific timeframe [13]. The concept of drought extends beyond mere water scarcity to encompass its broader impacts on society, the economy, and the environment [14].

One key characteristic of drought is its dynamics, particularly the time–space characteristics, which are vital for effectively understanding and managing drought events. These dynamics include temporal aspects such as the duration, frequency, and intensity of drought occurrences, providing insights into how long droughts persist, their recurrence rates, and their severity over time. Furthermore, the spatial characteristics address the extent and distribution of drought-affected areas, illustrating the significant variability of drought impacts across different regions [15].

While several approaches exist for characterizing drought, the use of drought indices is particularly common [16]. These indices are calculated by integrating various drought indicators into a single numerical value, facilitating drought analysis and enhancing decision-makers' awareness and preparedness for potential future drought events.

A wide array of indices is available for describing drought features, but no single index or indicator is universally applicable across all scenarios. Drought assessment methodologies can be broadly categorized into three main approaches: utilizing a single indicator or index, employing multiple indicators or indices, or creating composite indicators that integrate multiple measures using a converging evidence method [17].

Drought indices can also be classified based on the types of variables they incorporate, such as precipitation, soil moisture, evapotranspiration, and temperature. These variables, used either individually or in combination, contribute to a comprehensive drought evaluation. The resulting assessments are then interpreted to determine various drought characteristics, including severity, spatial extent, and duration.

Traditionally, drought quantification has relied on conventional meteorological data, which often have limitations in terms of regional coverage, accuracy, and real-time availability. In contrast, satellite-based data offer reliable accessibility and the ability to identify various drought characteristics and features. Current remote sensing applications for agricultural drought monitoring include vegetation condition assessment using reflective remote sensing, soil moisture monitoring via microwave remote sensing, and environmental stress detection through thermal and reflective remote sensing techniques [18]. In situ data are frequently used to validate and enhance the accuracy of these satellite-based observations.

Agricultural drought is a complex phenomenon that occurs due to the interplay between meteorological conditions and agricultural needs [19]. It occurs when there is an imbalance between available soil moisture and the water requirements of crops, leading to significant impacts on plant growth and crop yields [20].

Agricultural drought is not solely dependent on rainfall deficits. It also includes factors such as increased evapotranspiration rates, often driven by higher temperatures and wind speeds, which can exacerbate moisture loss from soil and plants. This type of drought typically occurs gradually, with a time lag following meteorological drought [21]. This delay is due to the fact that plants can initially draw upon soil moisture reserves, but as these become depleted, the effects on vegetation become more pronounced. Consequently, monitoring precipitation patterns can serve as an early indicator of potential agricultural drought risks [22].

To assess and quantify agricultural drought, researchers and agronomists have developed various indices and methods. Many of these are based on direct measurements of soil moisture or related indicators that reflect the water status of the soil–plant system.

3. Conventional Agricultural Drought Monitoring Methods

In situ agricultural drought monitoring indices are known for their accuracy and reliability [23]. These indices are derived from ground-based measurements of hydro-climatic variables, including precipitation, temperature, relative humidity, and soil moisture, collected from climatic, agricultural, and hydrologic stations. They offer both quantitative and qualitative insights into the area of interest [24].

This section describes fourteen conventional drought indices frequently used for monitoring and forecasting.

3.1. Soil Water Deficit Index (SWDI)

The SWDI is a measure used to characterize agricultural drought based on soil moisture series and basic soil water parameters. It indicates the soil water content in relation to field capacity and available water content. A positive SWDI value signifies an excess of water, zero indicates field capacity, and negative values indicate agricultural drought. SWDI helps identify drought events by considering their beginning, end, duration, and intensity. Zhou [25] evaluated the utility of the combined SM product and SWDI for monitoring agricultural drought in China and studied the relationships among meteorological, agricultural, and vegetation droughts. The study area covered four geographical regions in China. The results indicated that the SWDI, utilizing combined SM data, performed well in characterizing agricultural drought conditions in China. The evaluation showed that the SWDI had a high probability of detection at many stations, indicating its effectiveness in detecting actual drought events. Additionally, the study highlighted that when the SM data were within an acceptable range, the accuracy of the SWDI in identifying drought events was minimally affected. Martínez-Fernández [26] evaluated the SWDI for agricultural drought monitoring using satellite data, comparing it with other drought indices. The study was conducted in the Duero Basin, Spain, which encompasses a semi-arid Mediterranean agricultural region. The results indicated that different methods for calculating SWDI produced similar outcomes with a high correlation, suggesting its potential for widespread application. Comparisons with other indices, such as the Crop Moisture Index (CMI) and the Antecedent Water Deficit (AWD), demonstrated the effectiveness of SWDI in capturing soil–water dynamics during drought periods.

3.2. Soil Moisture Deficit Index (SMDI)

The SMDI, introduced by Narasimhan and Srinivasan [27], effectively characterizes short-term drought conditions and is not influenced by seasonal or climatic variations. It is derived using soil moisture estimates, incorporating both long-term characteristics and short-term periods to evaluate drought conditions. The SMDI removes seasonality and provides a scaled range between −100 and 100, indicating varying degrees of dry to wet conditions across different climate zones. Fang [28] evaluated drought conditions in Australia using the SMDI derived from SMAP soil moisture data. The study area was the Murray—Darling River Basin in Australia. The SMDI was implemented by integrating long-term GLDAS soil moisture data and 1 km SMAP soil moisture data through a temporally incremental method to overcome limitations in selecting appropriate time periods for studying droughts. The results showed clear seasonal and interannual variability in drought conditions, with comparisons made to other indices like the SWDI and in situ soil moisture measurements from ISMN stations. The study highlighted the advantages of the SMDI over other indices, as it effectively characterizes short-term drought conditions across different climate zones. Unlike the SWDI and in situ soil moisture measurements, the SMDI provides a standardized measure that removes seasonality and offers a scaled range to indicate varying degrees of dry to wet conditions, making it a valuable tool for accurate drought assessment.

3.3. Evapotranspiration Deficit Index (ETDI)

The ETDI is a drought index specifically designed to evaluate short-term agricultural drought conditions by measuring soil moisture availability in the top 2 feet of the soil profile. Unlike other indices, such as the SMDI, the ETDI has a lower auto-correlation lag, enabling it to react more swiftly to variations in soil moisture levels. This index is calculated with a high spatial resolution of 4 km x 4 km and is updated on a weekly basis, providing timely and detailed assessments of drought conditions [27]. Wu's study [29] aimed to identify regional agricultural drought in the North China Plain using the ETDI by estimating daily evapotranspiration (ET), comparing the ETDI with other drought indices, and quantifying drought-affected areas and crop failures. The results demonstrated that the ETDI is a reliable indicator of agricultural drought, showing high consistency with the Composite Index (CI) and surpassing other indices such as the Palmer Drought Severity Index (PDSI) and the Standardized Precipitation Index (SPI) in terms of correlation. The study reported significant agricultural losses due to severe droughts, particularly in the years 1994, 1997, and 2000, with drought-affected areas spanning millions of hectares. The ETDI effectively captured the severity and spatial distribution of drought across provinces, especially in regions with limited irrigation. Wambura [30] aimed to evaluate the sensitivity of the ETDI to its parameters and to data across different temporal scales in the Ruvu River basin, located in eastern Tanzania. The findings revealed that the ETDI is highly sensitive to its parameters, with different combinations resulting in varied drought characteristics. Furthermore, the analysis of temporal scale sensitivity showed that as the temporal scale increased (from 8 days to 16 days to 1 month), the number of detected drought events and the total duration of droughts decreased. This suggests that using inappropriate temporal scales could distort drought characteristics, highlighting the importance of parameter calibration and the use of data with shorter temporal scales to enhance the accuracy of ETDI-based assessments of agricultural drought.

3.4. Soil Moisture Agricultural Drought Index (SMADI)

The SMADI integrates soil moisture, surface temperature, and vegetation data to assess drought conditions in agricultural areas. It utilizes the ratio of the Land Surface Temperature (LST) to the Normalized Difference Vegetation Index (NDVI) to capture the inverse relationship between temperature and vegetation health. Souza [31] conducted a study to evaluate the impact of drought on agricultural productivity in Pernambuco State, Brazil, by correlating drought indices, specifically the SMADI, with data on corn and sorghum yields. The study's findings revealed severe drought conditions, with the SMADI identifying prolonged periods of drought, particularly in the Mata and Sertão regions. Additionally, the study demonstrated significant correlations between the severity of SMADI and corn productivity, underscoring the crop's sensitivity to water stress.

3.5. Bhalme—Mooley Drought Index (BMDI)

Bhalme and Mooley [32] developed an objective numerical drought index based on monthly monsoon rainfall and duration to assess drought intensity in India. The index serves the dual purpose of evaluating drought and flood intensity. It calculates the Drought Area Index (DAI) and Flood Area Index (FAI) to determine the percentage area of India experiencing moderate or higher drought severity or moderate or more severe wetness, respectively. The index helps to identify large-scale-drought years and provides a realistic assessment of drought and flood conditions in tropical countries like India. The index provides a relative measure of regional moisture anomalies by determining the highest accumulated negative moisture index values during various intervals of months in different areas. This allows for the numerical designation of extreme droughts in specific regions based on the duration and severity of dry conditions. Domenikiotis [33] evaluated the environmental effects on cotton production in Greece using the Vegetation Condition Index (VCI) and the BMDI. The study found that the BMDI indicated unfavorable conditions for cotton production in central and northern Greece at the start of the growing season. Low BMDI values suggested the presence of severe agricultural drought in the region. Sabău [34] conducted a study in the Crișurilor Plain region of Western Romania to evaluate agricultural drought risk and predict crop yields using the Standardized Precipitation Index (SPI) and the BMDI. The results indicated a medium risk of drought occurrence based on the BMDI, with higher frequencies of dry periods compared to the SPI. This suggests that the BMDI could be a valuable tool for predicting crop yields in the region, underscoring its potential significance in agricultural planning and risk management.

3.6. Reconnaissance Drought Index (RDI)

The RDI is a new drought index proposed for assessing drought severity based on cumulative values of precipitation and potential evapotranspiration. It is physically based, calculating the deficit between atmospheric evaporative demand and precipitation, making it ideal for monitoring and short-term forecasting [35]. The RDI can be calculated for any period, with 3-, 6-, 9-, and 12-month periods recommended for comparisons between different situations and locations, which is particularly effective for hydrological and agricultural drought assessments. Tigkas [36] focused on the assessment of agricultural drought using the RDI and its modified form (eRDI). The eRDI incorporates effective precipitation to enhance the link between drought severity and agricultural production reduction. The results showed that the eRDI outperforms the RDI, especially during critical crop development stages. The study highlights the importance of reference periods based on crop development stages for accurate drought assessment and the early prediction of drought impacts on specific crops. Zarei [37] conducted an analysis of changes in spatial drought patterns in southern Iran from 1980 to 2010, employing the RDI and time series models. The findings indicated that, on seasonal timescales, the percentage of areas classified as dry exhibited an increasing trend, whereas areas with wet conditions demonstrated a decreasing trend. On an annual timescale, the study observed decreasing trends in the percentage of areas classified as having very wet, moderately wet, and normal conditions.

3.7. Crop Moisture Index (CMI)

Palmer [38] developed the CMI to track crop moisture conditions nationwide. The CMI combines the evapotranspiration anomaly and wetness index to assess these conditions, indicating whether there is a surplus or deficit of moisture for crops. Negative values suggested a lack of moisture, while positive values indicated adequate or excess moisture. The CMI is instrumental in tracking and interpreting the status and trends of moisture conditions for crops on a broad scale. Li [39] aimed to develop a framework for assessing agricultural drought in Inner Mongolia, China, utilizing meteorological data, remote sensing, and observational data. They observed a strong positive correlation between the CMI and crop yield anomalies, particularly during the critical period from the second dekad in June to the second dekad in July. This period was identified as crucial for predicting agricultural drought and potential yield reductions in the study area.

Crop-Specific Drought Index (CSDI)

The CSDI is a model designed to monitor and assess the impact of weather on corn yields throughout the growing season. It utilizes variables such as projected yield, evapotranspiration, and crop sensitivity to calculate the probabilities of projected outcomes. The CSDI provides a tailored approach to evaluating weather's probable impact on corn production, offering advantages over other drought indices by assigning probabilities and enabling assessments at any point during the growing season. Meyer [40] introduced the CSDI index as a method to monitor and assess weather's impact on corn yields in Nebraska's East Central crop reporting district (CRD). They applied the CSDI by calculating projected CSDI values based on historical climate data and soil conditions during the 1990 growing season. The results showed that the CSDI model accurately identified and assessed drought's potential impact on yield during key periods of the crop's development, with the actual CSDI value at the end of the season being 0.83.

3.8. Agricultural Drought Index (DTx)

The DTx index, an agricultural drought index, was developed by the Hydrometeorological Service of ARPA Emilia Romagna-Bologna in Italy. This index is predicated on the daily transpiration deficit, calculated through the CRITeRIA water balance model. The primary objective of the DTx index is to monitor and evaluate the impact of agricultural drought by examining the disparity between maximum and effective transpiration over various temporal intervals. Empirical testing of the DTx index in three Mediterranean regions has demonstrated its efficacy in accurately reflecting the risk to crop production posed by drought conditions. Notably, the index exhibits high sensitivity to soil moisture levels. It is utilized within a regional drought observatory and is bolstered by a dedicated website, which disseminates pertinent information to support regional management programs [41].

3.9. Leaf Water Content Index (LWCI)

The LWCI is an index that reflects the moisture content of leaf canopies [42]. In the context of drought, the LWCI can provide valuable information on the water status of vegetation. During drought conditions, plants experience water stress, leading to a decrease in leaf water content. This decrease in water content can be captured by the LWCI, as it is sensitive to changes in moisture levels within the leaf canopy. By analyzing the LWCI values derived from satellite imagery, researchers can identify areas with lower LWCI values, indicating potential moisture stress or drought-affected regions. Sukmono [43] conducted a study that integrated the LWCI and Enhanced Vegetation Index (EVI) for the detection of stress in rice plants utilizing Landsat 8 satellite imagery. The research was carried out in Kendal Regency, Indonesia, a region noted for its agricultural importance. The findings revealed that the LWCI index values ranged from −0.351 to 0.985, signifying different degrees of moisture stress within the vegetation. Notably, lower LWCI values were observed in the northern part of Kendal, indicating reduced moisture content in comparison to the southern areas.

3.10. Moisture Availability Index (MAI)

The MAI is a tool developed for natural resource inventories to evaluate climate resources for agricultural production [44]. It has been used globally to assess the availability of moisture for agricultural purposes. MAI values indicate the adequacy of water for crops, which influences yield potential and the need for irrigation. By evaluating climate resource and water fertility interactions, MAI helps in identifying areas prone to moisture stress, guiding decisions on when and where to apply fertilizers, and estimating relative yields from rainfed agriculture. Fiala [45] conducted an evaluation of the impact of drought severity on agricultural production within the Hungarian–Serbian cross-border region, concentrating on Vojvodina and southeastern Hungary. The study's results demonstrated a marked increase in drought severity over the period under investigation, as indicated by persistently low MAI values, particularly during August. This ongoing moisture shortfall significantly negatively affected crop yields, with maize exhibiting particular susceptibility to the intensified drought conditions.

3.11. Soil Moisture Anomaly Index (SMAI)

The SMAI index, developed by Bergman [46] in the mid-1980s, was applied with a slight modification to obtain standardized data for easy comparison with other drought indices. The SMAI calculates deviations in soil moisture levels from the long-term mean using a water balance model. It considers factors like rainfall infiltration, evapotranspiration, and runoff to track soil moisture dynamics. The SMAI helps identify anomalies in soil moisture levels and potential drought conditions in agricultural regions, offering a more advanced and accurate evaluation compared to traditional drought indices. Jiménez [47] conducted an evaluation of a combined drought indicator, employing the SMAI alongside other indices. The study focused on five selected agricultural regions. The findings underscored the efficacy of the SMAI in detecting drought conditions within certain agricultural areas. However, the analysis also revealed that the SMAI successfully identified drought during significant dry periods in only two out of the five regions, indicating potential limitations in its sensitivity. This suggests that integrating in situ soil moisture measurements could enhance the accuracy of drought detection and improve the SMAI's performance in identifying agricultural drought risks more comprehensively. Adnan [48] conducted a comparative analysis of annual time series data from 15 different indices to evaluate their applicability and performance for drought monitoring in Pakistan. The SMAI was modified to a standardized version (SSMAI) to facilitate comparison with other drought indices. The SSMAI, along with other parameters, showed effective responses during drought periods. A trend analysis using linear regression indicated an overall increasing trend for most drought indices, with the exceptions of SC-PDSI and SSMAI, which exhibited a slight decreasing trend. These findings suggest a general worsening of drought conditions over time in the region, as reflected by the increasing values of most of the indices.

3.12. Soil Moisture Availability Index (SMAI)

The SMAI quantifies soil drought conditions based on actual monthly soil moisture compared to long-term maximum, minimum, and median values, ranging from −100 to

100. It considers both the current and the previous month's soil moisture and is calculated iteratively, with values ranging from −4 to 4. The SMAI is crucial for understanding soil moisture conditions and their impact on vegetation growth and drought events. Yang [49] analyzed soil drought and vegetation responses in North China from 2001 to 2015. This analysis utilized the SMAI to quantify soil drought conditions and the Vegetation Condition Index (VCI) to characterize vegetation status. The findings indicated a consistent decline in the SMAI in North China over the 15-year period. Similar patterns were observed in the SMAI values across the top three soil layers, while the fourth layer exhibited the smallest fluctuations. Notably, the most favorable soil moisture conditions were recorded between 2003 and 2005, with significant long-term drought periods before and after this interval. Furthermore, the severe drought in 2014 was particularly significant, as the SMAI averaged negative values for ten months of that year.

3.13. Standardized Vegetation Index (SVI)

The SVI was introduced by Peters [50]. The SVI is a quantitative measure used to assess vegetation conditions based on remote sensing data, particularly NDVI values. It calculates the probability of vegetation verdancy by converting z-scores from NDVI values into SVI values. The SVI index provides insights into changes in vegetation density over time, correlating low SVI values with poor vegetation health and high SVI values with good vegetation health. It is a reliable tool for evaluating drought severity and monitoring vegetation conditions based on the statistical relationship between SVI and rainfall data. Roylanakusol [51] aimed to evaluate drought conditions using the SVI in the Lower Northeastern region of Thailand. Their findings revealed a significant correlation between the SVI and rainfall, demonstrating that higher rainfall levels positively influenced SVI values. The analysis indicated that 2016 experienced the most severe drought compared to 2014 and 2015, based on SVI data.

Table 1 summarizes the most commonly used agricultural drought monitoring indices.

Table 1. Comprehensive summary of most commonly used conventional agricultural drought monitoring indices: descriptions, computational formulae, input data requirements, advantages, limitations, and source references.

Index	Formulae	Inputs	Strengths	Limitations	Ref.
SWDI	$SWDI = \left(\frac{\theta - \theta_{FC}}{\theta_{AWC}}\right)$ θ = soil water content θ_{FC} = soil water content at field capacity θ_{AWC} = available water content	soil water content; soil water content at field capacity; available water content	Effectively characterizes agricultural drought based on soil moisture data and basic soil water parameters; helps identify drought events by considering their beginning, end, duration, and intensity.	The need for accurate parameters, such as field capacity and wilting point, for precise calculations; Dependency on soil properties of the study area, which may limit generalization.	[26]
SMDI (Soil Moisture Deficit Index)	if $SW_j \geq MSW_j$ $SD_j = \left(\frac{SW_j - MSW_j}{MSW_j - minSW_j}\right) \times 100,$ if $SW_j < MSW_j$ $SD_j = \left(\frac{SW_j - MSW_j}{maxSW_j - MSW_j}\right) \times 100,$ $SMDI = 0.5 \times SMDI_{j-1} + \frac{SD_j}{50}$ SW_j = monthly averaged SM estimates $SMDI_{j-1}$ = SMDI from the past month	Long-term soil moisture records; averaged SM estimates for the period being evaluated; median (MSW_j); maximum $(maxSW_j)$; and minimum $(minSW_j)$ soil moisture values at the topsoil layer for any given month	Effectively characterizes short-term drought conditions; independent from different seasons or climate zones; removes seasonality and provides a scaled range between −100 and 100 for different climate zones; indicating very dry to very wet conditions.	Assumes all 1 km SM estimates within a GLDAS grid can be summarized by long-term SM records of that grid; requires high-spatial-resolution SM estimates and soil water parameters.	[28]
ETDI	$ETDI = 0.5ETDI_{j-1} + \frac{WSA_j}{50}$ WSA_j = monthly water stress anomaly	Potential evapotranspiration (PET); actual evapotranspiration (ET); water stress anomaly (WSA)	Applicable across different climatic zones; reliable indicators for short-term agricultural drought monitoring; high temporal resolution.	Inadequate performance in areas lacking observed meteorological data; in large catchments, only remote sensing products are relied upon for mapping ET and PET.	[27,29]
SMADI	$SMADI_i = SMCI_i \frac{MTCI_i}{VCI_{i+1}}$ $SMCI_i = \frac{(SM_{max} - SM_i)}{(SM_{max} - SM_{min})}$ $MTCI_i = \frac{(LST_i - LST_{min})}{(LST_{max} - LST_{min})}$ VCI_{i+1} = Vegetation Condition Index value	Land surface temperature (LST); normalized difference vegetation index (NDVI); soil moisture data (SM)	Early warnings of drought impact on rainfed agricultural systems; indication of adoption of more resistant crops to water stress conditions.	Reliance on remote sensing data; potential gaps in monitoring due to cloud cover and satellite availability; variable effectiveness, depending on regional climatic characteristics and soil types.	[31]
BMDI	$I_k = \frac{4M_k}{a+b} + (1+c)I_{k-1}$ $M_k = 100(\frac{P_k + P_{med}}{s})$ I_k = drought intensity in the current month (k). M_k = humidity index	Monthly precipitation; long-term mean monthly precipitation	Allows for the identification of extreme drought events based on the highest accumulated negative moisture values; the BMDI considers moisture contributions from the previous month, leading to longer durations and a higher scale of drought assessment; simple calculation.	Regional specificity: requires region-specific coefficients; less suitable for short-term or localized drought events; reliance on previous month's moisture may delay current drought monitoring.	[32,34]

Table 1. *Cont.*

Index	Formulae	Inputs	Strengths	Limitations	Ref.
CMI	$\mathrm{CMI}_i = \mathrm{Y_i} + \mathrm{G_i}$ $\mathrm{Y_i} = 0.67\mathrm{Y_{i-1}} + 1.8\frac{\mathrm{ET_i} - (\alpha \times \mathrm{ET_{oi}})}{\sqrt{\alpha}}$ $\mathrm{G_i} = \mathrm{G_{i-1}} - \mathrm{H_i} + (\mathrm{M_i} \times \mathrm{R_i}) + \mathrm{RO_i}$	Mean temperature; precipitation; evapotranspiration deficit (Y_i); excessive moisture (G_i); "return to normal" factor (H_i); average percent of field capacity (M_i); recharge (R_i); runoff (RO_i).	Combines evapotranspiration anomaly and wetness indices for a comprehensive measure; suitable for week-to-week appraisals on a nationwide or regional scale.	lack of local detail; does not account for local variations caused by factors like heavy rain or soil differences; reliance on meteorological data.	[38]
CSDI	$CSDI = \frac{Y_{proj}}{Y_{pot}} = \prod_{i=1}^{n} \left(\frac{\sum ET_{calc}}{\sum ET_{pc}} \right)_i^{\lambda_i}$ $\mathrm{Y_{proj}}$ = Projected yield $\mathrm{Y_{pot}}$ = maximum yield previously attained $\mathrm{ET_{calc}}$ & $\mathrm{ET_{pc}}$ = calculated and potential evapotranspiration of the corn crop, respectively λ_i = sensitivity coefficient	Projected yield; maximum yield previously attained; calculated and potential evapotranspiration of the corn crop; coefficients representing the crop's sensitivity to moisture stress during different growth periods	Provides crop-specific probabilities of projected outcomes, enabling reliable monitoring and assessment at a crop reporting district level; provides daily estimates of soil water availability across various zones and soil layers.	Relies heavily on accurate and timely meteorological data; requires sophisticated modeling techniques and specific crop-related parameters, which increases complexity; setting drought thresholds is difficult.	[40]
DTx	$\mathrm{DTx} = \sum_{\mathrm{today-x}}^{\mathrm{today}} (\mathrm{T_m} - \mathrm{T_e})$	Maximum transpiration (T_m); effective transpiration (T_e)	Tailorable to specific crops and growth stages for accurate drought impact assessment; compatible with models like WOFOST for detailed analysis of water-limited crop yields; calculable over different time frames.	Dependent on detailed hydro-meteorological data, which may not always be accessible or reliable in all regions; calculated using the complex CRITeRIA water balance model, potentially limiting accessibility for users without specialized training.	[41]
LWCI	$\mathrm{LWCI} = \frac{-\log[1 - (\mathrm{TMF4} - \mathrm{TM5})]}{-\log[1 - (\mathrm{TM4_{FT}} - \mathrm{TM5_{FT}})]}$ TM4 and TM5 = Landsat Thematic Mapper bands used to measure the reflectance of specific wavelengths related to water content in leaves. $\mathrm{TM4_{FT}}$, $\mathrm{TM5_{FT}}$ = reflectance values of Landsat Thematic Mapper Bands TM4 and TM5, respectively, for leaves at full turgor.	Reflectance values of Landsat Thematic Mapper Bands TM4 and TM5 for both a dry leaf (TM4 − TM5) and a fresh leaf $(TM4_{FT} - TM5_{FT})$	Captures variations in leaf water content, valuable for monitoring plant hydration and water stress; can be combined with other indices, like EVI, for a comprehensive understanding of plant stress and health; sensitive to moisture content.	Influenced by canopy architecture, leaf orientation, and density, complicating water content assessment; limited by satellite imagery resolution, affecting fine-scale vegetation moisture analysis; seasonal changes in vegetation phenology can impact LWCI readings, requiring careful interpretation; ground validation of LWCI values is difficult.	[42,43]

Table 1. *Cont.*

Index	Formulae	Inputs	Strengths	Limitations	Ref.
MAI	$\mathrm{MAI} = \frac{\mathrm{PD}}{\mathrm{PET}}$ Dependable Precipitation (PD) = the amount of precipitation that can be expected to occur at a seventy-five percent probability level (three years out of four years).	Dependable precipitation (PD) and potential evapotranspiration (PET)	Provides a relative measure of precipitation adequacy for moisture needs; suitable for assessing drought conditions and their impact on agriculture.	Primarily focuses on precipitation and evapotranspiration, not capturing the full complexity of agricultural systems; does not account for factors like soil characteristics or crop types.	[44]
RDI	$\mathrm{RDI} = \frac{\sum_{j=1}^{j=k} P_j}{\sum_{j=1}^{j=k} \mathrm{PET}_j}$ P_j = cumulative precipitation for each month	Cumulative precipitation and potential evapotranspiration (PET)	Calculates the aggregated deficit between atmospheric evaporative demand and actual evapotranspiration; includes potential evapotranspiration to avoid underestimating drought severity.	Reliance on precipitation and PET, which may not capture all aspects of drought impacts; sensitivity to reference periods, which can impact the result.	[9,35]
SMAI (Soil Moisture Anomaly Index)	$\mathrm{SMA} = \frac{\mathrm{SMI_t} - \overline{\mathrm{SMI}}}{\delta_{\mathrm{SMI}}}$ $\mathrm{SMI_t}$= Dekad average of soil moisture $\overline{\mathrm{SMI}}$= Long term average soil moisture δ_{SMI}= Standard Deviation	Precipitation, runoff, and evapotranspiration	Considers rainfall infiltration, evapotranspiration, and runoff for soil moisture dynamics; identifies soil moisture anomalies and potential drought conditions in agricultural regions; developed and extensively utilized to monitor the impact of drought on global agriculture and crop yields.	Relies on a water balance model, adding complexity to calculations and interpretation; estimates of potential evapotranspiration can vary greatly between regions.	[9,18,46]
SMAI (Soil Moisture Availability Index)	if $\mathrm{SW_j} \leq \mathrm{MSW_j}$ $\mathrm{SA_j} = \left(\frac{\mathrm{SW_j} - \mathrm{MSW_j}}{\mathrm{MSW_j} - \mathrm{SW_{(min)j}}}\right) \times 100$, if $\mathrm{SW_j} > \mathrm{MSW_j}$ $\mathrm{SA_j} = \left(\frac{\mathrm{SW_j} - \mathrm{MSW_j}}{\mathrm{SW_{(max)j}} - \mathrm{MSW_j}}\right) \times 100$	Actual monthly soil moisture data (SW_j) at month j; long-term maximum $(SW_{(max)j})$; minimum $(SW_{(min)j})$, and median (MSW_j) soil moisture values at month j	Considers current and previous month's soil moisture conditions; ranges from −100 to 100 for a broad interpretation of soil moisture conditions; iterative computation within −4 to 4 enhances accuracy and sensitivity in detecting soil drought events and variations.	Simplified view of soil moisture conditions, potentially missing nuances of complex soil–water interactions; may struggle to capture localized variations due to limited spatial resolution, especially in regions with heterogeneous soil and vegetation characteristics.	[49]
SVI	$\mathrm{SVI} = \frac{(\mathrm{Z_{ijk}} - \mathrm{Z_{ijMin}})}{\mathrm{Z_{ijMax}} - \mathrm{Z_{ijMin}}}$ $\mathrm{Z_{ijk}} = \frac{\mathrm{NDVI_{ijk}} - \overline{\mathrm{NDVI_{ij}}}}{\sigma_{\mathrm{ij}}}$ σ_{ij} = standard deviation of pixel i during week j over n years	Z-value for a specific pixel during a particular week for a given year (Z_{ijk}); maximum z-value for that pixel during the week (Z_{ijMax}); minimum z-value for that pixel during the week (Z_{ijMin})	Monitors drought conditions by assessing vegetation health and productivity; quantifies deviations in vegetation conditions from historical norms to indicate drought severity; shows high conformity in assessing rainfall impact on vegetation health through statistical analysis.	Depends on accurate NDVI data, which can be affected by cloud cover and sensor limitations; sensitive to changes in vegetation types and land cover; difficulty distinguishing between drought stress and other factors affecting vegetation health.	[50,51]

4. Satellite-Based Agricultural Drought Monitoring Methods

Most of conventional agricultural drought indices are based on in situ, satellite-based indices developed to address the spatial context limitation of conventional drought indices. Additionally, a single metric cannot adequately capture drought's multi-impact character in all its complexity. Agricultural drought is intimately linked to soil moisture and crop water deficit. In this regard, remotely sensed indices are based on unique spectral signatures of soil surface and canopy characters, particularly in red, near-infrared, shortwave-infrared, and thermal–spectral bands. In general, the use of remote sensing in agricultural drought monitoring relies on the fact that drought might affect the bio-physical and chemical properties of soil and vegetation, such as soil moisture, organic matter, vegetation biomass, chlorophyll, and canopy and soil temperature [52]. Thus, it may change their spectral and thermal responses, which can be used as indicators of drought occurrence. Therefore, the remotely sensed water elevation data of soil and plants is an efficient tool for the intensive monitoring of land and crop water deficits [53], and many remote sensing models and indices have been developed for investigating agricultural drought [54].

4.1. Normalized Difference Vegetation Index (NDVI)

The NDVI is a widely utilized remote sensing metric for assessing vegetation density and health [55]. The NDVI is an indicator of vegetation health, distinguishing between healthy and diseased or sparse vegetation, which may result from drought or insect infestation. This index is calculated by measuring the visible red spectral reflectance (R) and the near-infrared spectral reflectance (NIR) using the Advanced Very High-Resolution Radiometer (AVHRR). Chlorophyll, the green pigment essential for photosynthesis in plants, absorbs light and reflects less red light when vegetation is healthy. Consequently, higher NDVI values correspond to lower R values. Conversely, unhealthy vegetation exhibits higher R values, leading to a decrease in NDVI. West [56] conducted a comprehensive assessment of the impacts of drought on vegetation utilizing NDVI and other remote sensing techniques. The study encompassed various global regions, with a particular focus on North America, Europe, Asia, and Africa. The findings revealed that the NDVI demonstrated greater sensitivity to atypical dry conditions compared to traditional vegetation indices. Specifically, the NDVI values exhibited significant declines during drought periods, which was correlated with reduced soil moisture levels and indicated plant stress. Furthermore, the research underscored that although NDVI serves as a valuable tool for evaluating vegetation health, its effectiveness can be affected by factors such as spatial resolution and vegetation density. Consequently, the study advocated for the integration of additional datasets to enhance the accuracy of drought monitoring. Gandhi [57] conducted an analysis of vegetation cover and land use changes in the Vellore district of Tamil Nadu utilizing the NDVI. The findings demonstrate that the NDVI method is efficacious in identifying vegetation, revealing a vegetation percentage of 46.43% in 2006 at an NDVI threshold of 0.2. Furthermore, the analysis indicated that the NDVI values ranged from 0.1 to 0.5, with the lower values corresponding to sparsely vegetated soils, which suggests a high level of soil reflectance.

4.2. Vegetation Condition Index (VCI)

The VCI is a remote sensing tool developed to assess the impact of weather on vegetation, particularly in non-homogeneous areas, where traditional vegetation indices like the NDVI are less effective due to variations in geographic resources such as climate, soil, and topography. The VCI was introduced by Kogan [58] and is designed to normalize NDVI values relative to their historical maximum and minimum, thus filtering out the influence of geographical differences and focusing solely on weather-related vegetation changes. The VCI demonstrates a strong correlation with precipitation dynamics, outperforming the NDVI in accurately reflecting vegetation conditions influenced by weather. Sultana [59] conducted an assessment of agricultural drought severity in the northwest region of Bangladesh from 1990 to 2018, utilizing various indices including the VCI. The study revealed that in 1990, there was no extreme drought, with moderate drought affecting 1.06% of the area. However, by 2014, the VCI indicated a decline in vegetation conditions, with only 90.90% of the area remaining healthy. By 2018, the area experiencing severe drought had increased dramatically to 17.65%, while the moderate drought area expanded to 77.64%. This trend signifies a significant deterioration in vegetation health and an increase in drought prevalence. The VCI analysis underscored the overall decline in vegetation conditions, with only 2.10% of the area classified as healthy by 2018. Dutta [60] conducted an assessment of agricultural drought in Rajasthan, India, employing the VCI and the Standardized Precipitation Index (SPI). The study aimed to compare VCI estimates with meteorological drought indicators and yield-based indices to monitor the onset, duration, and spatial extent of drought. The results indicated that VCI values below 35% across most areas of Rajasthan in 2002 were indicative of drought-related stress. Additionally, the study identified a strong positive correlation ($r > 0.75$) between the VCI and the yield of major rain-fed crops, thereby demonstrating the effectiveness of the VCI in evaluating agricultural drought and its impact on crop yield.

4.3. Vegetation Health Index (VHI)

The VHI is a composite index that integrates the VCI and the Temperature Condition Index (TCI) to evaluate the health condition of vegetation using NDVI and temperature data. The calculation of the VHI involves equal weighting of the VCI and the TCI, with a coefficient (α) that measures the influence of individual components on the overall vegetation health [61,62]. The VHI index is instrumental in identifying extreme drought events, monitoring agricultural drought conditions, and providing insights into vegetation health based on historical data. Javed [63] conducted an investigation into drought characteristics across four sub-regions of China using multiple drought indices, including the Standardized Precipitation Index (SPI), the Standardized Soil Moisture Index (SSI), the Multivariate Standardized Drought Index (MSDI), and the VHI anomaly. The findings revealed that the VHI showed a significant increasing trend in all the sub-regions of China, except for North China, indicating an overall improvement in vegetation health over the study period, with the exception of the northern part of the country. Furthermore, the temporal patterns of the VHI anomaly were similar to those of the relative soil moisture, but slightly different from the precipitation patterns. Additionally, the correlations between the monthly VHI and the three drought indices (SPI, SSI, and MSDI) were stronger at the 3-month and 6-month timescales compared to the 1-month timescale, indicating that longer timescales are more suitable for assessing the impacts of agricultural drought on vegetation health.

4.4. Drought Severity Index (DSI)

The DSI is a global index developed by Mu [64]. It leverages operational satellite remote sensing to enhance the monitoring and mitigation of droughts in near-real time. The DSI employs satellite-derived data on evapotranspiration (ET), potential evapotranspiration (PET), and the NDVI to detect and monitor drought conditions worldwide. It is calculated at various temporal scales—over 8 days, monthly, and annually—with a high spatial resolution of 1 km, making it suitable for a broad range of water resource applications. Elhag [65] sought to evaluate and analyze the characteristics of drought in Sudan, with a particular focus on its impact on sorghum yield. The study utilized meteorological drought indices, such as the Standardized Precipitation Index (SPI) and the DSI, to monitor drought conditions and assess their effects on agriculture over the period from 2001 to 2011. The results indicate that the DSI demonstrated a significant positive correlation with agricultural lands, underscoring its effectiveness in identifying wet and dry conditions. Conversely, in mountainous areas, the DSI exhibited a negative correlation, suggesting that these regions may be influenced by distinct climate–land interactions. Additionally, the DSI showed significant positive correlations with sorghum yield, particularly during the months of August and September. Zhang [66] aimed to evaluate the DSI for monitoring drought conditions and its effectiveness in characterizing agricultural drought severity across various provinces. The study focused on North China, particularly on regions impacted by agricultural practices. The findings revealed that the DSI effectively quantifies moisture conditions at the provincial level, showing strong correlations with precipitation, especially during the winter wheat growing season (March–June). The most robust relationships were observed in April, during the jointing and booting stages of crop growth. Furthermore, the DSI demonstrated a significant capability for characterizing agricultural drought severity, with notable correlations with crop yield loss ratios.

4.5. Vegetation Drought Response Index (VDRI)

The VegDRI is a tool designed to monitor the effect of drought stress on vegetation [67]. It integrates climate-based drought indicators, satellite-derived vegetation indices, and biophysical data to generate detailed 1 km resolution maps of drought conditions. The methodology involves processing historical climate data, satellite imagery, and biophysical information to construct a database, which is then utilized to develop models predicting the effect of drought stress on vegetation. The VegDRI employs a rule-based, piecewise linear regression model derived using the Cubist data mining algorithm, rather than a single equation. The Cubist algorithm produces a set of rules and corresponding linear regression equations applied to the input data to compute the VegDRI value for each pixel in the study area. These rules are conditional statements that consider multiple variables, including the Standardized Precipitation Index (SPI), land cover type, soil available water capacity, irrigation, ecoregions, and satellite-derived vegetation metrics such as Percent Average Seasonal Greenness (PASG) and Start of Season Anomaly (SOSA). Tadesse [68] aimed to introduce the VegDRI-Canada methodology and present initial results for monitoring agricultural drought conditions in Canada, with a particular focus on the prairie region. The VegDRI-Canada model offers a more integrated approach by combining satellite observations, climate data, and biophysical information, thereby enhancing the accuracy and timeliness of drought assessments compared to traditional methods. The model effectively captured the spatial variability of drought conditions across the Canadian Prairies, showing strong correlations with historical canola yield data. The analysis revealed that the model's predictions aligned closely with observed drought impacts, especially during severe drought years, indicating its reliability for agricultural monitoring. Additionally, the study highlighted an increasing trend in historical crop yields due to advancements in agricultural technology and practices, which was accounted for in the model's assessments.

4.6. Normalized Difference Water Index (NDWI)

The NDWI, introduced by Gao [69], serves as an important tool for remotely sensing vegetation liquid water content from space. Unlike the NDVI, which utilizes red and near-infrared (IR) channels to measure vegetation density, the NDWI focuses on two specific near-IR channels, at wavelengths of 0.86 μm and 1.24 μm, to determine water content. This index is particularly responsive to variations in the liquid water content of vegetation canopies. Additionally, the NDWI is less influenced by atmospheric aerosol scattering effects compared to the NDVI and demonstrates reduced sensitivity to the reflectance of background soil, although it does not entirely eliminate these impacts. Consequently, the NDWI is considered a complementary index to the NDVI, as it provides distinct and independent information regarding vegetation canopies. Al-Quraishi [70] conducted a comprehensive analysis of drought trends in Sulaimaniyah Province, Iraq, employing remote sensing data and meteorological indices, namely the NDVI, NDWI, and SPI. The study identified the most severe drought years as 2000, 2008, 2009, and 2013, characterized by significant reductions in vegetation cover. The findings demonstrated a strong correlation between the NDWI index and drought conditions, evidenced by a decline in water availability during these critical drought periods. Notably, the NDWI values revealed a substantial reduction in water bodies, particularly in Lake Darbandikhan, where a marked decrease in surface area was observed during the severe drought years.

4.7. Temperature Vegetation Dryness Index (TVDI)

The TVDI is a simplified index developed to assess surface moisture status using remote sensing data [71]. It is based on the empirical relationship between surface temperature (Ts) and the NDVI, which is derived from satellite imagery. The TVDI is computationally straightforward and only requires satellite-derived information, making it suitable for operational applications in hydrological models. Yuan [72] conducted drought monitoring based on the TVDI and investigated the impact of anthropogenic pressure in the Poyang Lake Basin (PYLB), in China. The study revealed significant spatial variation in the TVDI across the basin, with a positive trend indicating increasing drought conditions in certain areas. Specifically, the Mann–Kendall test showed that regions with higher TVDI values experienced more severe drought, particularly in the southern part of the basin, where the vegetation cover was less dense. Conversely, areas with abundant water resources and dense vegetation cover exhibited lower TVDI values. Shi [73] evaluated the performance of the TVDI for monitoring drought across various land cover types in Eurasia. The study results demonstrated that the TVDI effectively captured the spatial and temporal dynamics of drought across Eurasia, with significant negative correlations observed between the TVDI and both the Standardized Precipitation Evapotranspiration Index (SPEI) and the Essential Climate Variable Soil Moisture (ECV-SM). Specifically, approximately 77.43%, 72.01%, and 75.95% of the total study area exhibited statistically significant negative correlations with SPEI-01, SPEI-03, and SPEI-06, respectively, indicating that as the drought intensity increased (higher TVDI values), moisture levels decreased. Furthermore, the analysis highlighted that the TVDI was particularly adept at identifying drought conditions in regions with moderate-to-high vegetation cover, while its performance diminished in wetter areas. Du [74] aimed to enhance the TVDI for more effective drought monitoring in semi-arid regions of China. The study found that the improved Temperature Vegetation Dryness Index (TVDIm) exhibited negative correlation coefficients with precipitation, the Standardized Precipitation Index (SPI), and the Standardized Precipitation Evapotranspiration Index (SPEI) of −0.67, −0.71, and −0.70, respectively, all of which were statistically significant (p-value < 0.05). In contrast, the original TVDI showed weaker correlations of −0.55, −0.57, and −0.68, with only the correlation between the TVDI and the SPEI being significant. Modifications to the model, including the removal of outliers and the adjustment of dry/wet edge simulations, resulted in coefficients of determination ranging from 0.86 to 0.96. This indicates a better fit and suggests that the TVDIm can more accurately reflect rainfall deficits and meteorological drought conditions in the study area.

4.8. Crop Water Stress Index (CWSI)

The CWSI was introduced by Idso [75] and further developed by [76]. This tool measures crop water stress by assessing canopy temperature through infrared thermometry. The underlying principle is that plant temperature indicates water availability, with higher temperatures signaling greater water stress. The CWSI is calculated using energy balance equations that consider the canopy–air temperature difference, air vapor pressure deficit, and net radiation. The index ranges from 0 to 1, where 0 indicates no water stress (the crop is transpiring at its potential rate) and 1 indicates maximum stress (no available water for transpiration). The CWSI effectively tracks changes in extractable soil water, validating its role as a stress indicator. This index is particularly valuable for irrigation scheduling, as it allows for timely water application based on the crop's actual water needs. As a result, irrigation practices can be optimized, water conserved, and crop health maintained. Ma [77] aimed to evaluate the effectiveness of the CWSI for drought monitoring in Inner Mongolia. The study revealed a significant negative correlation between CWSI and precipitation, with 96.58% of the area showing this relationship, indicating that CWSI decreases as precipitation increases. Additionally, a positive correlation between CWSI and temperature was observed, affecting 82.04% of the area, suggesting that higher temperatures contribute to increased water stress. Jamshidi [78] conducted a study in a semi-arid region of southern Iran to evaluate the effectiveness of in situ and remotely sensed methods for assessing the

CWSI in citrus orchards, with a specific focus on orange trees. The study developed two approaches to estimating CWSI from remote sensing data. The first approach utilized Landsat thermal data with hot–cold patches, while the second combined Landsat and Sentinel-2 data with an iterative method to calculate aerodynamic resistance. The second approach proved to be more accurate and effective in capturing the variability of water stress across the orchard. The proposed method effectively reduced errors in CWSI calculations by accurately capturing canopy temperature variations.

4.9. Deviation of the Normalized Difference Vegetation Index (Dev_NDVI)

The Dev_NDVI, introduced by Berhan [79], is a measure used to study vegetation and drought conditions. It reflects the difference between current NDVI values and the long-term average NDVI values for a specific area and time. This deviation helps identify whether vegetation conditions are below, at, or above the normal range, which is crucial for monitoring drought. The key difference between the NDVI and the Dev_NDVI is that while the NDVI provides a snapshot of the vegetation status at a given time, the Dev_NDVI offers a comparative analysis by considering historical averages. This comparison is essential for understanding whether current vegetation conditions are within the expected range or whether they deviate significantly, indicating a drought or other anomalies affecting plant health and agricultural productivity. The Dev_NDVI is particularly useful for tracking changes over time and for early warning systems, enabling decision-makers to take timely actions to mitigate the impacts of drought.

4.10. Enhanced Vegetation Index (EVI)

The EVI is a satellite-derived metric designed to optimize the vegetation signal, particularly in high biomass regions, and to address some of the limitations of the traditional NDVI. The EVI exhibits improved sensitivity to canopy variations in areas of high biomass, where the NDVI is often saturated. It incorporates a blue band to correct for aerosol influences, reducing susceptibility to atmospheric effects. Additionally, EVI includes a term to adjust for canopy background signals, enhancing vegetation monitoring in areas with significant bare soil or non-vegetated surfaces [80]. Shahzaman [81] evaluated the effectiveness of the Evaporative Stress Index (ESI), VHI, Standardized Anomaly Index (SAI), and EVI in assessing agricultural drought using satellite remote sensing data from 2002 to 2019. The study focused on four major South Asian countries: Afghanistan, Pakistan, India, and Bangladesh. The findings revealed that while the EVI is closely associated with the leaf area index, canopy cover, biomass, and fraction of photosynthetically active radiation, it has limitations in effectively capturing the impact of drought on vegetation. The EVI did not show a significant correlation with the Yield Anomaly Index (YAI) across the study region, suggesting that it may not be as effective as other indices, such as the ESI, in detecting agricultural drought conditions linked to crop production anomalies. Additionally, the EVI was noted to have a saturation issue in areas with high vegetation diversity, further limiting its effectiveness in certain contexts. Zhao [82] conducted an evaluation of the TVDI, which integrates NDVI, LST, and EVI data, to assess its efficacy in monitoring soil moisture across extensive temporal and spatial scales in China. The findings demonstrated that the EVI-based TVDI (TVDIEVI) was particularly effective for monitoring soil moisture at a depth of 0–10 cm in northwestern China during the cold season. Conversely, the NDVI-based TVDI (TVDINDVI) generally exhibited superior performance in other regions and during the warm season, spanning April to September. Notably, the TVDIEVI outperformed the TVDINDVI in accurately reflecting soil moisture conditions in northwestern China during the cold season. The study also revealed that the performances of the TVDINDVI and TVDIEVI varied based on factors such as the goodness of fit for wet/dry edge equations, the inherent variability of the NDVI/EVI/LST, soil depth, season, and geographic region.

4.11. Normalized Difference Temperature Index (NDTI)

The NDTI is a remote sensing metric designed to evaluate moisture availability by eliminating seasonal variations from daytime thermal data [83]. By integrating thermal data with meteorological parameters, the NDTI calculates the ratio of actual to potential evapotranspiration (ET), thereby offering valuable insights into regional water balance and drought conditions. This index is particularly sensitive to fluctuations in resource availability, making it effective for mapping moisture conditions across various landscapes. The NDTI categorizes drought severity by correlating moisture availability with surface temperature data, where higher NDTI values indicate wetter conditions with greater moisture availability, and lower values denote drier conditions, indicating potential drought stress. Peng [84] focused on evaluating the feasibility of estimating the NDTI from top-of-atmosphere (TOA) radiances and analyzed the sensitivity of these estimates to surface and atmospheric variations in the Poyang Lake basin, China. The findings indicated that changes in NDTI are primarily influenced by variations in surface emissivity rather than its absolute values. Additionally, the study identified that the largest uncertainties in NDTI estimates were due to spatial variations in total column water vapor profiles, especially under high-humidity conditions. This implies that the estimation method may be less reliable in environments where the water vapor content exceeds 3 g.cm^{-2}.

Table 2 provides an overview of the most frequently used satellite-based indices for monitoring agricultural drought.

Table 2. Comprehensive summary of most commonly used satellite-based agricultural drought monitoring indices: descriptions, computational formulas, input data requirements, advantages, limitations, and source references.

Index	Formulae	Input	Strengths	Limitations	Ref.
NDVI	$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}}$	Near-infrared reflectance (NIR); red reflectance value (RED)	Simple algorithms; extensive land area coverage by AVHRR, despite its 1 km resolution compared to meteorological stations; current NDVI algorithms reduce noise from atmospheric conditions and sun-surface geometry; effectively identifies vegetated areas from other surfaces; quantitatively assesses dryness, unlike interpolation or extrapolation methods.	Non-equal reflection from soil moisture in two bands, especially in rainy conditions, may affect NDVI accuracy; NDVI tends to saturate in areas with dense vegetation or multilayered canopies; clouds, aerosols, haze, and other atmospheric interferences can contaminate pixels, affecting NDVI accuracy; assuming soil moisture is the only source of vegetative stress can limit NDVI effectiveness.	[9,85]
VCI	$\mathrm{VCI} = (\mathrm{NDVI}_j - \mathrm{NDVI}_{min}) / (\mathrm{NDVI}_{max} - \mathrm{NDVI}_{min}) \times 100$	Normalized Difference Vegetation Index (NDVI) values for each pixel; maximum and minimum NDVI values calculated for each month	High spatial resolution for detailed assessment; strong positive correlation with crop yield.	Reliance on satellite data; potential inaccuracies due to cloud cover and atmospheric conditions; challenges with diverse land cover types.	[60]
VHI	$\mathrm{VHI} = \alpha \times \mathrm{VCI} + (1 - \alpha) \times \mathrm{TCI}$ α = relative contributions of moisture and temperature to vegetation health TCI = Temperature Condition Index and calculated from brightness temperature data	Vegetation Condition Index; Temperature Condition Index	Combination of VCI and TCI with equal weight.	Assumption of equal contributions of moisture and temperature; dependence on historical data; limited consideration of changing environmental conditions.	[61,86]
DSI	$\mathrm{DSI} = \frac{Z - \overline{Z}}{\sigma_Z}$ Z = sum of the ET, PET and NDVI values $\overline{Z}$ = mean of Z σ_Z = standard deviation of Z	ET; PET; NDVI	Comprehensive composite index combining vegetation and evapotranspiration variables; provides consistent global coverage with a 1 km spatial resolution, enabling comprehensive drought monitoring; uses ET and PET data, which are less prone to uncertainties compared to precipitation data.	Relies on satellite data, which may have limitations in accuracy and coverage; the DSI's short historical record (from 2000 to present) may not suffice for accurate drought detection in regions with high interannual climate variability.	[64]

Table 2. *Cont.*

Index	Formulae	Input	Strengths	Limitations	Ref.
VDRI	if : Land cover in {crop land} : $SPI \leq 1.5$ $AWC \leq 5.46$ $SOSA < 2$ $IrrigAg < 1$ Then: $VegDRI = -1.5 + 0.6PASG + 1.48SPI - 0.14AWC + 0.25IrrigAG - 0.5DEM + 0.14SOSA$	NDVI; Percent Average Seasonal Greenness (PASG); Standardized Precipitation Index (SPI); Palmer Drought Severity Index (PDSI); land use and land cover data, soil characteristics (AWC); start of season anomaly (SOSA); Irrigation Index (IrrigAg); Digital Elevation Model (DEM)	Combines climate-based drought indicators, satellite-derived vegetation indices, and biophysical variables for a comprehensive view of drought conditions; provides detailed spatial information at a 1 km resolution, aiding local-scale decision-making; enables near-real-time map production, facilitating timely responses to emerging drought conditions by stakeholders.	Difficulty differentiating drought-impacted areas from other vegetation stress causes like flooding, pests, and diseases using satellite data alone; challenges in establishing thresholds to discriminate between drought and non-drought conditions, and varying levels of drought severity; reliance on various data inputs affects the accuracy and reliability of VegDRI, depending on data availability and quality.	[67,68]
NDWI	$NDWI = \frac{[p(0.86\mu m) - p(1.24\mu m)]}{\{p(0.86\mu m) + p(1.24\mu m)\}}$ $p(0.86\mu m)$ and $p(1.24\mu m)$ = reflectance at 0.86 μm and 1.24 μm	Reflectance values at specific wavelengths, specifically at 0.86 μm and 1.24 μm	NDWI is less sensitive to atmospheric scattering effects than the NDVI; near-infrared bands are used by NDWI, making it effective for early detection of agricultural drought; high sensitivity to liquid water content in vegetation canopies is exhibited by NDWI.	Background soil reflectance effects can influence NDWI values, especially with partial vegetation coverage; negative soil contributions and positive green vegetation contributions complicate NDWI interpretation in varied areas; complex relationship between NDWI and vegetation conditions may require additional information for accurate analysis.	[69]
TVDI	$TVDI = \frac{LST - LST_{min}}{LST_{max} - LST_{min}}$ LST = land surface temperature LST_{min} = lower horizontal line of the triangle/trapezoid defining the wet edge LST_{max} = maximum surface temperature defining the dry edge	LST, NDVI	TVDI is conceptually and computationally simple; TVDI accurately describes drought scenarios by considering atmospheric precipitation, surface temperature, vegetation coverage, and soil moisture; ability to capture drought events over large areas.	TVDI range may not capture extreme drought conditions; TVDI may be less accurate in areas with low vegetation coverage or limited NDVI.	[71,73]
CWSI	$CWSI = 1 - \frac{E}{E_P}$ E = Actual evapotranspiration E_P= Potential evapotranspiration	Net radiation (R_n); canopy temperature (T_c); air temperature (T_a); vapor pressure deficit (VPD); and the ratio of aerodynamic resistance (r_a) to canopy resistance (r_c).	Detects stress before visual observation; quantifies water stress accurately by considering canopy temperature and meteorological factors; reliable tool for irrigation scheduling; widely applicable across various crops.	Difficulties in measuring crop surface temperature, especially during early growth stages with partial vegetation cover; applicable only in cases of full vegetation coverage.	[76,78]

Table 2. *Cont.*

Index	Formulae	Input	Strengths	Limitations	Ref.
Dev_NDVI	$\text{Dev\_NDVI} = \frac{(\text{NDVI}_{\text{current}} - \text{NDVI}_{\text{mean}})}{\text{NDVI}_{\text{mean}}}$	Current NDVI values; historical mean NDVI values	Indicates below-normal vegetation conditions and detects drought situations with negative values; provides a quantitative measure by comparing current NDVI values with long-term averages.	The Dev_NDVI index may not account for other factors influencing vegetation health beyond NDVI values; it relies on satellite data accuracy and may be affected by cloud cover or sensor limitations.	[79]
EVI	$\text{EVI} = \text{G} \times \frac{\rho_{\text{NIR}} - \rho_{\text{RED}}}{\rho_{\text{NIR}} + (\text{C}_1 \times \rho_{\text{RED}} - \text{C}_2 \times \rho_{\text{BLUE}}) + \text{L}}$ G = Gain Factor C_1, C_2= coefficient for dust particles in the atmosphere L = Canopy background adjustment	Percentage of reflection in the near-infrared spectrum (ρ_{NIR}); percentage reflection in the visible red spectrum (ρ_{RED}); percentage reflection in the visible blue spectrum (ρ_{BLUE})	EVI is more sensitive in areas with dense vegetation; addresses light reflection issues for accurate spatial leaf surface representation.	Involves multiple spectral bands, making calculations complex; susceptible to atmospheric conditions impacting accuracy.	[80]
NDTI	$\text{NDTI} = \frac{\text{T}_\infty - \text{T}_\text{s}}{\text{T}_\infty - \text{T}_0}$	Surface temperature (T_s); modelled surface temperature with infinite surface resistance ($\text{ET} = 0$) (T_∞); modelled surface temperature with zero surface resistance ($\text{ET} = \text{ET}_\text{P}$) ($T_0$).	Capable of precisely capturing the spatial and temporal changes in soil moisture.	The NDTI calculation requires additional input variables (e.g., solar radiation, wind speed, and leaf area index), which are difficult to obtain.	[83,87]

5. Identification of Severity of Drought

Drought can be classified into parameters such as normal, mild, moderate, severe, and extreme. Table 3 illustrates the thresholds used to identify the classes of drought and a comparison of drought severity indices.

Table 3. Drought monitoring indices and severity classification levels.

Index	Values	Classification	Ref.
SWDI	≥ 0 0 to −2 −2 to −5 −5 to −10 ≤ -10	No drought Mild drought Moderate drought Severe drought Extreme drought	[26]
SMDI (Soil Moisture Deficit Index)	+2 to +4 0 to +2 −2 to 0 −4 to −2	Wet conditions Normal conditions Mild drought Severe drought	[27]
ETDI	+2 to +4 0 to +2 −2 to 0 −4 to −2	Wet conditions Normal conditions Mild drought Severe drought	[27]
SMADI	0 to 0.99 1 to 1.99 2 to 2.99 3 to 3.99 ≥ 4	Normal conditions Mild drought Moderate drought Severe drought Extreme drought	[31]
RDI	> 2 1.5 to 1.99 1 to 1.49 −0.49 to 0.99 −0.99 to −0.5 −1.49 to −1 −1.99 to −1.5 < -2	Extremely humid Severely humid Moderately humid Normal conditions Mild drought Moderate drought Severe drought Extreme drought	[16]
BMDI	≥ 4 3 to 3.99 2 to 2.99 1 to 1.99 0.99 to −0.99 −1 to −1.99 −2 to −2.99 −3 to −3.99 ≤ -4	Extremely wet Very wet Moderately wet Slightly wet Near normal Mild drought Moderate drought Severe drought Extreme drought	[32]
CMI	>3 2 to 3 1 to 2 0 to 1 −1 to 0 −2 to −1 < -3	Excessively moist Wet Abnormally moist Slightly dry Abnormally dry Excessively dry Severely dry	[88]
DTx	0.25 to 0.75 0.75 to 0.90 0.90 to 0.95 0.95 to 0.99 >0.99	Normal conditions Mild drought Moderate drought Severe drought Extreme drought	[41]
LWCI	0.9 to 1 0.8 to 0.9 Below 0.8	Non-stressed (wet conditions) Moderately Stressed Severely stressed (dry conditions)	[42]
MAI	All months with MAI in the range of 0 to 0.33 One or two months with MAI of 0.34 or above Three or four months with MAI of 0.34 or above Five or more consecutive months with MAI 0.34 or above	Very arid Arid Semi-dry Wet–dry	[44]

Table 3. *Cont.*

Index	Values	Classification	Ref.
SMAI	≤−2 −2 to −1.5 −1.5 to −1 −1 to 1 1 to 1.5 1.5 to 2 ≥2	Extreme drought Severe drought Mild drought Near normal conditions Unusually moist Very moist Extremely moist	[46]
SVI	0.95 to 1 0.75 to 0.95 0.25 to 0.75 0.05 to 0.25 0.00 to 0.05	Very good vegetation density (minimum drought) Good vegetation density Average vegetation density Poor vegetation density Very poor vegetation density (worst drought)	[50]
NDVI	>0.6 0.4 to 0.6 0.2 to 0.4 <0.2	Normal conditions Moderate drought Severe drought Extreme drought	[56]
VCI & VHI	40 to 100 30 to 40 20 to 30 10 to 20 0 to 10	No drought Mild drought Moderate drought Severe drought Extreme drought	[25,89]
DSI	0.29 to −0.29 −0.3 to −0.59 −0.6 to −0.89 −0.9 to −1.19 −1.2 to −1.49 <1.5	Normal conditions Incipient drought Mild drought Moderate drought Severe drought Extreme drought	[64]
TVDI	0 to 0.67 0.67 to 0.74 0.74 to 0.80 0.80 to 0.86 0.86 to 1.00	Normal conditions Slight drought Moderate drought Severe drought Excessive drought	[73]
CWSI	≈0 0 to 0.3 0.3 to 0.6 0.6 to 0.8 0.8 to 1	No water stress Mild water stress Moderate water stress Severe water stress Extreme water stress	[76]
Dev_NDVI	≤−0.2 −0.2 to −0.05 −0.05 to 0.1 > 0.1	Severe drought Moderate drought Near-normal conditions Above optimum (extremely wet)	[79]

6. Summary

Climate variability significantly impacts regions worldwide, with drought being a major consequence. Drought affects human populations and economic stability, and increasing global temperatures and extreme weather events are escalating the frequency and intensity of droughts. Drought is classified into four types, meteorological, agricultural, hydrological, and socioeconomic, each with unique consequences such as depleted soil moisture, reduced crop yields, diminished water levels, and socioeconomic impacts. The agricultural sector is particularly vulnerable to drought, as it is a primary cause of crop failure and poses a significant threat to global food security.

Effective early warning systems for agricultural drought rely on drought indices. Various indices are used for drought monitoring, each reflecting different aspects of this complex phenomenon. This paper provides a brief review of the definitions of agricultural drought and examines a variety of agricultural indices, detailing each one for monitoring purposes.

Conventional and satellite-based drought indices differ significantly in their data sources, methodologies, and coverage. Conventional indices rely on ground-based observational data, such as precipitation, temperature, and soil moisture. This reliance often results in limited spatial coverage and coarser temporal resolution, typically offering data on a monthly or seasonal basis. Conversely, satellite-based drought indices utilize remote sensing data to monitor environmental conditions, providing broad, often global coverage with higher spatial resolution, thereby enabling consistent drought monitoring across vast and remote areas. Although conventional indices are valuable for long-term historical analysis, their focus on a limited number of variables, like rainfall or temperature, may not adequately capture the complex nature of drought impacts. Additionally, these indices often require specialized datasets and technical expertise for computation. Satellite-based indices, while offering a more comprehensive view by integrating multiple variables such as vegetation health, soil moisture, and land surface temperature, generally have shorter historical records, limiting their utility in long-term drought analysis.

Despite challenges like data inconsistencies and varying spectral and spatial resolutions, integrating machine learning techniques into agricultural drought monitoring holds potential for enhancing both accuracy and effectiveness. Moreover, combining satellite-based indices with conventional methods could lead to a more comprehensive approach to drought monitoring in agriculture.

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