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Review

Remote sensing of agricultural drought monitoring: A state of art review

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Abstract: Agricultural drought is a natural hazard that can be characterized by shortage of water supply. In the scope of this paper, we synthesized the importance of agricultural drought and methods commonly employed to monitor agricultural drought conditions. These include: (i) *in-situ* based methods, (ii) optical remote sensing methods, (iii) thermal remote sensing methods, (iv) microwave remote sensing methods, (v) combined remote sensing methods, and (vi) synergy between *in-situ* and remote sensing based methods. The in-situ indices can provide accurate results at the point of measurements; however, unable to provide spatial dynamics over large area. This can potentially be addressed by using remote sensing based methods because remote sensing platforms have the ability to view large area at a near continuous fashion. The remote sensing derived agricultural drought related indicators primarily depend on the characteristics of reflected/emitted energy from the earth surface, thus the results can be relatively less accurate in comparison to the in-situ derived outcomes. Despite a significant amount of research and development has been accomplished in particular to the area of remote sensing of agricultural drought, still there are several challenges. Those include: monitoring relatively small area, filling gaps in the data, developing consistent historical dataset, developing remote sensing-based agricultural drought forecasting system, integrating the recently launched and upcoming remote sensors, and developing standard validation schema, among others.

Keywords: optical remote sensing; thermal remote sensing; microwave remote sensing; synergy between in-situ and remote sensing

1. Introduction

Drought is a natural hazard that can be defined as the deficiency of water over an extended period of time causing problems to some activities, groups, and other environmental sectors [1]. It can be broadly classified into four common types, such as [2,3]:

- Meteorological drought: the deficiency of precipitation comparing to average conditions over specific location and period of time (e.g., weeks, months, or years).
- Agricultural drought: the deficiency of soil moisture below the optimal level required for the proper growth of plants during different growing stages, resulting in growth stress and yield reduction.
- Hydrological drought: the shortage of natural and/or artificial surface or ground water resources.
- Socio-economic drought: the affected human activities by one or more of the previous three types of drought.

These types of drought are linked to each other; however, our focus would be concentrated on agricultural drought as it is considered as one of the most important issues in most of the countries in terms of economic, food security, and social stability. Generally, agricultural drought occurs as a result of two factors: (i) short-term precipitation shortage that reduces soil moisture levels, and/or (ii) temperature increasing that causes increase in evapotranspiration levels above water supply. The impacts of drought on agricultural fields depend on timing, intensity, spatial extent and duration of drought [1]. For example, if drought occurs occasionally over long time period, plants may be able to reach maturity before the drought causes severe impacts. On the other hand, a short-lived drought coinciding with the fully grown stage of the plants (when they are ready to flowering or graining), it may have severe impact as the plants usually require the highest amount of water at this time. Actually, a comprehensive understanding of the causes and consequences of the historical and occasional agricultural droughts are very important in food production, planning, and management as its impacts were found to be evident at all plants growth stages [4], however some stages may be adversely impacted [5].

To date, various methods have been developed and used for agricultural drought monitoring, these methods are usually known as agricultural drought indices [6]. In the scope of this article, we divided the existing methods into three categories: *in-situ*, remote sensing, and synergic based indices. Generally, they are represented in mathematical equations that integrate different variables to study drought, either quantitatively or qualitatively, therefore they may be more effective than the direct use of raw data [7]. Recently, many countries have established different frameworks for monitoring and mitigating agricultural drought impacts on their economic, social, and environmental sectors [8], however many of these studies have relied on a single data source [9]. Therefore, their spatial or temporal resolutions are limited. This encourages developing and applying meaningful methods that integrate data from different sources in order to provide high spatial and temporal data quality for agricultural drought research [10]. Currently, remote sensing satellites provide advanced products for agricultural drought monitoring that include vegetation indices, precipitation information, evapotranspiration, and soil moisture measurements [11]. Although these provides adequate spatial coverage and continuous data, the trade-off between their spatial and temporal resolutions may restrict their use at agriculture fields' level and during the plants growing seasons [12]. However, recent advances in remote sensing data fusion of multi satellite data have assisted in mitigating these limitations [13-16]. In the scope of this paper, we synthesized the importance of agricultural drought and methods commonly employed to monitor agricultural drought conditions (that include in-situ, remote sensing, and synergy between in-situ and remote sensing-based methods in particular) and their limitations.

2. Importance of monitoring agricultural drought

Continuous water supply throughout the growing season is required for the proper growth of agricultural crops. This can be met through irrigation, however, with the absence of irrigation facilities especially in developing countries and semi-arid regions, crops are mainly relying on the spatial and temporal distribution of precipitation and soils ability to store water, which, in turn, controls crops yield and production. Thus, effective and timely monitoring of agricultural drought during the growing season might be greatly helpful in minimizing agricultural losses.

Agricultural drought monitoring is one of the three main actions in agricultural drought risk management plans, which also include drought preparedness and drought response actions. Monitoring actions include: ongoing monitoring and evaluating surface wetness conditions, precipitation amounts and patterns; and temperature in the agricultural areas during the growing season. The ongoing monitoring includes measuring different agro-climate parameters such as precipitation, temperature, evaporation, soil moisture, etc. in near real time collection in order to develop adequate agricultural drought evaluation indicators. These evaluations are then interpreted in drought reports that objectively and accurately determine the severity, extent and duration of drought conditions. Usually, such combined information helps in providing guidance for decision makers (i.e., government ministries) and farmers to the existing situation. The drought preparedness actions focus on the efforts that increase the awareness and readiness of decision makers and farmers, especially during non-drought periods, to the proper respond to the next drought event if occurred. Lastly, drought response actions provide appropriate strategies during and immediately following a drought events to reduce drought impacts on agricultural operations [17].

Agricultural drought is a widespread natural hazard phenomenon (see Figure 1) recently, large scale intensive droughts events have occurred and affected large areas in Europe, Africa, Asia, Australia, South America, Central America, and North America. For example, during the growing seasons over the period 1980–2003 in United States of America, drought accounted for $144 billion (41.2%) of the estimated $349 billion total cost of all weather-related disasters [18]. In Canada, the Canadian Prairies are the most drought susceptible area due to high variability of precipitation, for example, the drought event during 2001 and 2002 growing seasons resulted in an estimated loss of $3.6 billion in agricultural production [19]. In Australia the winter cereal crop was reduced by 36% and costed around AUD$3.5 billion during the 2006 drought event [20]. During the past 30 years in Europe, several major drought events occurred. The most severe drought event in the Iberian Peninsula in 2005 caused 10% reduction in the overall European cereal yields. Since 1991, the European Union has estimated a yearly average economic impact of drought by €5.3 billion [21].

In Asia, the Intergovernmental Panel on Climate Change reported that most of rice, maize, and wheat production has declined in many Asian countries in the last few decades [22]. For examples, around 60 million people in Central and Southwest Asia were affected by drought during 1999–2000 growing seasons, and around 40 million hectares of agricultural areas were affected in China alone. In India, drought has been reported at least once in every three years in the last five decades [23].

The West Asia—including Jordan—and North Africa region experienced several drought events in the last three decades represented by reduced food production. For example, in 1999, aggregate cereal production in the West Asia sub-region was 16% lower than in the previous year and 12% lower than the average over the previous five years. In Turkey, the grain production fell by 6% as compared to the five-year average. In Iraq, rainfall was 30% below average resulting in 70% failure in rain-fed agriculture crops. Similar situation faced North African countries such as, Morocco, Algeria, and Tunisia during that drought event as cereal crop was reduced by 31% comparing to the previous year's harvest [4].

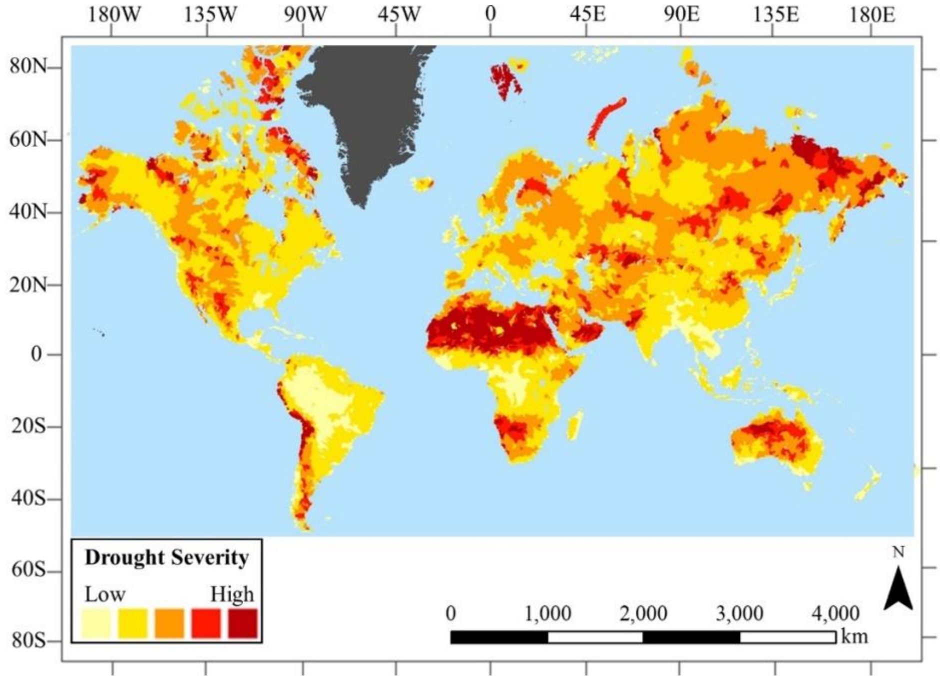

Figure 1. World drought severity distribution map computed over the 1901–2008 period (modified after [24]). Drought is defined as a continuous period where soil moisture remains below the 20th percentile at monthly scale [25].

3. *In-situ* based agricultural drought monitoring methods

The *in-situ* based agricultural drought monitoring indices are the most accurate and historic ones among the others [26]. They are based on ground measurements of hydro-climatic variables (including precipitation, temperature, relative humidity, and soil water content etc.) available from climatic, agricultural, and hydrologic stations; and able to provide quantitative and qualitative information over an area of interest [27]. Some of the examples include: (i) Palmer drought severity index (PSDI) uses precipitation and temperature [28]; (ii) crop moisture index (CMI) incorporates soil moisture, precipitation and temperature [29]; (iii) crop water stress index (CWSI) is based on actual and potential evaporation [30]; (iv) crop specific drought index (CSDI) employs temperature, precipitation, evapotranspiration information [31]; and (iv) standardized precipitation index (SPI) uses precipitation regimes [32]. Although some of these indices were initially developed for meteorological drought; however, they were effectively applied in agricultural drought monitoring in

Table 1. Most commonly used *in-situ* based agricultural drought monitoring indices.

Index	Inputs	Ref.	Pros	Cons
Palmer Drought Severity Index (PSDI)	Temperature, precipitation, soil moisture, evapotranspiration	[28]	Provides more comprehensive view of drought conditions	Sophisticated computation process
Crop Moisture Index (CMI)	Temperature, precipitation	[29]	Easley computable using precipitation and temperature data	Not suitable for long-term agricultural drought
Stress Degree Days (SDD)	Canopy and air temperature	[37]	A simple measure calculated by the difference between canopy and air temperature	Environmental conditions such as air humidity and soil moisture can affect the index
Standardized Precipitation Index (SPI)	Precipitation	[32]	Simple, requires only precipitation data, measures drought conditions at different time scales	Use only precipitation, hard to interpolate over large areas
Crop Specific Drought Index (CSDI)	Temperature, precipitation, evapotranspiration	[31]	Provides daily estimates soil water availability for different zones and soil layers	Too many requirements including soil type, crop phenology, and climatological data
Evapotranspiration Deficit Index (ETDI)	Weekly soil moisture and evapotranspiration values simulated by the Soil and Water Assessment Tool (SWAT)	[38]	Considers the water stress ratio in its calculation, and provide weekly values which reflects short term dry conditions	The spatial variability of its values increases during summer season due to increase of evapotranspiration and variable precipitation.
Soil Moisture Drought Index (SMDI)	Weekly soil moisture and evapotranspiration values simulated by the Soil and Water Assessment Tool (SWAT)	[38]	Improves the ability for modeling and monitoring hydrologic system and soil moisture deficient at a finer resolution	Irrespective to soil properties across different climatic conditions

different studies because agriculture is often the first affected sector by the onset of drought due to precipitation deficiency [33-35]. Table 1 shows the most commonly used in situ based agricultural drought monitoring indices. Note that the World Meteorological Organization (WMO) recommends that all national meteorological, agricultural and hydrological services should use SPI for monitoring drought [36] due to its simplicity and flexibility to monitor drought at either weekly or 10 days, 1, 3, 6, 9, 12 and 24 months intervals, with four drought classes (i.e., near normal, moderate, severe and extreme droughts) [32].

In general, these indices usually provide very accurate estimates of agricultural drought conditions at the point locations where the input variables are acquired. However, the uneven spatial distribution of the hydro-meteorological stations across the landscape often imposes uncertainty in delineating spatial context. In order to address this, geographic information system (GIS)-based interpolation techniques (e.g., inverse distance, krigging, nearest neighbour, etc.) are usually employed. However, these techniques often generate different outcomes despite using the same set of input variables [39]. It is worthwhile to mention that in-situ methods can also be used with gridded spatial data and remote sensing derived data such as rainfall estimates.

4. Remote sensing based agricultural drought monitoring methods

In order to address the spatial context of agricultural drought based *in-situ* based indices, remote sensing-based indices have been widely used for agricultural drought monitoring. These indices are based on unique spectral signatures of soil surface and canopy characters, particularly in the 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 [40]. Thus, it may change their spectral and thermal responses, which can be used as indicators of drought occurrence. Therefore, many remote sensing models and indices have been developed and employed in investigating agricultural drought [9,41]. Basically, remote sensing-based agricultural drought monitoring methods can be grouped into four groups: (i) optical remote sensing methods, (ii) thermal remote sensing methods, (iii) microwave remote sensing methods, and (iv) combined remote sensing methods. It is worthwhile to mention that the usability of remote sensing based methods depends on different factors including satellite data availability, cost, data quality, pre-processing, and post-processing requirements.

4.1. Optical remote sensing methods

Because agricultural drought is naturally related to vegetation and soil status; optical remote sensing data in the range 0.4 and 2.5 μm have been used as inputs to the agricultural drought indices [41]. In this spectral range, red, near infrared (NIR), and shortwave infrared (SWIR) are the most commonly used bands due to their distinct response to agricultural drought condition through both vegetation greenness and vegetation wetness conditions. In case of vegetation greenness, heathy vegetation is often more green and tend to absorb most of the incident visible light (e.g., red spectrum) and reflect significant amount in the NIR spectrum. In contrast, both unhealthy or sparse vegetation reflects more in the visible spectrum and less in the NIR spectrum. In case of vegetation wetness, NIR spectrum is found to be less sensitive while SWIR spectrum is significantly responsive to the vegetation water content. In fact, when analysing the spectral response of vegetation at various levels of water content, generally surface reflectance increases with higher levels of water deficiency in particular to the SWIR spectrum [41].

In general, optical remote sensing-based agricultural drought indices can be divided into three groups according to their purpose: (i) soil drought monitoring indices, (ii) vegetation drought monitoring indices, and (iii) soil and vegetation drought indices. The soil drought monitoring indices were found to be more applicable over bare soil surfaces than vegetated surfaces. The rationale behind this was that vegetation could resist drought conditions by utilizing different reactions in their leaves and roots [42]. This might delay the identification of agricultural drought conditions especially over more densely vegetated areas, and cause uncertainties in the results of these indices. Such examples of these indices include perpendicular drought index (PDI; [43]) and distance drought index (DDI; [44]). On the other hand, vegetation drought indices were found to be more applicable over moderate to densely vegetated areas than sparse vegetated areas; this was because soil background reflectance might affect the calculations and cause uncertainties in monitoring drought [43]. Examples on such indices are, normalized difference vegetation index (NDVI; [45]), leaf water content index (LWCI; [46]), normalized difference water index (NDWI; [47]), NDVI anomaly (NDVIA; [48]), vegetation condition index (VCI; [49]), standardized vegetation index (SVI; [50]), SWIR perpendicular water stress index (SPSI; [43]), and vegetation water stress index (VWSI; [43]).

In general, semi-arid areas are described as sparse vegetated areas [51]; therefore, neither vegetation drought indices nor soil drought indices solely can provide accurate monitoring of drought in these regions. Some possible solutions might include performing land cover classification and assigning a suitable index for each class [52] or applying different drought indices at different plant growing stages. However, such solutions might add additional uncertainty and complexity to the final results of agricultural drought monitoring. In addressing these issues, some indices were developed for monitoring agricultural drought for both soil and vegetation at the same time such as, shortwave infrared water stress index (SIWSI; [53]), normalized multiband drought index (NMDI; [54]), and the visible and shortwave drought index (VSDI; [55]). In conclusion, these indices did not only provide mapping of vegetation and soils on a pixel basis, they also provided qualitative and quantitative measurements of their conditions (i.e., greenness and wetness) within a pixel. However, these indices ignored the temperature (i.e., thermal properties) as an indicator of agricultural drought in their formulations. Table 2 shows the most commonly used optical remote sensing based agricultural drought monitoring indices.

Thermal inertia is a measurement describes the resistance of the materials (e.g., soil and vegetation) to temperature variations; it depends on the bulk density, thermal conductivity, and heat capacity of the materials [59]. It has a proportional relationship with water content levels, therefore if water content decrease, thermal inertia decreases as well. Thus, it can be used as an indicator of agricultural drought. However, since different materials have different thermal inertia, and bulk density, thermal conductivity, and heat capacity cannot be derived from remote sensing data, mapping thermal inertia was inapplicable through remote sensing. A proposed alternative was the apparent thermal inertia which can be derived from remote sensing data by measuring the surface albedo and the diurnal temperature range [60,61]. However, the application of this method was found to be restricted to arid regions with bare land or very sparse vegetation areas [62].

Table 2. Most commonly used optical remote sensing agricultural drought monitoring indices.

Type	Index	Expression*	Ref.	Pros	Cons
Soil drought index	Perpendicular Drought Index (PDI)	$PDI = \frac{1}{\sqrt{M^2+1}} (\rho_R + M * \rho_{NIR})$	[43]	Simple and effective in calculating drought conditions	Unable to provide high accuracy over variable land cover types especially bare soils and densely vegetated fields.
Vegetation drought index	Normalized Difference Vegetation Index (NDVI)	$NDVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R}$	[45]	Provides a measure of vegetation health or greenness conditions	Sensitive to darker and wet soil conditions; also demonstrates time lag in response to soil moisture
Vegetation drought index	Moisture Stress Index (MSI)	$MSI = \frac{\rho_{SWIR_2}}{\rho_{NIR}}$	[46]	More sensitive at canopy level rather than leaf level	Applicable for densely vegetated areas
	Simple Ratio Water Index (SRWI)	$SRWI = \frac{\rho_{NIR}}{\rho_{SWIR_1}}$	[56]		
	Normalized Difference Water Index ($NDWI_1$)	$NDWI = \frac{\rho_{NIR} - \rho_{SWIR_1}}{\rho_{NIR} + \rho_{SWIR_1}}$	[47]	Effective in monitoring vegetation water content	Uncertainties increased considerably in the presence of soil and sparsely vegetated or bare surfaces
	Normalized Difference Infrared Index (NDII)	$NDII = \frac{\rho_{NIR} - \rho_{SWIR_2}}{\rho_{NIR} + \rho_{SWIR_2}}$	[57]		
	Land Surface Water Index (LSWI)	$LSWI = \frac{\rho_{NIR} - \rho_{SWIR_2}}{\rho_{NIR} + \rho_{SWIR_2}}$	[58]		
	Vegetation Condition Index (VCI)	$VCI = \frac{NDVI_i - NDVI_{min}}{NDVI_{max} - NDVI_{min}}$	[49]	Provides vegetation greenness conditions	Requires data over longer time period
Soil and vegetation drought index	Modified Perpendicular Drought Index (MPDI)	$MPDI = \frac{1}{1-f_v}(PDI - f_v * PDI_v)$	[43]	Applicable over variable topography, soil types and ecosystems	Assumption fixed soil line; however, it is highly dependent on the soil type, level of fertilization, and soil moisture

Continued on next page

Table 2. Most commonly used optical remote sensing agricultural drought monitoring indices—continued.

Type	Index	Expression*	Ref.	Pros	Cons
Soil and vegetation drought index	Shortwave Infrared Water Stress Index (SIWSI)	$SIWSI = \frac{\rho_{SWIR_{1,2}} - \rho_{NIR}}{\rho_{SWIR_{1,2}} + \rho_{NIR}}$	[53]	Similar to NDII	Similar to NDII
	Normalized Multiband Drought Index (NMDI)	$NMDI = \frac{\rho_{NIR} - (\rho_{SWIR_1} - \rho_{SWIR_3})}{\rho_{NIR} + (\rho_{SWIR_1} + \rho_{SWIR_3})}$	[54]	Applicable for estimating both vegetation and soil water content	Requires further investigation over moderately dense vegetation
	Visible And Shortwave Drought Index (VSDI)	$VSDI = 1 - [(\rho_{SWIR_2} - \rho_B) + (\rho_R - \rho_B)]$	[55]	Applicable for estimating both vegetation and soil water content	Performs unwell if temperature is more dominant over the precipitation

*ρ is the surface reflectance value of blue (B), red (R), near infrared (NIR), and shortwave infrared ($SWIR_1$, $SWIR_2$, and $SWIR_3$ centred at ~1.24, ~1.64, and ~2.14 µm) bands; M is the slope of the soil line; fv is the vegetation fraction.

Table 3. Most commonly used thermal remote sensing-based agricultural drought monitoring indices.

Index	Expression *	Ref.	Pros	Cons
Apparent Thermal Inertia (ATI)	$ATI = C \times \frac{1-a}{\Delta Ts}$	[60]	Suitable for bare land areas	Not applicable over vegetated regions
Temperature Condition Index (TCI)	$TCI = \frac{Ts\ \max - Ts}{Ts\ \max - Ts\ \min}$	[66]	Easy to get the required input data	Requires clear-sky conditions at the time of imaging
Normalized Difference Temperature Index (NDTI)	$NDTI = \frac{T\infty - Ts}{T\infty - To}$	[67]	Able to accurately reflect the spatial-temporal variations of soil moisture	Requires other input variables (e.g., solar radiation, wind speed and leaf area index) that not complicated to acquire

*C is the solar correction factor; a is the surface albedo; ΔTs is the difference between afternoon and midnight land surface temperature; Ts max and Ts min are the maximum and minimum Ts from all images in the dataset respectively; T∞ and To are the modeled surface temperature if there is an infinite or zero surface resistance, respectively.

The Ts-based methods employed the surface temperature retrieved from remote sensing systems in measuring agricultural drought over different spatial scales. It was found that Ts-based methods were better indicators over sparse canopies or bare lands than vegetative lands. In general, the accuracy of detecting drought conditions depends on the accuracy of retrieving surface temperature from remote sensing data [63] and the heterogeneity of the earth surfaces which increases the uncertainty of these methods to detect drought [64]. Some researchers applied the crop water stress index (CWSI) with satellite measurements of surface temperature, and found that CWSI was restricted to full-canopy conditions; this limited its applicability over partial or sparse vegetative conditions. Kogan [65,66] proposed the temperature condition index (TCI) as a proxy for vegetation thermal condition based on long time series of satellite-derived surface temperature data. Although TCI was found to be simple drought index, it was only suitable for homogeneous areas. Another index was developed by [67], the normalized difference temperature index (NDTI), to remove seasonal trends from the analysis of land surface temperature derived from the AVHRR sensor, although it had more robust physical foundations than TCI, it was complicated to calculate its parameters. Table 3 shows the most commonly used thermal remote sensing based agricultural drought monitoring indices.

4.3. Microwave remote sensing methods

Microwave remote sensing provides unique information of water content through detecting the change in the dielectric constants between water, soil and vegetation [68]. In this context, passive and active microwave remote sensing based models/indices showed promising results for water content estimation and agricultural drought studies [63,14]. Passive microwave remote sensors [e.g., Scanning Multichannel Microwave Radiometer (SMMR), Special Sensor Microwave/Imager (SSM/I), Soil Moisture and Ocean Salinity (SMOS), and Soil Moisture Active and Passive (SMAP)] have been used for surface water content monitoring through measuring the intensity of microwave emission from soil and vegetation which is related to water content [63,69]. Based on this data, different models have been developed, e.g.,

- Surface emission models that can be grouped into three groups such as: (i) bare soil emission models which are basically a function of surface roughness and dielectric properties (e.g., Q/H model and its modifications, [70-72]; (ii) vegetative areas emission models which is based on the optical depth and albedo (e.g., t~w model, [73]. (iii) Soil and vegetation model (e.g., Microwave Polarization Difference Index (MPDI; [74,75]).
- Soil moisture retrieval methods which include statistical and forward model inversion techniques [73,76,77]. It is worthwhile to mention that, though passive microwave has solid physical basis for water content retrieval and high temporal resolution, it has different major challenges including spatial resolution (i.e., 10–20 km), the available wavelength does not provide adequate water content sensitivity over different levels of vegetation covers, and technical and engineering challenges.

In active microwave remote sensing, sensors (e.g., Synthetic Aperture Radar (SAR) systems) send microwave energy and receive backscattered pules in different frequencies (e.g., C-band, L-band, and X-band). This data is then used for measuring backscattering coefficient which used for retrieving water content of soils and vegetation at higher spatial resolutions (i.e., tens of meters) through the contrast of the dielectric constants between bare soil, vegetation and water [63,78]. To date, different approaches have been developed under this concept which can be grouped into three groups such as: (i) theoretical approaches (e.g., Integral Equation Model [79] (IEM)); (ii) empirical approaches (e.g., Normalized Backscatter Moisture Index (NBMI; [80])), Wetness Index (WI; [81]); and (iii) semiempirical approaches (e.g., [78]). Actually, although active microwave sensors are having the capability to provide higher spatial resolution (i.e., ~tens of meters), they have a poor temporal resolution (i.e., ~one month). Some of the commonly used microwave remote sensing based agricultural drought monitoring indices are described in Table 4.

4.4. Combined remote sensing-based methods

Since different remote sensing indices have different capabilities in monitoring and detecting agricultural drought, researchers have worked on combining them into unified drought indices assuming that this combination may provide better characterization of drought conditions [82,83]. For example, in the optical remote sensing domain, indices have been combined in one index since they showed different sensitivity to drought conditions even when applied to the same location. Such examples include Normalized Difference Drought Index (NDDI; [84]) and Normalized Moisture Index (NMI; [85]) which have been calculated as a function of NDWI and NDVI.

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

Index	Expression *	Ref.	Pros	Cons
TRMM Precipitation Condition Index (PCI)	$PCI = \frac{TRMM\text{-}TRMM\ min}{TRMM\ max\text{-}TRMM\ min}$	[86]	Works well at regional scale under most of the weather conditions	Low spatial resolution and unable to acquire images at higher latitudes
Soil Moisture Condition Index (SMCI)	$SMCI = \frac{SM\text{-}SM\ min}{SM\ max\text{-}SM\ min}$	[86]		
Microwave Polarization Difference Index (MPDI)	$MPDI = \frac{T_{BV} - T_{BH}}{T_{BV} + T_{BH}}$	[74]	Able to provide soil moisture and vegetation optical depth	Low spatial resolution. Also requires further improvements for its applicability during day time
Normalized Backscatter Moisture Index (NBMI)	$NBMI = \frac{B_{t1}\text{-}B_{t2}}{B_{t1} + B_{t2}}$	[80]	Provides high spatial resolution in comparison to PCI, SMCI, and MPDI	Poor temporal resolution and unable to penetrate vegetation canopy

* $TRMM_{min}$ and $TRMM_{max}$; SM_{min} and SM_{max} are the minimum and maximum values of TRMM and SM of the pixel during the period of study, respectively. T_{BV} and T_{BH} are brightness temperature at V and H polarization, respectively; B_{t1} and B_{t2} are the backscatter coefficients at different time steps.

Other forms of combinations were done between thermal and optical remote sensing based indices. For instance, the combination between Ts and VIs has been presented in two approaches.

First, the mathematical approach, in which Ts and VIs have been integrated directly in mathematical operations, such as Vegetation Health Index (VHI; [49]), which is a combination of the VCI and TCI to determine the overall vegetation health status and to detect drought affected areas in agricultural dominant regions. Temperature-Vegetation Index (TVX; [87]), vegetation water supply index (VWSI; [88]), and the Normalized Vegetation Supply Water Index (NVSWI; [89]), which were based on Ts/VIs ratio operations. Second, the Ts-VIs scatter plot approach, in which Ts and VIs are presented in scatter plots that typically generate either triangular or trapezoidal forms [90] (see Figure 2).

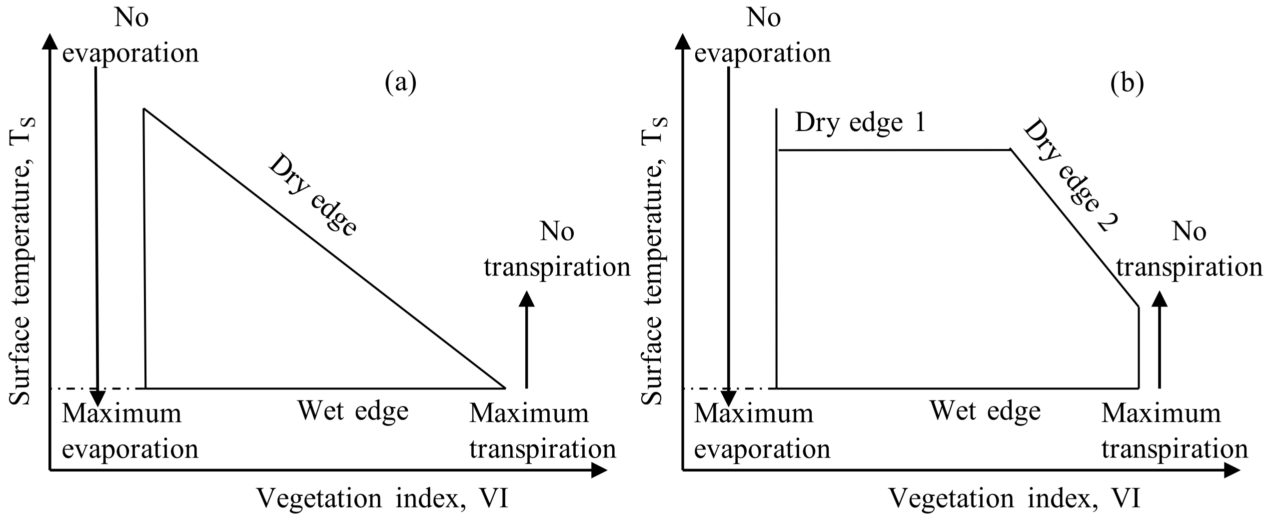

Figure 2. (a) Triangular and (b) trapezoidal forms based on a relationship between Ts and VIs (modified after [100] and [87]).

The triangular or trapezoidal shapes in the Ts-VIs scatter plots emerge due to the negative relationship between them. For instance, Ts has low sensitivity to water content variations over vegetated areas, while it has high sensitivity over bare soils [91]. For example, when VIs values increase along the x-axis, the Ts values decrease along the y axis due to the cooling effects of evapotranspiration indicating none water stress condition, and vice versa [92,93]. In the Ts-VIs scatter plots, the x axis is represented by the VIs values, and the y axis is represented by the Ts values. Referring to Figure 2a and 2b, the theoretical dry edge (i.e., water stress condition) is represented by a line connecting the *no evaporation* and the *no transpiration* points. While, the theoretical wet edge (i.e., well-watered condition) is represented by a horizontal line connecting the *maximum evaporation* and the *maximum transpiration* points. In Figure 2, variations along the Ts axis reflects the effects of water content and topography across bare soil areas, while variations along VIs axis reflects the effects water content and vegetation cover density across the vegetative area. The remaining points (pixels) within the triangular or trapezoidal represents pixels with varying vegetation cover between the bare soil and dense vegetation. The triangular and trapezoidal shapes of the Ts/VI scatterplot are driven by many factors including, (i) evaporation from soil and the vegetation [94]; (ii) vegetation fractional cover, surface moisture status and local climate [95]; (iii) the number of pixels in the scene and the spatial resolution [96]; (iv) incident radiation variations, and (v) other specific study area characteristics (e.g., soil type, land cover, spatial heterogeneity, and latitude) [87]. In the literature, a number of different methodologies have been developed to estimate water content from satellite-derived Ts/VI scatterplots. They can be grouped into five classes such as, (i) surface temperature and simple vegetation index; (ii) surface temperature and albedo; (iii) surface-air temperature difference and vegetation index; (iv) day-night surface temperature difference and vegetation index; and (v) coupling of the Ts/VI data with a Soil Vegetation Atmosphere Transfer (SVAT) model [91]. Ts-VIs scatter plots have been given different names, such as the surface moisture status (SMS; [95]), Water Deficit Index (WDI; [63]), Moisture Index (MI; [97]), Vegetation Supply Water Index (VSWI; [98]), Vegetation Temperature Condition Index (VTCI; [99]), Temperature-Vegetation Dryness Index (TVDI; [100]), Temperature-Vegetation Wetness Index (TVWI; [90]), Evaporative Stress Index (ESI; [101]). Despite of the individual limitations of these indices, they have been widely used in agricultural drought studies, as they may easily estimate water content status of soil and vegetation without any ancillary data [59]. However, it has difficulty in defining the dry and wet edges due to two reasons, (i) the probability of the distribution of Ts-VI points in a narrow range within the scatter plot (e.g., during rainy season or in areas with a narrow VI range); (ii) the high heterogeneity of study area. Furthermore, as the triangular and trapezoidal shapes are empirically determined based on an image at a specific date, they may be hardly compared to other dates [102]. Table 5 shows the most commonly used Ts-VIs based agricultural drought monitoring indices.

In other studies, the combination has been done using composite of microwave and/or other optical or thermal based indices. For example, (i) Microwave Integrated Drought Index (MIDI; [105]) integrated the Precipitation Condition Index (PCI), Soil Moisture Condition Index (SMCI), and Temperature Condition Index (TCI) obtained from precipitation based TRMM data and soil moisture and land surface temperature data from the Advanced Microwave Scanning Radiometer–EOS (AMSR-E); and used for monitoring short-term drought over semiarid regions; (ii) Scaled Drought Condition Index (SDCI; [104]) employed TRMM-based precipitation data in conjunction with MODIS-based T_S and NDVI information for agricultural drought monitoring over both arid/semiarid and humid regions. It is worthwhile to mention that before combining multiple indicator/indices in a composite drought index they should not be fully correlated with each other [106]. Recent advances in microwave remote sensing showed the ability to measure agricultural drought under different topographic and land cover conditions using both active and passive microwave measurements. In this context, the ALOS-PALSAR, SMOS, and SMAP missions offer combined passive/active microwave data which is expected to increase the accuracy of soil moisture and vegetation water content retrievals which can provide high accurate drought monitoring products.

Table 5. Most commonly used combined remote sensing-based agricultural drought monitoring indices.

Type	Index	Expression *	Ref.	Pros	Cons
Combined optical based indices	Normalized Difference Drought Index (NDDI)	$NDDI = \frac{NDVI\text{-}NDWI}{NDVI + NDWI}$	[84]	Combines both vegetation greenness and wetness conditions.	Not applicable for short-term drought monitoring
	Normalized Moisture Index (NMI)	$NMI = NDVI + NDWI$	[85]		
Ts-VIs Mathematical approach	Vegetation Health Index (VHI)	$VHI = 0.5 * VCI + 0.5 * TCI$	[49]	Provides more comprehensive drought monitoring capabilities	Requires appropriate data fusion for VCI and TCI
	Temperature-Vegetation Index (TVX)	$TVX = \frac{Ts}{NDVI}$	[87]	Depicts drought conditions at regional scale	TVX/VSWI slopes may vary from one place to another
	Vegetation Water Supply Index (VWSI)	$VSWI = \frac{NDVI}{Ts}$	[88,98]		
Ts-VIs scatter plot approach	Vegetation Temperature Condition Index (VTCI)	$VTCI = \frac{Ts_{NDVI_{max}} - Ts_{NDVIi}}{Ts_{NDVI_{max}} + Ts_{NDVI_{min}}}$	[99]	Works better at regional scale	Unable to calculate: (i) over small study area; and (ii) variable topography
	Temperature-Vegetation Dryness Index (TVDI)	$TVDI = \frac{Ts - Ts_{min}}{Ts_{max} + Ts_{min}}$	[103]		
	Water Deficit Index (WDI)	$WDI = \frac{(Ts - Ta) - (Ts - Ta)_{min}}{(Ts - Ta)_{max} + (Ts - Ta)_{min}}$	[63]		
	Temperature-Vegetation Wetness Index (TVWI)	$TVWI = \frac{\theta_{dry} - \theta_s}{\theta_{dry} + \theta_{wet}}$	[90]	Eliminates the issue of variable topography	Unable to calculate over small study area

Continued on next page

Table 5. Most commonly used combined remote sensing-based agricultural drought monitoring indices—continued.

Type	Index	Expression *	Ref.	Pros	Cons
Combined Microwave and/or optical/thermal approach	Microwave Integrated Drought Index (MIDI)	$MIDI = \alpha * PCI + \beta * SMCI + (1 - \alpha - \beta)TCI$	[86]	Applicable over semi-arid regions in particular	Non sensitive to water content over different levels of vegetation covers
	Scaled Drought Condition Index (SDCI)	SDCI = (1/4) * Scaled T_S + (2/4) * Scaled TRMM + (1/4) Scaled NDVI	[104]	Applicable over both arid and humid regions	The coefficients are ecosystem-specific

*$VSWI_{min}$ and $VSWI_{max}$ are the minimum and maximum values of VSWI of the pixel during the period of study; T_{max} is the maximum surface temperature at the dry edge; T_{min} is the minimum surface temperature at the wet edge; $Ts_{NDVImax}$ and $Ts_{NDVImin}$ are the maximum and minimum land surface temperatures of pixels which have same NDVI value in a study area, respectively, Ts_{NDVIi} is the land surface temperature of one pixel whose NDVI value is $NDVI_i$; Ta is the air temperature; ET is the actual evaporation, θ_{dry} is the dry edge; θ_{wet} the wet edge; θs is the surface potential temperature.

Table 6. Most commonly used synergic based agricultural drought monitoring indices.

Index	Description *	Ref.	Pros	Cons
US Drought Monitor (USDM)	Integrates VHI with other drought indices such as, PDSI, SPI, PNP, and soil moisture model percentiles, daily stream flow percentiles, and many other supplementary indicators.	[114]	Provides a general assessment of drought	Limited use at local scales
Vegetation Drought Response Index (VegDRI)	VegDRI is a hybrid drought index that integrates satellite-based observations of vegetation conditions with climate-based drought index data and biophysical characteristics of the environment to produce 1-km spatial resolution maps that depict drought-related vegetation stress.	[118]	Depicts drought-related vegetation stress at regional scales	Outcome highly depends on the spatial distribution of the ground-based weather stations
Integrated Surface Drought Index (ISDI)	Integrates PDSI and the traditional climate-based drought indicators, satellite-derived vegetation indices, and other biophysical variables. ISDI can be used not only for monitoring the main drought features such as precipitation anomalies and vegetation growth conditions but also it indicates the earth surface thermal and water content properties by incorporating temperature information.	[121]		
Vegetation Outlook (VegOut)	An experimental tool that provides a series of maps depicting future outlooks of general vegetation seasonal greenness conditions based on the analysis of: climate-based drought indices (i.e., PDSI and SPI); satellite-based observations of vegetation (i.e., SSG and SOSA); biophysical characteristics of the environment (i.e., eco-region, elevation, irrigated lands, and land use/cove type); and oceanic indicators (i.e., MEI, SOI, PDO, NAO, PNA, MJO, and AMO)	[120]	VegOut provides drought conditions at 1 km spatial resolution	Requires significant amount of data, which is quite challenging in most of regions of the world

* PNP is the percent of normal precipitation; SSG is the standardized seasonal greenness; SOSA is the Start of season anomaly; MEI is the multivariate ENSO index; SOI is the southern oscillation index; PDO Pacific decadal oscillation index; NAO is the north Atlantic oscillation index; PNA Pasific north American index; MJO Madden-Julian oscillation index; and AMOis the Atlantic multi-decadal oscillation index.

5. Synergy between remote sensing and *in-situ* based methods

In most of the instances, the majority of drought studies concentrated on assessing drought using single data source drought index [107-113]. As each index has its own data type, complexity, strengthens, and weakness; they often provide different results for the same event of interest [114,113]. A combination of various drought indices from different data sources may provide more comprehensive assessment of drought conditions than the use of a single one [115]. However, the use of synergic methods has been challenging due to the lack of systematic methods for the combining, implementing, and also evaluating of this phenomenon, in addition to the variations in the nature, quality, and availability of input requirements [116]. For example, remote sensing-based indices are unable to discriminate vegetation stress caused by sources other than drought [117]. So, the combination of various indices may offer better understanding and better monitoring of drought conditions. Such indices include: US Drought Monitor (USDM; [114]), Vegetation Drought Response Index (VegDRI; [118]), Hybrid Drought Index (HDI; [119]), Vegetation Outlook (VegOut; [120]), Integrated Surface Drought Index (ISDI; [121]) and Multi-Index Drought (MID; [115]). Table 6 shows the most commonly used synergic remote sensing/*in-situ* based agricultural drought monitoring indices.

6. Conclusion

In the scope of this article, we found that a significant amount of research and development has been accomplished in the area of remote sensing of agricultural drought. Despite, there are quite a few challenges, which require further research. Those include:

- **Monitoring relatively small area:** Agricultural drought requires high proficiency methods for accurate drought monitoring in terms of the spatial (i.e., scale and coverage) and temporal properties over relatively small area. The *in-situ* based monitoring methods provide high frequent data (i.e., daily measurements recorded at ground stations), however they are spatially restricted to the specific measuring locations. Currently, remote sensing satellites acquire images in optical and thermal spectrum in different spatial and temporal resolutions for agricultural drought monitoring. For example, some remote sensing satellites such as MODIS, AVHRR, and SPOT-VEG can provide high temporal resolution (i.e., daily) with low spatial data in the range 250–1000 m. On the contrast, other satellites provide data at low temporal resolution with high spatial resolutions such as Landsat, ASTER, and SPOT5 (i.e., 16–26 day intervals with 10–120 m spatial resolutions). Similar issue with passive and active microwave remote sensing are also prevailing. For example, passive microwave has a low spatial with high temporal resolutions, while active microwave acquires data with high spatial and low temporal resolutions. However, for the practical monitoring of agricultural drought at field scale, both high spatial and high temporal data are required due to the small size of agricultural fields and the rapid changes in plants during the growing season [122-124]. For example, high spatial resolution data (i.e., 30 m) is necessary for studying agriculture at field scale [12], and high temporal resolution data (i.e., weekly) is required for monitoring rapid changes in reflected or emitted energy during plants growing season [125,126]. These changes, in some cases, may reflect specific agricultural problems such as drought [68].

However, due to technical and cost issues, none of the currently operational satellite systems has the capability to provide such accompanied high resolution data [127]. Therefore, it is necessary to apply multi-sensor data fusion techniques that compensate these limitations and provide high quality data for such applications [128-130]. Furthermore, it will be worthwhile to investigate the impact of land use practices on the drought. Also, more studies should be formulated for monitoring drought for landscapes with different levels of vegetation density and coverage.

- **Filling gaps in the data:** In case of both optical and thermal remote sensors, they are incapable of acquiring surface properties in the presence of cloud, haze, and fog in particular. As a result, we often observe gaps in the data, which may potentially require the adoption of some gap-infilling algorithm. Though different types of such algorithms can be found in the literature; however, it should be capable to in-fill upon considering the data acquired until the day of monitoring of the drought conditions as illustrated in [131] for instance.
- **Developing consistent historical dataset**: Though remote sensing sensors have been operational since early 1970's; however, they differ in their spatial, spectral, temporal, and radiometric resolutions. In case of optical and thermal sensors, platforms like Landsat series (operational since 1972), NOAA AVHRR series (since 1978), and MODIS (since 2000) acquire images with great similarities in their spectral resolution in particular. In generating a lengthy data record consisting of optical and thermal images, data fusion techniques such as described in [14] and [15] can be adopted where they should be thoroughly evaluated over various ecosystems across the world. In case of microwave platforms, the passive platforms have been operational since 1978 so that development of algorithms to fuse the optical, thermal, and microwave images may potentially enhance our capacity to comprehend the drought conditions better.
- **Developing remote sensing-based agricultural drought forecasting system:** Due to the fact that the remote sensors capture the condition of the feature of interest at particular moments, thus they are often used as 'monitoring' mechanisms. However, in the recent times, there are some efforts to develop primarily remote sensing-based systems to forecast: (i) fire danger conditions at daily to eight-day time scale [131-134]; and (ii) crop yields prior to their harvesting [135,136]. Thus, attempt to develop such systems for forecasting agricultural drought conditions at shorter time-scale in the range daily to ten-day will be critical to manage and mitigate the upcoming events more efficiently. In addition, it may also be possible to forecast regional-scale agricultural droughts upon detecting El-Niño phases using remote sensors [137]. In addition, other efforts are concentrating on forecasting drought based on weather forecasts such as global drought forecasts based drought indices (e.g., SPI) computed with monthly weather forecasts [138].
- **Integrating the recently launched and upcoming remote sensors:** In the recent years, several new sensors have been launched, such as Soil Moisture and Ocean Salinity in 2009, Suomi NPP in 2011, Landsat-8 in 2013, Soil Moisture Active Passive in 2015, and Sentinel series 2014–2016. In addition, a series of new satellites under the name JPSS are to be launched during the period 2017–2038. Thus, new algorithms need to be developed in order to integrate these platforms-derived products.
- **Developing standard validation schema:** Depending on the spatial resolution of a remote sensing platform, the derived agricultural drought indication can have different cell size, such

as 30 m, 1 km, or even several kilometers. Usually, if the spatial resolution is high enough (e.g., less or equal to 30 m), then it is relatively easy to compare with ground-based measurements. Otherwise, in cases of low spatial resolution products, it may be possible to employ aerial photography or unmanned automated vehicles-based estimates. In addition, model-based outcomes as described in [139,140] can also be used for validation purposes. Thus, developing standard protocols for validating the remote sensing-based indicators is an emerging sub-area of research within the broad agricultural drought research. Finally, it is worthwhile to mention that such standardizations are not only required for remote sensing-based agricultural drought methods but also applicable for in-situ based methods as well.

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Conflict of interest

The authors declare no conflict of interest.

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