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CHAPTER 3.1: Algorithms for drought and evapotranspiration estimation based on satellital information

INDEX

1. Introduction.

Drought is a natural hazard that results from a deficiency of precipitation from expected or normal over a specific region for a specific period of time (Rossi, 2000). This situation has negative agricultural, environmental, social and economic impact (Vicente-Serrano et al., 2010), which includes greater risks of wildfire, water scarcity, loss of crops and livestock, increased food prices, migration, and indirect health effects (Mukherjee et al., 2018). As indicated Van Loon and Van Lanen (2013), drought is a natural hazard and its impacts can only be mitigated by adapting to the climate variability through previous measures.

Within the ClimAlert project, it is important to detect the drought in the Sudoe zone to manage the most vulnerable areas and to anticipate its effects.

Based on its nature, the droughts have been classified in different categories (Mishra and Singh, 2010; Pedro-Monzonís et al., 2015; Wilhite and Glantz, 1985):

- Meteorological drought: lack of precipitation over a region for a period of time.
- Agricultural drought: moisture deficit in the root zone to meet the needs of a crop, affecting the crop development and declining crop yields.
- Hydrological drought: period of low flows in watercourses, lakes and groundwater levels below normal. It is related to a period with a decrease in surface and groundwater water resources availability for established water uses of a given water resources system.
- Socio-economic drought: associated with failure of water resources systems to meet water demands and thus associating droughts with supply of and demand for an economic good. This type of drought presents features of the three previous types (meteorological, agricultural and hydrological).

Usually, the interconnection between various types of drought makes it difficult to distinguish between one drought type from the other, because these can occur simultaneously or sequentially (Mukherjee et al., 2018). Meteorological drought is the most frequent and common type, and usually trigger the other types (Zhang and Jia, 2013). Drought can be characterized according to: severity, duration, spatial distribution, frequency, magnitude (cumulated deficit), predictability, rate of onset and timing (G Tsakiris et al., 2007; Zargar et al., 2011). Typically, to know the severity of the drought, standard indicators based on different components of the hydrologic budget are used. These indicators can be meteorological, hydrological, or water supply-and-demand in nature. According to Zargar et al. (2011), meteorological indicators include precipitation, evapotranspiration (ET) and cloud cover; hydrological indicators include stream flow and groundwater level; and water supply-and-demand indicators include reservoir storage. Drought indices are quantitative measures that characterize drought levels by assimilating data from one or several variables into a single numerical value (Zargar et al., 2011). Authors like Niemeyer (2008) indicate that more than 150 drought indices have been developed. Many of them are normalized with respect to a long-term climatology, which allows the results to be compared among different locations in different climatic regimes (Sahoo et al., 2015). Comprehensive reviews on these indices can be found in specific paper and publications (Heim, 2002; Mishra and Singh, 2010; Niemeyer, 2008; Pedro-Monzonís et al., 2015; Smakhtin and Hughes, 2004; Zargar et al., 2011; etc.).

2. Review of drought indices.

Among the multitude of drought indices found in the bibliography to characterize various types of drought, one of the most widely used is the **Palmer Drought Severity Index (PDSI)** (Palmer, 1965) together with the **Standardized Precipitation Index (SPI)** (Mckee et al., 1993).

PDSI is a meteorological drought index, which indicates standardized moisture conditions, using monthly precipitation, temperature data and local available water content of the soil. PDSI computes soil water storage using a simple two-layer soil water balance equation driven by precipitation data. Positive values indicate wet conditions, while negative values indicate dry conditions. Palmer (1965) classified drought severity considering the dry and the wet periods (see Table 8). Alley (1984) indicated that this classification is an arbitrary method, since Palmer was confronted with the designation of the beginning and end of a drought or wet period. PDSI has been sparsely used outside the United States (Kogan, 1995a), and offers unsatisfactory results in regions where rainfall variability is high (Smakhtin and Hughes, 2004). Although authors like Smakhtin and Hughes (2004) have indicated that PDSI allows comparing between locations and between periods of time, other like Alley and Alley (1984) have showed that PDSI is not spatially comparable across the neighbouring United States nor directly comparable between months. Regarding the estimation of potential ET necessary in the soil water balance, this is done through Thornthwaite's method based on empirical relationship between ET and temperature (Thornthwaite, 1948). A physically-based method such as the FAO Penman-Monteith equation (Anderson and French, 2019) has been suggested to improve this estimation of potential ET (Narasimhan and Srinivasan, 2005).

Table 1. Palmer Drought Severity Index (PDSI) categories (Palmer, 1965).

PDSI	MOISTURE CATEGORY
≥ 4	Extremely wet
3.00 to 3.99	Very wet
2.00 to 2.99	Moderately wet
1.00 to 1.99	Slightly wet
0.50 to 0.99	Incipient wet spell
0.49 to -0.49	Near normal
-0.50 to -0.99	Incipient drought
-1.00 to -1.99	Mild drought
-2.00 to -2.99	Moderate drought
-3.00 to -3.99	Severe drought
≤ -4.00	Extreme drought

SPI is based just on precipitation and provides information on precipitation deficit, percent of average and probability. SPI is a meteorological drought index, which can be deployed for longer time scales to reflect agricultural and hydrological droughts (Zargar et al., 2011). The index requires a long-term precipitation record, ideally a continuous period of at least 30 years. The precipitation record is fitted to a probability distribution and this is transformed into a normal distribution so that the mean SPI is zero. The SPI can be calculated at different temporal scales according to user's interest for monitoring meteorological, agricultural or hydrological drought (e.g. 1, 3, 6, 12, 24 or 48 months) which allows to evaluate the effects of a precipitation deficit on different water-resources components (snowpack, reservoir storage, streamflow, soil moisture, and groundwater). Mckee et al. (1993) defined a drought event for a considered time scale as a period in which the SPI is continuously negative and the SPI reaches a value of -1.0 or less. According to the SPI values, drought intensity may be classified as: mild drought (0 to -0.99); moderate drought (-1.0 to -1.49); severe drought (-1.50 to -1.99); and extreme drought (≤ -2.0). SPI is typically calculated through monthly dataset, but daily and weekly values can also be used. SPI can be employed in all climate regimes, and its values can be compared between different climatic areas (Svoboda and Fuchs, 2016). Guttman (1999) indicated that the SPI was developed to give a better representation of abnormal wetness and dryness than PDSI. The World Meteorological Organization (WMO) recommended this index as a global measure of meteorological drought (Hayes et al., 2011). Guttman (1998) showed the SPI as a simple index, spatially invariant in its interpretation, and probabilistic, and therefore it can be used in the analysis of risks and decisions. However, Svoboda and Fuchs (2016) indicated that events with similar SPI values but different thermal conditions are difficult to compare because temperature is not considered in SPI calculation. Like temperature, other variables such as ET, wind speed, and soil water holding capacity can affect drought events, however, these variables are not considered in SPI estimation (Vicente-Serrano et al., 2010).

Based on SPI, Vicente-Serrano et al. (2010) developed the **Standardized Precipitation Evapotranspiration Index (SPEI)**, which is a meteorological drought index based on precipitation and temperature data, combining both variables. SPEI is based on a monthly (or weekly) climatic water balance (Thornthwaite, 1948) (precipitation minus potential ET), which is adjusted using a three parameters log–logistic distribution. The values are accumulated at different time scales, following the same approach used in the SPI, and converted to standard deviations with respect to average values. Vicente-Serrano et al. (2010) indicated that drought indices that incorporate temperature data in their calculations, such as SPEI or PDSI, improve the application in future climate scenarios. Furthermore, these indices include the ET effect in their calculations, thereby improving the estimation of drought severity. As an advantage, SPEI requires less input data and is a simpler index than PDSI.

Another index used to measure the precipitation variation from the normal (average) for a location is the **Percent of Normal Precipitation (PN)**. PN is a meteorological drought index, which is calculated as observed precipitation divided by long-term mean precipitation (ideally at least 30 years). The long-term precipitation may be calculated for a day, a month, a season or a year, and it is considered to be 100%. This index is simple, transparent and easy to understand by general public, but the same percent of normal can have different impact at different locations, and what is normal can be observed differently in different places (Smakhtin and Hughes, 2004). Furthermore, PN cannot be used to compare drought across seasons because the distribution for seasons is different (Zargar et al., 2011).

The **Deciles** (Gibbs and Maher, 1967) method is also applied to characterize and monitor drought. Monthly precipitation totals from a long-term record (30-50 years) are ranked from highest to lowest to construct a cumulative frequency distribution. Then, the distribution is divided in 10 parts. The first decile is the precipitation amount not exceeded by the lowest 10% of the precipitation occurrences, the second decile is between the lowest 10% and 20% precipitation occurrences, and these deciles continue until the tenth decile, which is the largest precipitation amount in the studied period. The period considered can be daily, weekly, monthly, seasonal and annual. The use of different timescales allows this index to be used in meteorological, hydrological and agricultural drought conditions. Moreover, this index can be used in dry and wet conditions. Deciles are grouped into five classes (two deciles per class): "much below normal", deciles 1-2 (lowest 20%); "below normal", deciles 3-4 (20-40%); "near normal", deciles 5-6 (40-60%); "above normal", deciles 7-8 (60-80%); "much above normal", deciles 8-10 (80-100%) (Smakhtin and Hughes, 2004). Like other drought indices based solely on precipitation, this index does not consider other important variables in its calculation that may affect drought periods (Svoboda and Fuchs, 2016).

The **Effective Drought Index (EDI)** (Byun and Wilhite, 1999) is a meteorological drought index, which was developed to assess drought severity worldwide. EDI is an intensive measure that considers daily water accumulation with a weighting function for time passage, which can be used to detected droughts in the long and short-term (Byun and Kim, 2010). EDI is calculated as a function of daily effective precipitation considering its deviation from the mean for each day. EDI values are standardized, allowing drought severity at two or more locations to be compared with each other regardless of climatic differences between them (Smakhtin and Hughes, 2004). EDI allows to detect the beginning, end, and duration of drought periods. According to EDI values, drought can be classified into different ranges: extreme drought at EDI ≤ -2.0; severe drought at -2.0 < EDI ≤ -1.5; and moderate drought at -1.5 < EDI ≤ -1.0 (Byun and Kim, 2010).

The **Reconnaissance Drought Index (RDI)** (G. Tsakiris et al., 2007; Tsakiris and Vangelis, 2005) is a meteorological drought index, based on cumulative values of precipitation and potential ET. This index can be directly compared to SPI and can assess of drought severity. RDI is obtained as a ratio between accumulated precipitation and ET for a given time period, preferably periods of 3, 6, 9 and 12 months. For simplicity, the authors recommend the Thornthwaite formula to estimate potential ET. Two analytical forms of the index have been formulated, the normalised RDI and the standardised RDI. Positive values of standardised RDI indicate wet periods, while negative values indicate dry periods compared with the normal conditions of the area. RDI can be used for monitoring purposes and for short period drought forecasting. Tigkas et al. (2013) used RDI to detect possible climatic change of a geographical area.

The **Crop Moisture Index (CMI)** (Palmer, 1968) is an agricultural drought index, which was developed to monitor short-term changes in moisture conditions affecting crops. CMI considers the ET and the soil moisture recharge at the begging of the week and during the week. Thus, the index is computed with a weekly time step using PDSI parameters (mean temperature, total precipitation, and soil moisture conditions from the previous week). Concretely, CMI is computed as the difference between potential ET and soil moisture. CMI begins and ends near zero each growing season. This index is not appropriate for long-term droughts. CMI allows comparison between different climate regimes because it is a weighted index (Svoboda and Fuchs, 2016).

The **Palmer Hydrological Drought Index (PHDI)** (Palmer, 1965) is a hydrological drought index, which is used for long-term monitoring of hydrologic moisture conditions. PHDI is considered as an intermediate index in the PDSI computation, and it represents accumulations derived during an established wet or dry spell (Anderson et al., 2011). PHSI is computed using monthly precipitation, temperature data and local available water content of the soil. PHDI can be computed in the current time interval, while PDSI can be computed only when the drought event finished (G Tsakiris et al., 2007). The PHDI classification is the same as the PDSI classification shown in Table 8.

Most of these standard drought indices require spatially distributed observations of precipitation as a primary input, acquired either through rain gauge networks, radar estimates, satellite observations, or some combination thereof (Anderson et al., 2011). This combination is important because many parts of world present serious difficulties in obtaining dense and reliable data from meteorological stations and radar systems. However, dense series of RS images are able to monitor the land surface in real time with suitable temporal and spatial resolutions. In addition, authors such as Hao and Singh (2015) indicated that drought description from a multivariate perspective is necessary to alleviate the inadequacy of drought characterization from a single aspect.

3. Remote sensing for drought monitoring.

Earth observation satellites provide time series of multispectral images, which accurately describe the growth and development of the crop canopy. The information obtained through satellite images allows monitoring the vegetation dynamic thanks to its wide coverage and temporal frequency. Numerous works have analysed the drought through the information derived from satellite images with optical, thermal, and active and passive microwave sensors. Numerous reviews on these analyses can be found in specific papers and publications (AghaKouchak et al., 2015; Hazaymeh and K. Hassan, 2016; Niemeyer, 2008; Zargar et al., 2011). Many of the drought indices mentioned above have been estimated using the information obtained through satellite images, mostly through meteorological satellites equipped with microwave and thermal infrared sensors (Pierre et al., 2011; Sahoo et al., 2015; West et al., 2019). Unlike most classical methods to estimate drought, many RS methods are not precipitation driven, mainly because the estimation of meteorological drought presents the problem of low spatial resolution. In such cases, RS methods monitor vegetation stress or soil moisture status through diagnostic observations of key land surface states (Choi et al., 2013). Typically, these methods are based on Vegetation Indices (VIs), Land Surface Temperature (LST) and empirical methods using a certain combination of LST from thermal band data versus VIs from visible and near infrared data (Ghulam et al., 2007a). In these cases, agricultural drought is mainly analysed.

a. Remote sensing drought indices

VIs have been widely used to monitor drought. Spatially continuous VIs data can facilitate the monitoring of vegetation dynamics over large areas. VIs are linear combinations or some other transformation of the spectral data in different bands that can enhanced the sensitivity of reflected radiation of certain canopy agronomic variables (Neale et al., 1989). Vegetation lamina tissues strongly absorb incident radiances in blue, purple and red wavelengths and intensively reflect the near infrared spectrum (Ghulam et al., 2007b). Most VIs are obtained through differences, proportions or linear combinations between the red and near infrared spectral bands (Pinter et al., 2003). VIs are useful in the assessment of active photosynthesizing and transpiring foliage (Glenn et al., 2011, 2007). VIs can attenuate factors such as soil, lighting conditions, dry vegetation remains and the atmosphere, which could cause interference in the radiometric signal (Martín de Santa Olalla et al., 2005).

The **Normalized Difference Vegetation Index (NDVI)** (Rouse et al., 1973) is the most popular and widely used VI (Pettorelli et al., 2005). NDVI is defined as the normalized difference of the near infrared and red reflectances. West et al. (2019) indicated that many studies have employed the NDVI to analyse drought, underlining that more than 30% of the 300 agricultural drought related papers reviewed used the NDVI as key index. These studies have been developed using different sensors and different spatial scales throughout the world. NDVI alone may not be able to detect vegetation drought effectively because many factors, such as land cover change, fire, biomass harvesting, flooding, plant disease and pest infestation, can lead to an NDVI anomaly similar to that caused by drought (AghaKouchak et al., 2015; Heim, 2002). Based on NDVI, Kogan (1995a) developed the **Vegetation Condition Index (VCI)** by normalizing NDVI values to the maximum range of a specific area, with the main objective of monitoring drought over nonhomogeneous areas to detect the onset of drought and measure its intensity, duration and impact. For this purpose, numerous authors have employed the VCI using satellite images (Domenikiotis et al., 2004; Dutta et al., 2015; Han et al., 2020; Jiao et al., 2016; Khan et al., 2020; Kogan, 1997; Quiring and Ganesh, 2010). VCI can be employed to analyse the effects of weather on different environments (Zhang and Zhou, 2016). Authors as Kogan (1997) indicated that VCI improves with respect NDVI by showing the long-term weather condition rather than short-term weather. The **Standardized Vegetation Index (SVI)** (Peters et al., 2002) was developed to standardise, by time of year, the NDVI to increase drought monitoring techniques. SVI describes the probability of vegetation condition deviation from normal, based on calculation from weekly NDVI values. For that, SVI is estimated through the z-scores of NDVI distribution. The **Soil Adjusted Vegetation Index (SAVI)** (Huete, 1988) has also been used to drought monitoring. SAVI was developed to minimize soil brightness influences from VIs involving red and near infrared wavelengths. The **Normalised Difference Water Index (NDWI)** (Gao, 1996) is an index sensitive to changes in liquid water content in vegetation canopies. NDWI uses near infrared and shortwave infrared reflectances that are sensitive to changes in both canopy water content (which tends to absorb shortwave infrared radiation) and spongy mesophyll in vegetation (Anderson et al., 2010). NDWI is insensitive to the atmospheric conditions (Zhang and Zhou, 2016). Gu et al. (2007) showed a faster response of NDWI values to drought conditions than NDVI. The **Enhanced Vegetation Index (EVI)** (Huete et al., 2002) has also been used to analyse the canopy cover state under drought conditions. EVI was developed to minimize soil and atmospheric sensitivity observed in the NDVI by including the blue band for atmospheric correction. Ghulam et al. (2007b) developed the **Perpendicular Drought Index (PDI)** based on the spatial characteristics of moisture distribution in near–infrared-red reflectance space to reflect drought conditions. PDI is derived directly from the atmospherically corrected of the near infrared and red reflectances, and a perpendicular geometrical construction on the two bands' reflectance space. PDI performs well for bare soil surfaces, but not well for vegetated surfaces. Consequently, an improved drought monitoring method, the **Modified Perpendicular Drought Index (MPDI)**, was developed introducing the fraction of vegetation coverage, which takes into account both soil moisture and vegetation growth (Ghulam et al., 2007a). Besides, for non-flat topography with variable soil types and ecosystems MPDI outperforms PDI.

LST derived from thermal sensors has been employed single or in combination with different VIs to study the surface moisture conditions. LST is a good indicator of the energy balance at the Earth's surface because it is one of the key parameters in the physics of land-surface processes and water balance at local to global scales (Li et al., 2013; Wan et al., 2004). LST is also a biophysical factor sensitive to surface water stress (Jackson et al., 1981). LST shows increments in soil and canopy temperatures due to drought events. Moreover, high ET values show a decrease in the surface temperature of leaves and plants. For this reason, different ET algorithms have been developed to use LST derived from thermal satellite images (Khanal et al., 2017). Satellite-derived ET (explained in more detail below) had also been widely used in drought monitoring. ET-based drought indices can be very sensitive to flash drought, since ET is able to quantify abnormal rates of water use and loss (Anderson et al., 2013). The **Normalised Difference Temperature Index (NDTI)** (McVicar and Jupp, 2002, 1999) was developed to reflect soil moisture conditions through maps of the ratio of actual to potential ET. The effects of seasonal variations of LST are eliminates with NDTI (Zhang and Zhou, 2016). NDTI is computed through the inversion of a resistance energy balance model. This model requires meteorological data along with vegetation parameters obtained from satellite images (McVicar and Jupp, 1998). Like the rest of the indices based on temperature, NDTI has the advantage that it can monitor drought before plants decrease their chlorophyll content. The **Crop Water Stress Index (CWSI)** (Idso et al., 1981; Jackson et al., 1981) is based on potential and actual ET **and** has been widely used to detect plants drought. CWSI was calculated by Jackson et al. (1981) through measurements of canopy temperatures acquired by infrared thermometry, measurements of dry and wet bulb air temperatures, and estimation of net radiation. Moran et al. (1994) used CWSI combining VIs with composite surface temperature measurements on partial canopy covers without knowledge of foliage temperatures. CWSI has also been estimated through multi-source thermal imagery such as meteorological and Earth surface observation satellites, airborne and unmanned aerial systems, and hand-held radiometers (Ghulam et al., 2007a). Thus, Wu et al. (2019) showed an appropriate drought pattern based on CWSI through MODIS products. Other authors as Ciezkowski et al. (2019) found high correlation between CWSI estimated using Landsat 8 thermal images and meteorological tower data. Using the thermal channels, Kogan (1995b) developed the **Temperature Condition Index (TCI),** which was used to determine the vegetation stress related to temperature and the stress triggered by an excessive wetness. Table 9 shows the main optical and thermal RS-based drought indices analysed.

Usually, the development of drought produces a decrease in VIs, albedo and LST increase, and soil moisture decreases provided that other factors are stable. Combination of those parameters in a single measure may provide useful methods for quantitative detection of spatial and temporal distribution of drought (Ghulam et al., 2007b). Furthermore, a time lag between precipitations events and vegetation response is usual, according to regional rainfall patterns, soil type, land cover and vegetation type (Zhang and Jia, 2013). The use of reliable land cover maps is of particular importance in interpreting the monitoring results (Zhang and Zhou, 2016). Accordingly, there are diverse tools that offer easy access to soil data and information such as the Land Cover and Use Information System of Spain (SIOSE) at national level or the CORINE Land Cover (CLC) and the European Soil Data Centre (ESDAC) at European level, among other (Büttner et al., 2004; Panagos et al., 2012; Valcarcel et al., 2008).

Different RS-based drought indices have been combined into a single index, improving drought monitoring. Thus, the **Normalized Difference Drought Index (NDDI)** (Gu et al., 2007) combines information from NDVI and NDWI improving sensitivity for drought monitoring. Thus, NDDI combines information from visible, near infrared, and shortwave infrared bands. The **Vegetation Healthy Index (VHI)** (Kogan, 2001, 1995b) combines the VCI and the TCI, thereby combining the NDVI and temperature, to monitor the increase in canopy temperature that occurs when plants are stressed. Thus, VHI assumes that the relation between vegetation and temperature is negative (Almamalachy et al., 2020). Kogan (1995b) indicates that excessive soil wetness and/or long cloudiness may decrease VCI value, so this situation can be misinterpreted as a drought. In these cases, the TCI allows to distinguish drought periods. Water vapour has less effect on LST than on visible light reflectances, so the cloud cover produces a lower impact on TCI and then on VHI (Rojas et al., 2011). Usually, it is assumed that the contribution between VCI and TCI in VHI is the same because, in general, the contribution of moisture and temperature during a vegetation cycle is unknown (Almamalachy et al., 2020). Almamalachy et al. (2020) evaluated VHI to analyse the relationship with rainfall in Iraq and showed a good agreement between the Temperature Vegetation Dryness Index (TVDI) and precipitation data. Brema et al. (2019) monitored agricultural drought through VHI derived from Landsat 8 images and indicated that VHI can be used to monitor the onset of agricultural drought as early warning system. Similarly, the **Temperature Vegetation Dryness Index (TVDI)** (Sandholt et al., 2002) and the **Vegetation Temperature Condition Index (VTCI)** (Wang et al., 2001) combine LST and NDVI. These indices are based on the LST-NDVI scattering space technique to monitor drought (Hu et al., 2019), where LST is plotted as a function of NDVI by building a triangle space to represent the entire range of surface moisture contents from wet to dry and from bare soil to fully vegetated surface. Like VHI, these indices assume that the relation between vegetation and temperature is negative (Almamalachy et al., 2020). Unlike the TVDI that uses a constant minimum LST, VTCI uses various minimum LST for each NDVI, thereby producing better results than TVDI because the cold edges are not directly horizontal in most LST-NDVI triangle spaces (Hu et al., 2019). Almamalachy et al. (2020) has highlighted the uncertainty presented by TVDI, which considerers that air temperature is constant over the studied area. The same authors found a poor performance with TVDI in distinguishing between specific drought events over Iraq. Anderson et al. (2011, 2007a, 2007b) developed the **Evaporative Stress Index (ESI)**, which is defined as the standardized anomalies in a normalized ratio of the actual ET to the potential ET expected under non-moisture-limiting conditions. The index combines vegetation cover and LST to estimate ET, in order to obtain information on surface moisture status. ESI is developed using a two-source energy balance (Atmosphere-Land Exchange Inverse, ALEXI) approach which identifies the thermal state of the evaporating land surface under varying vegetation cover fraction, radiation load, and ambient meteorological conditions. Authors such as Anderson et al. (2011, 2007b) estimated potential ET through a modified Priestley-Taylor method (Priestley and Taylor, 1972), while others such as Anderson et al. (2013) improved their ESI estimates by incorporating a Penman-Monteith reference ET (Allen et al., 1998). Choi et al. (2013) found better results with ESI in estimating droughts under moderate conditions than under severe conditions at watershed scale. Otkin et al. (2013) demonstrated that ESI change anomalies may showed early warning in flash drought events on agricultural systems. Mu et al. (2013) developed the **Drought Severity Index (DSI)** using satellite-derived ET, potential ET, and NDVI information to monitor and detect drought conditions on a global scale. DSI provides monitoring of drought occurrence, severity, and duration with a spatial resolution of 1 km based on MODIS product. The method calculates satellite-derived ET through Penman-Monteith equation (Allen et al., 1998), and combines both

Penman-Monteith and Priestley-Taylor (Priestley and Taylor, 1972) methods to estimated potential ET. Zhang et al. (2019) showed good performance in monitoring agricultural droughts in space and time using DSI over China. However, these authors indicated that DSI was unable to determine the end of a drought. Table 10 shows the combined RS-based drought indices analysed.

Other indices have combined RS-based drought indices with data from different sources such as climate data or biophysical characteristics with the objective to improve drought estimations. The use of diverse drought indices obtained from different data sources allow a comprehensive evaluation of drought conditions better than the use of a single index (Hao and Singh, 2015; Hazaymeh and K. Hassan, 2016). The Uni**ted State Drought Monitor (USDM)** (Svoboda et al., 2002) was developed to monitor the magnitude, spatial extent and impacts drought in United States. The USDM was the first operational composite method used in the United States to analysed drought conditions (Svoboda and Fuchs, 2016). A single USDM map is generated weekly, which classifies drought severity into five categories based on intensity levels, from abnormally dry conditions to exceptional drought conditions. The composite index uses a variable number of indicators such as RS observations, climatological input, soil moisture and hydrological inputs, among other. Furthermore, the index is interpreted and refined from more than 350 experts observers around country (Hao and Singh, 2015). The USDM is widely employed by federal, state, and local government agencies and research communities in the United States (Hao and Singh, 2015). USDM is also used for national drought monitoring in Canada and Mexico (Heim and Brewer, 2012). Nevertheless, USDM cannot be applied at global scale because meteorological stations and expert knowledge are not always available (Jiao et al., 2019). Moreover, this composite index can inherited the weaknesses of the other indices it uses, such as the PDSI, according to the characteristics of the analysed area (Mu et al., 2013). Brown et al. (2008) developed the **Vegetation Drought Response Index (VegDRI)** to monitor drought-induced vegetation stress. VegDRI combines climate-based drought indices (SPI and PDSI), satellite-based VIs (NDVI) and biophysical characteristics of the environment (e.g. land cover, soil water capacity, irrigated agriculture, ecological regions, elevation). The final product is a 1 km spatial resolution VegDRI map that integrates coarse-resolution climate data with higher-resolution satellite-based vegetation observations to improve monitoring and characterization the intensity, spatial pattern, and local variability of vegetation drought (Brown et al., 2008). VegDRI has been used in the USDM composite index to improve the spatial resolution of drought monitoring since 2015 (West et al., 2019). Based on the concept of VegDRI, Wu et al. (2013) developed the **Integrated Surface Drought Index (ISDI)**. The model developed uses PDSI as the dependent variable along with different factors as independent variables, including the classical climate-based drought indices, RS VIs, and other biophysical variables. ISDI can be used to monitor precipitation anomalies, vegetation growth, and land surface water and thermal environmental properties.

Table 2. Optical and thermal remote sensing-based drought indices (ρ_{NIR}: near infrared reflectance; ρ_{RED}: red reflectance; ρ_{BLUE}: blue reflectance; ρ_{SWIR}: shortwave infrared reflectance; LST: land surface temperature).

RS drought indices	Equation	Notes	Reference
Normalized Difference Vegetation Index (NDVI)	$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}}$	NDVI values range from –1 to +1; dense vegetation has a high NDVI, while soil values are low but positive, and water is negative due to its strong absorption of near infrared (Glenn et al., 2008).	(Rouse et al., 1973)
Vegetation Condition Index (VCI)	$VCI = 100 * \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}\right)$	$NDVI_{min}$ is the minimum NDVI and $NDVI_{max}$ is the maximum NDVI, calculated during the selected period of time of a specific area. This index shows the difference between the current NDVI and historical NDVI time series minimum with respect to the NDVI dynamic range. The VCI varies from 0 for extremely unfavorable conditions, to 100 for optimal conditions.	(Kogan, 1995a)
Standardized Vegetation Index (SVI)	$SVI = \frac{NDVI_{ijk} - \overline{NDVI}_{ij}}{\sigma_{ij}}$	SVI is computed for each pixel (i), week (j), and year (k). The terms $\overline{NDVI}_{ij}$ and σ_{ij} denote the mean and standard deviation of the pixel (i) over k = 1,…, n years.	(Peters et al., 2002)
Soil Adjusted Vegetation Index (SAVI)	$SAVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED} + L} 1 + L$	L is a correction factor usually set at 0.5 to account for soil background effects.	(Huete, 1988)
Normalised Difference Water Index (NDWI)	$NDWI = \frac{\rho_{NIR} - \rho_{SWIR}}{\rho_{NIR} + \rho_{SWIR}}$		(Gao, 1996)
Enhanced Vegetation Index (EVI)	$EVI = G \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + C_1 \times \rho_{RED} - C_2 \times \rho_{BLUE} + L}$	ρ_{BLUE} corrects for aerosol influences in the red band, C_1 and C_2 are the coefficients of the aerosol resistance term, G is a gain factor and L is a canopy background adjustment. The coefficients adopted in the EVI algorithm are, L = 1, $C_1 = 6$, $C_2 = 7.5$, and G = 2.5.	(Huete et al., 2002)
Perpendicular Drought Index (PDI)	$PDI = \frac{1}{\sqrt{M^2 + 1}} (\rho_{RED} + M\rho_{NIR})$	M is the slope of the soil line.	(Ghulam et al., 2007b)
Modified Perpendicular Drought Index (MPDI)	$MPDI = \frac{\rho_{RED} + M\rho_{NIR} - f_v(\rho_{v,RED} + M\rho_{v,NIR})}{(1 - f_v)\sqrt{M^2 + 1}}$	f_c is the fractional cover vegetation. $\rho_{v,RED}$ and, $\rho_{v,NIR}$ are vegetation reflectances in the red and near infrared bands, respectively.	(Ghulam et al., 2007a)
Temperature Condition Index (TCI)	$TCI = 100 * \left(\frac{LST_{max} - LST}{LST_{max} - LST_{min}}\right)$	LST_{min} is the minimum LST and LST_{max} is the maximum LST, calculated during the selected period of time of a specific area. LST shows low-to-high temperature in term of range. High values of TCI indicate extreme drought condition and vice versa.	(Kogan, 1995b)
Normalised Difference Temperature Index (NDTI)	$NDTI = \frac{LST_{\infty} - LST}{LST_{\infty} - LST_0}$	LST_{∞} and LST_0 are the modelled LST of the infinite and zero surface resistance, respectively, which are the upper (extremely dry state) and lower (extremely wet state) boundary conditions for the LST at specific meteorological conditions and surface resistances.	(McVicar and Jupp, 2002, 1999)
Crop Water Stress Index (CWSI)	$CWSI = 1 - \frac{AET}{PET}$	AET is the actual evapotranspiration and PET is de potential evapotranspiration. CWSI values range from 0 (no stress) to +1 (maximum stress).	(Idso et al., 1981; Jackson et al., 1981)

Table 1. Combined remote sensing- based drought indices (NDVI: normalizes difference vegetation index; NDWI: normalised difference water index; LST: land surface temperature).

RS drought indices	Equation	Notes	Reference
Normalized Difference Drought Index (NDDI)	$NDDI = \frac{NDVI - NDWI}{NDVI + NDWI}$		(Gu et al., 2007)
Vegetation Healthy Index (VHI)	$VHI = a(VCI) + b(TCI)$	*a* and *b* are coefficients quantifying a share of VCI (Vegetation Condition Index) and TCI (Temperature Condition Index) contribution in the combined condition.	(Kogan, 2001, 1995b)
Temperature Vegetation Dryness Index (TVDI)	$TVDI = \frac{LST - LST_{min}}{a + bNDVI - LST_{min}}$	LST is the observed surface temperature at the given pixel, LST_{min} is the minimum LST in the concept of LST-NDVI triangle space, and *a* and *b* are parameters defining the dry edge modelled as a linear fit to data ($LST_{max} = a + b$ NDVI), where LST_{max} is the maximum LST observation for a given NDVI. TVDI presents values between 1 for dry conditions and 0 for wet conditions.	(Sandholt et al., 2002)
Vegetation Temperature Condition Index (VTCI)	$VTCI = \frac{LST_{NDVI_{i,max}} - LST_{NDVI_i}}{LST_{NDVI_{i,max}} - LST_{NDVI_{i,min}}}$ $LST_{NDVI_{i,max}} = a + bNDVI_i$ $LST_{NDVI_{i,min}} = a' + b'NDVI_i$	Some pixels have similar NDVI values yet different LST. Then, a maximum LST and a minimum LST is available for each NDVI value in theory. The maximum LSTs vary along with NDVIs and can be linearly regressed as $LST_{NDVIi,max}$. The regression line is called the warm or dry edge of the triangle, while the regression line between the minimum LST and NDVI ($LST_{NDVIi,min}$) is called the cold or wet edge. The denominator is computed as the difference between the maximum and minimum LSTs for the specified $NDVI_i$, while the numerator is computed as the difference between the maximum and current pixel LSTs (LST_{NDVIi}). a, b, a′, and b′ are the coefficients for the linear regression. VTCI can only be used in warm seasons (late spring and summer periods) when negative correlations between LST and NDVI are observed. VTCI can be divided into five drought levels: $0.0 < VTCI \leq 0.2$ (severely dry); $0.2 < VTCI \leq 0.4$ (dry); $0.4 < VTCI \leq 0.6$ (water balanced); $0.6 < VTCI \leq 0.8$ (wet); and $0.8 < VTCI \leq 1.0$ (very wet).	(Wang et al., 2001)
Evaporative Stress Index (ESI)	$ESI(w,y) = \frac{V(w,y) - \frac{1}{n_y}\sum V(w,y)}{\sigma}$	V (*w*, *y*) is the composite ET fraction (ratio of the actual evapotranspiration to the potential evapotranspiration) for week *w* and year *y* at a given grid point, the second term is the mean ET fraction for week *w* averaged over all years (n_y = number of years), and σ is the standard deviation. The values obtained are normalized between values from 0 at the dry conditions to ≈ 1 at the wet conditions.	(Anderson et al., 2011, 2007a, 2007b)
Drought Severity Index (DSI)	$Ratio = \frac{ET}{PET}$; $Z_{Ratio} = \frac{Ratio - \overline{Ratio}}{\sigma_{Ratio}}$ $Z_{NDVI} = \frac{NDVI - \overline{NDVI}}{\sigma_{NDVI}}$ $Z = Z_{Ratio} + Z_{NDVI}$; $DSI = \frac{Z - \bar{Z}}{\sigma_Z}$;	ET is the satellite-derived evapotranspiration, PET is the potential evapotranspiration, Z_{Ratio} is the standardized Ratio, σ_{Ratio} is the standard deviation of Ratio, $\overline{Ratio}$ is the Ratio average, Z_{NDVI} is the standardized NDVI, σ_{NDVI} is the standard deviation of NDVI, $\overline{NDVI}$ is the NDVI average. DSI is calculated as the standardized Z value. DSI is a dimensionless index ranging theoretically from unlimited negative values (drier than normal) to unlimited positive values (wetter than normal).	(Mu et al., 2013)

4. Remote sensing-based estimates of evapotranspiration.

In drought analysis, other approaches have considered water accounting. Water accounting is a method of organising and presenting information relating to the physical volumes of water in the environment and economy as well as the economic aspects of water supply and use (Vardon et al., 2007). The methodology can be based on a water balance approach where, based on conservation of mass, the sum of inflows must equal the sum of outflows plus any change in storage (Molden and Sakthivadivel, 1999). The crop evapotranspiration (ET) is the main component in a soil water balance. ET describes the loss of water from the Earth's surface to the atmosphere by the combined processes of evaporation (E) from the open water bodies, bare soil and plant surfaces, etc. and transpiration (T) from vegetation or any other moisture-containing living surface (Li et al., 2009). ET can be estimated through traditional approaches based on field methods (eddy covariance techniques, weighing lysimeters, energy balance bowen ratio, surface renewal, scintillometry, sap flow, etc.), which are mainly based on a variety of complex models. Furthermore, these approaches cannot be directly extended to large-scale ET due to natural heterogeneity of the land surface and complexity of hydrologic processes and due to the need for a variety of surface measurements and land surface parameters (Liou and Kar, 2014). Over last decade, ET estimation has been improved through RS techniques, increasing the spatial extent of the measurements from a field scale to regional and global scales.

According to Glenn et al. (2007), there are mainly two methods to estimate ET from RS data: empirical or statistical relationship that project ET measured or estimated on the ground to larger scales, principally through RS VIs; and physical models that are based on solving the surface energy balance (SEB) equation through RS estimates of LST and other terms in the SEB, where the ET is estimated as the residual term of the SEB equation (Calera et al., 2017; Gonzalez-Dugo et al., 2009). In addition, these methods are usually complemented, validate and/or calibrate with micrometeorological flux tower measurements (Rana and Katerji, 2000) and micrometeorological stations in agricultural and natural ecosystems.

Usually, the estimation of ET based on RS data is based on the big leaf area model and further developments of the Penman-Monteith equation (Equation 14). This approach allows to determined ET through the SEB and the resistances approach for describing the transport of water vapour, distinguishing between bulk surface and aerodynamic resistances (Monteith and Unsworth, 2013).

$$\lambda ET = \frac{\Delta(R_n - G) + \rho_a c_p \frac{(e_s - e_a)}{r_a}}{\Delta + \gamma\left(1 + \frac{r_s}{r_a}\right)} \qquad (1)$$

where λET is the latent heat flux that representing evapotranspiration rate, R_n is the net radiation, G is the soil heat flux, (e_s - e_a) represents the vapour pressure deficit of the air, ρ_a is the mean air density at constant pressure, c_p is the specific heat of the air, Δ represents the slope of the saturation vapour pressure temperature relationship, γ is the psychrometric constant (ratio of the specific heat of the air to the latent heat of water vapour), and r_s and r_a are the (bulk) surface and aerodynamic resistances. r_s is the resistance to vapour flow from the soil and transpiring vegetation surfaces in the canopy, and it is related to soil moisture content and soil resistance to water transport (for E from the soil), and plant Leaf Area Index (LAI) and stomatal resistances (for T from the canopy).

r_a is the resistance to vapour flow from the canopy into the air above the canopy, and it is related to the height and architecture of the canopy and the wind speed over the canopy (Glenn et al., 2007).

The direct calculation of the Penman-Monteith equation needs to know determinates characteristics of the crops analysed, such as hemispherical surface albedo, LAI and height, as well as meteorological conditions and soil water status. Numerous works have estimated the main canopy parameters, such as surface albedo and LAI, through visible and near infrared observations. These works have employed empirical relationships with different VIs or physically-based methods, such as radiative transfer models (Calera et al., 2017; Glenn et al., 2007).

Some parameters of the equation for a particular crop or vegetation type are usually unknown. So, idealized values for a well-watered hypothetical grass surface crop are been used to calculate reference ET (ET_o) for a given set of local meteorological conditions. The FAO-56 manual has defined a standard reference surface for calculating ET_o as a hypothetical reference crop with a crop height of 0.12 m, a fixed surface resistance of 70 s m^{-1} and an albedo of 0.23 (Anderson and French, 2019). FAO-56 allows to estimate ET through two calculation approaches based on the concept of crop coefficient: the single and the dual crop coefficient approach. In the first case, ET is estimated as a product of the evaporative power of the atmosphere, ET_o, and the crop coefficient, K_c. In the second case, K_c, in turn, is split into two factors describing separately the differences in evaporation and transpiration between the crop and reference surface: the soil evaporation coefficient, K_e, and the basal crop coefficient or the transpiration coefficient, K_{cb}. The effects of soil water stress are described by multiplying the K_c or K_{cb}, as appropriate, by the water stress coefficient, K_s, which is estimated through the water balance in the root soil layer.

VIs have been used to estimate crop coefficients through satellite images for individual and mixed crops, as well as in natural ecosystems (Glenn et al., 2011). The use of the crop coefficients values obtained through satellite images allows these coefficients to be adapted to the real growth conditions of the vegetation and its temporal dynamics. Thus, numerous K_c-VI and K_{cb}-VI relationships have been developed (Bausch and Neale, 1987; Belmonte et al., 2005; Campos et al., 2017, 2010; Duchemin et al., 2006; González-Dugo and Mateos, 2008; Hunsaker et al., 2005; Johnson and Trout, 2012; Mateos et al., 2013). These relationships argue that there are strong and direct correlations between the crop coefficients and different biophysical parameters of canopy cover (such as LAI, fractional cover vegetation (f_c), fraction of absorbed photosynthetically active radiation by vegetation (fAPAR) or biomass, among others) as well as between these parameters with the VIs (Calera et al., 2017; Campos et al., 2018; Choudhury et al., 1994; Glenn et al., 2011, 2007; Neale et al., 1989). The relationships between the crop coefficients and the VIs consider that stomata closure caused by soil water deficit or water vapour deficit have a relatively small effect on the reduction of ET. For this reason, this stress should be considered and estimated through soil water balance (K_s) or energy balance methods, among others. On the other hand, VIs show a more pronounced stress that induces a reduction or less expansion of canopy cover. Thus, this effect is taken into account by the relationships between the crop coefficients and the VIs (Mateos et al., 2013).

The SEB describes the partitioning of natural radiation absorbed at Earth's surface into physical land surface processes (Karimi and Bastiaanssen, 2015). SEB methods calculate ET as a residual of the surface energy equation.

$$LE = R_n - G - H \quad (2)$$

where LE is the latent heat flux, R_n is the net radiation flux, G is the soil heat flux, and H is the sensible heat flux (all in W m^{-2}). ET is one of the key processes of energy balance because latent heat (energy) is needed to trigger evaporation. LE is the equivalent energy amount (W m^{-2}) of the ET flux (kg $m^{-2}s^{-1}$ or mm day^{-1}). Thus, LE is converted to ET (mm day^{-1}) by dividing it by the latent of vaporization (λ_v,~2.45 MJ kg^{-1}) and an appropriate time constant. The R_n component is the net radiation absorbed at the land surface, which is subtracted from shortwave and longwave radiation exchanges. G is a function related to the temperature difference between the land surface and the top soil, and G is positive when the soil is warming and negative when the soil is cooling. H is a similar function of the temperature difference between the canopy surface and the lower part of the atmosphere, representing the rate of heat loss to the air by convection and conduction. In SEB models, the main RS parameters are the bi-hemispherical surface reflectance, which determines R_n, and the LST, derived from thermal band imagery, and used to compute H. SEB models differ from each other in how the difference between LST and the aerodynamic temperature is addressed, and this difference is needed to compute H. LST and the aerodynamic temperature are highly related but this relationship is very complex, since LST depends on the temperature of the different elements that occupy the radiometer view, while aerodynamic temperature depends on surface aerodynamic roughness, wind speed and the coupling of soil and canopy elements to the atmosphere (Calera et al., 2017).

In recent decades, numerous satellite-based SEB models have been developed. Models as Surface Energy Balance Algorithm for Land (SEBAL) (Bastiaanssen et al., 1998a, 1998b), Mapping Evapotranspiration at high Resolution using Internalized Calibration (METRIC) (Allen et al., 2007a, 2007b), Surface Energy Balance Index (SEBI) (Menenti and Choudhury, 1993), Simplified Surface Energy Balance Index (S-SEBI) (Roerink et al., 2000), Surface Energy Balance System (SEBS) (Su, 2002), among others, are frequently single-source SEB models based on the difference between wet and dry limits to derive pixel by pixel ET and ET from the relative evaporative fraction combining surface parameters obtained from RS data and ground-based variables measured at local or regional scale (Gowda et al., 2008). These models differ mainly in how to estimate the sensible heat flux. On the other hand, there are two-source SEB models as Two-Source Energy Balance (TSEB) (Kustas et al., 2004), and Simplified Two Source-Energy Balance model (STSEB) (Sánchez et al., 2008), among others. Two-source models separately model the heat and water exchange and interaction between soil and atmosphere and between vegetation and atmosphere (Li et al., 2009). Thus, these models divided the directional radiometric LST into their two main components, the temperature of vegetation and soil.

Among all these SEB models, we highlight the SEBAL and METRIC models for their relevance. SEBAL was developed to estimate the energy distribution at the regional scale using minimum ground data. R_n is computed from satellite-measured broadband surface albedo, VI and LST, along with ground measurements of global radiation. G is estimated as a fraction of R_n, LST and VI. H is estimated from LST, surface roughness, and wind speed. A vital component is the solution of extreme values for H, prior to its pixel-to-pixel computations. The extreme values agree with H = 0 for water surfaces and H = Rn- G for desert surfaces (Zwart and Bastiaanssen, 2007). Finally, LE is calculated as the residual of SEB. An advantage of SEBAL model is that the near-surface temperature gradients are indexed to the radiometric surface temperature, eliminating the need for absolutely accurate surface temperature and the need for air-temperature measurements for estimating H at the surface (Allen et al., 2007b). Based on SEBAL model, in METRIC, R_n is calculated from the satellite measured narrow-band reflectance and LST; G is estimated from R_n, LST, and VIs; and H is estimated from surface temperature ranges, surface roughness, and wind speed. METRIC differs from SEBAL principally in the H calibration for each specific satellite image. The model performs an internal calibration on H to absorb all intermediate estimation errors and biases. For this purpose, the internal calibration at two extreme conditions, dry and wet, is performed using local weather data. This calibration is done for each image using an alfalfa-based reference ET computed from hourly weather data. The autocalibration along with the use of temperature gradient delete the need for atmospheric correction of surface temperatures and reflectance (albedo) measurements using radiative transfer models.

ET estimation through RS methods also includes deterministic models based on complex models such as Soil-Vegetation-Atmosphere Transfer models (SVAT), which compute the different components of energy balance. These models describe the exchanges between soil plant and atmosphere according to the physical processes occurring in each compartment with generally a fine time step (second, hour) (Courault et al., 2005). Through these models, the vegetation layers have been represented through the big leaf approach with one surface resistance and also through multi-layer models, where radiative and energy budgets are computed for each layer (Olioso et al., 1999). In these models, RS parameters are introduced in different ways: forcing the model input directly with the RS measurements; correcting the course of state variables in the model at each time RS data are available; re-initializing or changing unknown parameters using data sets acquired over temporal windows of several days/weeks (Courault et al., 2005). In general, the main RS parameters introduced in these models are f_c, LAI, albedo, and emissivity. Roughness and stomatal resistance are more difficult to obtain, and usually they are derived from knowledge of the canopy type and the phenological stage, relationships with VIs data or from LIDAR data, among others.

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