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REVIEW

Evaluating the utility of various drought indices to monitor meteorological drought in Tropical Dry Forests

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Abstract

Even though existing remote-sensing-based drought indices are widely used in many different types of ecosystems, their utility has not been widely assessed in tropical dry forests (TDFs). The aim of this study is to evaluate the performance of three remote-sensing-based drought indices, the Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and Vegetation Health Index (VHI), for meteorological drought monitoring in TDFs using the moderate-resolution imaging spectroradiometer (MODIS) products. The correlation between the VCI, TCI, and VHI and multiple time scales of the Standardized Precipitation Index (SPI) (1, 3, 6, 9, 12, 15, 18, 21, 24 months) for each month (January to December) and each season (dry season, dry-to-wet season, wet season and wet-to-dry season) were conducted using the Pearson correlation analysis. We also correlated year-to-year changes of satellite-based drought indices with the changes of the in situ annual SPI (A_SPI) which provides annual information on the mean meteorological drought. The analysis reveals that the ability of these remote-sensing-based drought indices for meteorological drought monitoring varies with timing, and the TCI outperforms the VCI and VHI in terms of seasonal and annual scale. These remote-sensing indices performed well in monitoring meteorological drought in the dry season, poorly in the in the dry-to-wet season, and moderately in the wet season. The TCI performed best in monitoring meteorological drought in the wet-to-dry period, followed by VHI, whereas the VCI performed worst. All of these remote-sensing-based drought indices failed to detect drought in May during the green-up period and in September, October, and November when the water content in the root regions was abundant. Our results indicate that the evapotranspiration of TDFs is more sensitive than canopy greenness to detect meteorological drought. Results from this study increase the ability to provide real-time drought monitoring and early warnings of drought in TDFs.

Keywords Meteorological drought · SPI · VCI · TCI · VHI · TDFs

Introduction

Tropical dry forests (TDFs) are defined as a vegetation type where more than half of its species are drought deciduous, there are 4 to 6 months with low or no precipitation (< 100 mm per month), a mean annual temperature of 25 °C, and total annual precipitation between 700 and 2000 mm (Sanchez-Azofeifa et al. 2005). TDFs comprise about 42% of all tropical forests worldwide (Murphy and Lugo 1986). TDFs are habitat with abundant plant and animal species, many of them endemic (Du et al. 2013). In Latin America, 60% of all TDFs have been replaced by other land cover types such as agriculture and pasture for cattle ranching (Portillo-Quintero and Sanchez-Azofeifa 2010). This ecosystem is estimated to store close to 22 Pg of carbon (Du et al. 2013).

As TDFs undergo tremendous human disturbances (Rodriguez et al. 2017), ongoing climate change is affecting the provision of ecosystem services (Kalacska et al. 2004). Much of these changes are via droughts (Zhang et al. 2013). In general, drought is defined as a precipitation deficit that occurs over a period of time and that impacts both water resources and ecosystem services (Du et al. 2013). Droughts can

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introduce great damages to tropical forests in terms of their biophysical properties and ecosystem services (Portillo-Quintero et al. 2015).

Increases in the frequency, duration, and severity of droughts can change the structure, composition, and function of tropical forests, which in turn contribute to declines in forest productivity (Choat et al. 2012; Engelbrecht et al. 2007; Zhang et al. 2013). Droughts can also lead to an increase in tree mortality rates of tropical forests and an impact on the hydrological dynamics in the neotropics (Allen et al. 2010; Phillips et al. 2009, 2010; Portillo-Quintero et al. 2015). Allen et al. (2010) reviewed the potential of droughts to amplify tree mortality around the world and found any forest type and any climate zone is vulnerable to climate change in terms of tree mortality. Phillips et al. (2009) found that the Amazon forests were vulnerable to growing moisture deficit, with the potential for losing large amounts of carbon (1.2 to 1.6 petagrams) in response to drought. Phillips et al. (2010) indicated that mortality rates of tropical forests tended to increase disproportionately when the moisture stress is at higher levels, and trees in Borneo are more vulnerable than those in the Amazon. Portillo-Quintero et al. (2015) indicated that droughts are potential threats to water resources in the neotropics where a large fraction of population (approximately 90 million) lived.

Meteorological drought occurs mainly when rainfall is significantly lower than the average precipitation for a sustained period of time (Olukayode Oladipo 1985). High temperatures and associated increases on potential evapotranspiration are important drivers associated to meteorological droughts (Williams et al. 2013). Many drought indices have been developed to characterize meteorological drought in terms of its severity, magnitude, duration, and spatial extent. Popular drought indices, such as the Palmer Drought Severity Index (PDSI, Palmer 1965) and the Standardized Precipitation Index (SPI, McKee et al. 1993), are derived from data coming from in situ weather stations. The PDSI considers prior precipitation, soil moisture, runoff, and evaporation demand; however, its fixed time scale (between 9 and 12 months) precludes its use for identifying drought lasting shorter time periods (e.g., less than 9 months). The PDSI has been widely applied to determine the areal extent and severity of the drought in the northeastern United States over the years (Alley 1984; Palmer 1965). The SPI is a precipitation-based drought index, which considers the essential character of the drought as the deficiency of usable water, including the soil moisture, rivers and streams, groundwater, and reservoirs (McKee et al. 1993). The SPI can be calculated for flexible scales depending on the purpose of the study. Its applications have encompassed a wide range of ecosystems at varying scales (Guttman 1999; McKee et al. 1993; Patel et al. 2007).

Uncertainties associated with the in situ meteorological indices depend on the density and distribution of the meteorological stations (Brown et al. 2008). In a remote area where the meteorological stations are limited, the use of the in situ indices for drought monitoring faces a great risk of low accuracy (Rhee and Carbone 2010). Remote sensing, which can characterize meteorological and terrestrial biophysical attributes from a regional to global coverage, has gained much attention over the past several decades in drought monitoring. Many remote-sensing-based drought indices have been proposed as substitutes to in situ drought indices (Kogan 1995; Ji and Peters 2003; Quiring and Ganesh 2010; Rhee and Carbone 2010; Zhang et al. 2013; Nichol and Abbas 2015; Zhang et al. 2017). Their abilities vary with climate zone, ecosystem, and land cover (Zhang et al. 2017).

Among remote-sensing vegetation indices, the Normalized Difference Vegetation Index (NDVI) and the Vegetation Condition Index (VCI, scaled inter-annual NDVI), have been extensively used for drought monitoring (Kogan 1995, 1997; Quiring and Ganesh 2010). Bhuiyan et al. (2006) carried out a detail analysis of spatial and temporal drought dynamics during monsoon and non-monsoon seasons for the years 1984 to 2003 in Rajasthan (India) and found the correlation between the VCI and SPI increased in the monsoon season because the growth of vegetation was largely dependent on rainfall, while it was partly controlled by irrigation in the non-monsoon season. Dutta et al. (2015) conducted the correlation analysis of NDVI and VCI derived from NOAA-AVHRR data and precipitation in the northwest of Iran between 1997 and 2001 and found that good correlations were obtained between average NDVI and VCI and average 3-month precipitation, indicating that NOAA-AVHRR-derived NDVI can reflect the precipitation fluctuation in the study area. Quiring and Ganesh (2010) examined the relationship between the VCI, and meteorological drought indices during Texas' growing seasons. Results suggested that the VCI responded to relative prolonged moisture stress instead of short-term precipitation deficiency. The authors also reported that the correlations between the VCI and meteorological indices varied significantly across the State, being the correlation between the SPI and PSDI weaker in east Texas than west Texas due to higher permeable soils in the east.

The Temperature Condition Index (TCI, scaled inter-annual LST) is another index that has been proposed for drought monitoring due to its potential ability to quantify evapotranspiration (Kogan 1995). Seiler et al. (1998) used the TCI and VCI to assess drought conditions in Argentina and found a close relationship with precipitation patterns. Karnieli et al. (2006) compared satellite-based drought indices, such as the TCI and VCI, with the PDSI across the desert regions of Mongolia, and concluded that there was little agreement among those indices. The vegetation heath index (VHI), a combination of the VCI and TCI (Kogan 2002), was an early warning tool for drought. Rhee and Carbone (2010) tested various remote-sensing-based drought indices in the arid regions of Arizona and New Mexico and humid regions of

North Carolina and South Carolina and found that the VHI performed better than the VCI and TCI in both arid and humid regions when tested against in situ meteorological drought indices. Shamsipour et al. (2011) conducted correlation analysis of various remote-sensing indices and meteorological drought indices in semi-arid central plains of Iran confined to the spring season from 1998 to 2004 and found that VCI better correlated to meteorological drought indices than TCI, and VHI is not a reliable measure of drought condition in this region. Amalo and Hidayat (2017) compared the remote-sensing-based drought indices in East Java and found that TCI was sensitive to drought in dry season or months; VCI is proved to detect drought more sensitive in wet season than TCI and VHI; VHI provided better comprehension about drought occurrence. Zhang et al. (2017) compared various satellite-based drought indices to monitor drought events in the Continental United States. They found that VHI performed better than the VCI and TCI in most climate regions.

Despite the fact that there is a considerable amount of scientific literature associated to the development, testing, and evaluation of drought indexes across many different types of ecosystems, little has been done in tropical dry forest ecosystems. As such, the objective of this study is to evaluate the performance of three remote-sensing-based drought indices to monitoring meteorological drought conditions in a TDF at the local scale. We focus this study on the monthly, seasonal, and yearly correlations between remote-sensing-based drought indices and SPIs. This evaluation we did uses the MODIS NDVI and LST products from 2000 to 2017, as well as local precipitation data from 1979 to 2017.

Methods

Study area

This study was conducted at the Santa Rosa National Park Environmental Monitoring Super Site (SRNP-EMSS), Northwest Costa Rica (Fig. 1). The total study area covers 109 km^2 with an average slope of 7%. For over 200 years, the region was part of a cattle ranch until it became a National Park in the early 1970s (Castillo et al. 2012; Janzen 2000; Cao and Sanchez-Azofeifa 2017). Currently, the SNRP-EMSS is a mosaic of diverse vegetation types dominated by secondary tropical dry forests with three stages of ecological succession: early, intermediate, and late (Kalacska et al. 2004; Cao and Sanchez-Azofeifa 2017; Li et al. 2017). The early stage of regeneration is composed of shrubs, small trees with grasses, and bare soil in open areas. The intermediate stage is composed of fast growing deciduous species, Lianas, and shade-tolerant species. The late succession is consisted of dominant evergreen species and regeneration of tolerant shade species (Kalacska et al. 2004).

This area receives between 915 and 2558 mm of annual precipitation, and mean annual temperature is stable at 26.6 °C (Sanchez-Azofeifa et al. 2005). The SNRP-EMSS experiences a 3-month dry season (January to March) when the precipitation is extremely scarce (Fig. 2), and the majority of the deciduous vegetation loses its leaves (Fig. 3). April and May are considered as a transition from dry to wet season (dry-to-wet season) because precipitation starts to grow in April and sharply increases in May. The wet season is usually from June to October. Then, SNRP-EMSS goes through a transitional season from November to December (wet-to-dry season) when the rainfall decreases significantly. The dominant factor that affects the phenology of secondary TDFs with various successions at this TDF site is water availability (Sanchez-Azofeifa et al. 2005).

Data preprocessing

This study employed a set of Terra Moderate Resolution Imaging Spectroradiometer (MODIS) products between March 2000 and March 2017. Specifically, the 16-day MODIS NDVI product at 250 m resolution (MOD13Q1, collection v006) and the 8-day MODIS LST product at 1000 m resolution (MOD11A12, collection v006) were obtained at the "Reverb Echo" portal (http://reverb.echo.nasa.gov/reverb/). Both products were re-projected to WGS 1984 UTM Zone 16 North. The Land Surface Temperature (LST) product was then resampled to 250 m so that it had the same resolution with the NDVI product. We converted the 16-day NDVI and 8-day LST products to monthly data by considering the number of days belonging to each month for each phase of image products (Rhee and Carbone 2010). Quality flags in both products were used to extract the ideal quality pixels for reliable analysis. Specifically, the pixels where the values in the quality flags layer of MODIS products equal to zero were selected as ideal quality pixels.

We also collected daily precipitation data between June 1979 and March 2017 in a meteorological station (10°50.408′ N, 85°37.055′ W) within the SNRP-EMSS. The daily precipitation data were also aggregated to monthly data.

Remote-sensing drought indices

The Normalized Difference Vegetation Index (NDVI) is a good indicator of the chlorophyll content and vegetative cover and indicates the capacity of the photosynthesis of the canopy (Karnieli et al. 2010); in addition, the LST is a proxy for assessing the evapotranspiration of vegetation canopy and soil moisture (Karnieli et al. 2010). The VCI and the TCI, calculated on monthly NDVI and LST data using the eq. (1) and (2), reflect relative greenness and temperature of plants (Kogan 1995; Kogan 1997). Specifically, VCI and TCI as the normalizations of NDVI and LST emphasize the relative

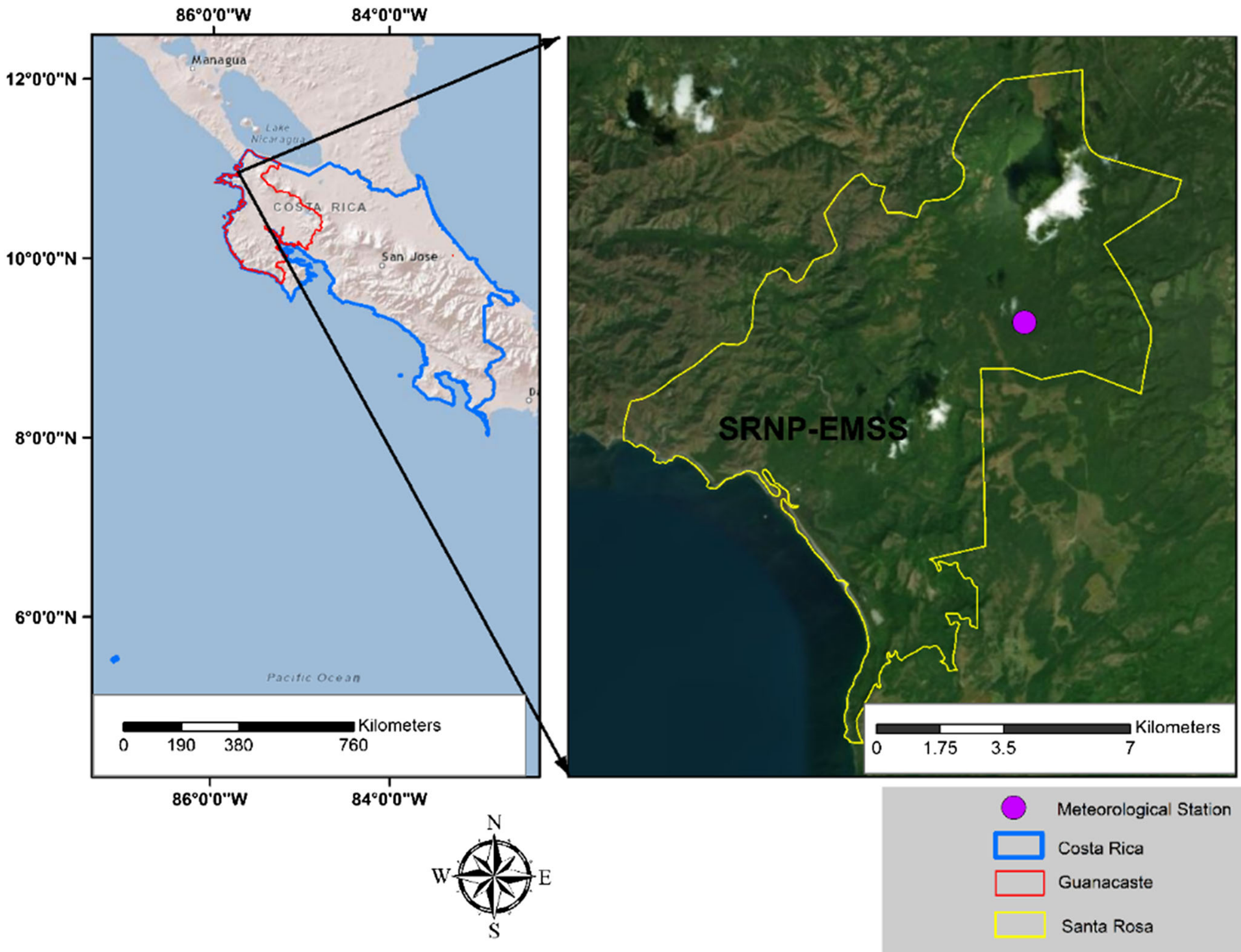


Fig. 1 Study area: Santa Rosa National Park Environmental Monitoring Super Site (SRNP-EMSS), and the location of the source of meteorological information used in this study

changes in the local NDVI and LST through time while reducing the influences of local climate conditions and ecosystems. The VHI, indicating vegetation health, is an additional combination of the VCI and TCI with the same weight assuming an even contribution from two elements (eq. (3)), indicating the health condition of the vegetation.

$$VCI_{ij} = \left(NDVI_{ij} - NDVI_{j\ min}\right) / \left(NDVI_{j\ max} - NDVI_{j\ min}\right) *100 \tag{1}$$

$$TCI_{ij} = \left(LST_{j\ max} - LST_{j}\right) / \left(LST_{j\ max} - LST_{j\ min}\right) *10 \tag{2}$$

$$VHI_{ij} = 0.5*\left(VCI_{ij} + TCI_{ij}\right) \tag{3}$$

where i describes the ith year and j represents the jth month.

These indices could indirectly reflect the meteorological drought conditions based on vegetation stress related to leaf vigor, evapotranspiration in the leaf, or surface temperature in the leaf. The values of these drought indices range from 0 to 100, the low values (close to 0) show the stressed vegetation condition, middle values show fair conditions (close to 50), and high values (close to 100) indicate the optical conditions (Kogan 1995; Kogan 1997). Specifically, the drought grades based on three drought indices can be defined as following (Table 1):

In situ meteorological drought index (SPI)

The Standardized Precipitation Index (SPI) is a ground station-based meteorological drought index (McKee et al. 1993). As a standardized index, the SPI is comparable with each other both temporally and spatially. Higher values of the SPI indicate humid conditions, and lower SPI values represent drought. McKee et al. (1993) proposed a classification for the SPI as follows: extremely wet (SPI > 2.0), very wet (1.5 < SPI < 1.99), moderately wet (1.0 < SPI < 1.49), near normal (− 0.99 < SPI < 0.99), moderately dry (− 1.49 < SPI < − 1.0), severely dry (− 1.99 < SPI < − 1.5), and extremely dry (SPI < −

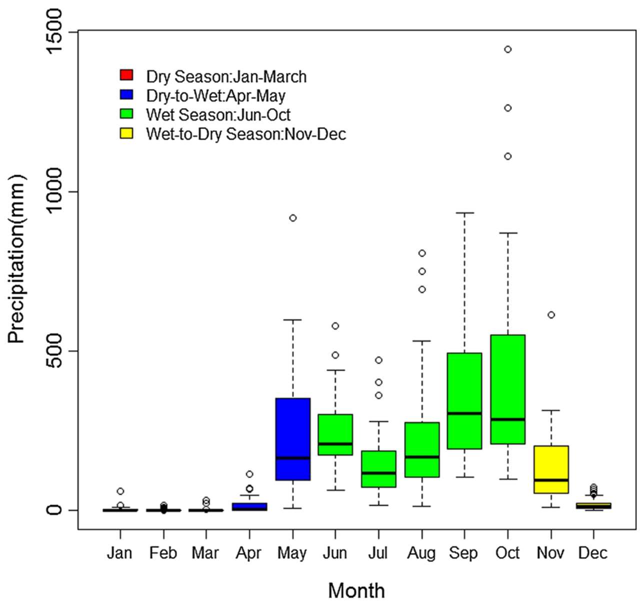


Fig. 2 Precipitation distribution at the SRNP-EMSS in the dry, dry-to-wet, wet, and wet-to-dry seasons. The dry season includes January to March (red); the dry-to-wet transitional season includes April and May (blue); the wet season includes June to October (green); the wet-to-dry transitional season includes November and December (yellow)

2.0). Because the SPI is strongly affected by the record length and longer records provide more consistent and accuracy SPI values (Quiring 2009), the calculation of an SPI requires long-term historical precipitation data. As such, this study used information from the local meteorological station from

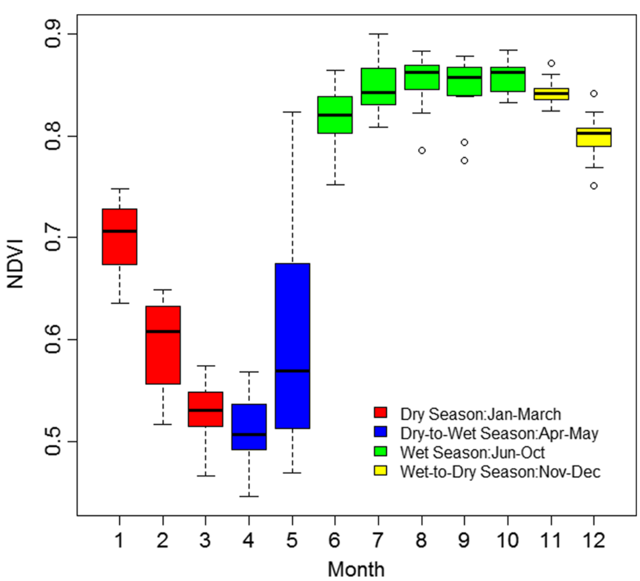


Fig. 3 The NDVI distribution at the SRNP-EMSS in the dry, dry-wet, wet, and wet-dry seasons. The dry season includes January–March (red); the dry-wet transitional season includes April–May (blue); the wet season includes June–October (green); the wet-dry transitional season includes November–December (yellow). The monthly NDVI distributions were extracted from MODIS products (MOD13Q1, collection v006)

Table 1 Classification of remote-sensing-based drought indices VCI, TCI, and VHI

Name of class	VCI	TCI	VHI
Extreme drought	0–10	0–10	0–10
Severe drought	10–20	10–20	10–20
Moderate drought	20–30	20–30	20–30
Mild drought	30–40	30–40	30–40
Abnormally dry	40–50	40–50	
No drought	50–100	50–100	40–100

June 1979 to March 2017. In this calculation of the SPI, we assumed that the precipitation records followed a Gamma distribution (Patel et al. 2007); as such, the data will be transformed, using studentized residual normalization techniques, to a normal distribution, with a mean value of 0 and a variance value of 1. The z-scores for each record are therefore calculated as the SPI.

This study calculated SPIs of different time scales from short and medium term to long term (1, 3, 6, 9, 12, 15, 18, 21, and 24 months) (McKee et al. 1993). One- and three-month SPIs reflect short-term drought conditions, indicating soil moisture and vegetation stress; 6- and 9-month SPIs reflect medium-term precipitation trends, showing the precipitation over distinct seasons; 12-month or more SPIs indicate long-term precipitation trends, which are tied to streamflow and groundwater level (Zargar et al. 2011).

The correlation and regression analysis

To evaluate the performance of the remote-sensing-based indices in monitoring meteorological droughts in TDFs, we built relationships between the VCI, TCI, and VHI and the multiple-scale SPIs using the Pearson correlation analysis (Quiring and Ganesh 2010; Rhee and Carbone 2010). Since the relationships could vary with season timing and time scales (Quiring and Ganesh 2010), the Pearson correlation analysis was conducted at multiple time scales (1, 3, 6, 9, 12, 15, 18, 21, 24 months) for each month (January to December) and each season (dry season, dry-to-wet season, wet season, and wet-to-dry season), respectively. We also correlated year-to-year changes of satellite-based drought indices with the changes of in situ annual SPI (A_SPI) which was calculated as 12-month SPI ending in Decembers of each year. The A_SPI is considered as the annual mean meteorological drought condition. Correlation coefficients (r) and p values were obtained to determine whether and how meteorological drought conditions affect vegetation conditions in different phases of the phenology cycle.

Result

The precipitation distribution at SRNP-EMSS

Figure 2 shows monthly and seasonal precipitation distributions at the SRNP-EMSS based on historical records from 1979 to 2017. The precipitation in the dry season is extremely low with a median amount of 2.9 mm and average amount of 7.9 mm. The precipitation increases sharply in the dry-to-wet season (median rainfall: 188.2 mm; average rainfall: 236.6 mm). In the wet season, the precipitation is generally abundant (median rainfall: 1152.9 mm; average rainfall: 1389 mm) even though July is a relatively dry month (median rainfall: 117.2 mm; average rainfall: 144.5 mm). The SNRP-EMSS experiences sharp decline in the wet-to-dry season (median rainfall: 115.8 mm; average rainfall: 157.4 mm).

Seasonal correlations between remote-sensing-based drought indices and multiple-scale SPIs

Figure 4 shows the correlation coefficients between satellite-based drought indices and multiple-scale SPIs over the SRNP-EMSS in four seasons. The correlations varied with season timing. The TCI had an overall better performance than the VCI and VHI in terms of seasonal scale.

In the dry season, three remote-sensing-based drought indices had very similar correlations with SPIs: they had moderate correlations with the short- (3-month) and long-term (18-, 21-, and 24-month) SPIs ($r \approx 0.5$), and they had high correlations with the medium- to long-term (6-, 9-, 12-, and 15-month) SPIs ($r \approx 0.70$). The maximum correlated values for VCI, TCI, and VHI (dry season) and SPI (12 months, 12 months, 12 months) are 0.69, 0.64, and 0.72, respectively. The VCI, TCI, and VHI also presented similar correlations with the SPIs in the wet season: for all time scales except for the 24-month SPI with which VCI was not significantly correlated, they were moderately correlated ($r \approx 0.40$) with SPIs. The maximum correlated values for VCI, TCI, and VHI (wet season) and SPI (9 months, 12 months, 12 months) are 0.38, 0.47, and 0.43, respectively. In the dry-to-wet season, three drought indices had poor performances: none of them could reflect meteorological drought conditions for any given scales. The performance of three drought indices differed in the wet-to-dry season: the VCI did not correlate with SPIs at all time scales; the TCI had significant correlations with SPIs at all time scales, especially for 6-, 9-, 12-month SPIs; and the VHI had moderate correlations with SPIs from 1-month to the 12-month time scale. The maximum correlated values for TCI and VHI (wet-to-dry season) and SPI (12 months, 12 months) are 0.62 and 0.38, respectively.

Monthly correlations between remote-sensing-based drought indices and multiple-scale SPIs

Figure 5 describes monthly correlations of the VCI-SPIs, TCI-SPIs, and VHI-SPIs at the SRNP-EMSS. Three drought indices had a similar performance in February, June, and July: they responded to the short-, medium-, and long-term SPIs in February (1 month to 15 months) and July (1 month to 24 months) and the medium- and long-term SPIs in June (9 months to 24 months). The VCI and VHI performed better than the TCI in February. The TCI and VHI performed better than the VCI in June. The VHI performed best in July.

Three drought indices had different performances in January, March, April, August, and December. In January, the VCI moderately responded to the middle-term SPIs; meanwhile, the TCI and VHI can respond to the short-, medium-, and long-term SPIs. In March and April, the VCI was more sensitive to shorter-term SPIs than TCI and VHI while TCI and VHI could also well monitor the medium- and long-term SPIs. In August, the VCI and VHI responded to short- and medium-term SPIs; and the TCI only responded to 24-month SPI. In December, there were no correlations between the VCI and SPIs, the TCI was able to respond to SPIs of all-time scales, and the VHI was significantly correlated the SPIs of 1 to 12 months. All of the three-remote-sensing-based drought indices failed to correlate to SPIs in May, September, October, and November.

Yearly correlations between remote-sensing-based drought indices and A_SPI

Figure 6 shows the correlations between the annual mean values of satellite-based drought indices, the VCI, TCI and VHI, and the A_SPI. The TCI presented a significantly strong correlation ($r^2 = 0.63$, $p < 0.01$, and $RMSE = 0.81$) with the A_SPI, the VHI presented a moderate correlation ($r^2 = 0.39$, $p < 0.01$, and $RMSE = 1.03$) and the VCI did no significantly respond to the A_SPI ($r^2 \approx 0$, $p = 0.92$, and $RMSE = 1.03$).

Discussion

The performance of the remote-sensing-based drought indices in monitoring droughts is phenologically and seasonally dependent at the SRNP-EMSS. In the dry season, the correlation between the remote-sensing indices and the SPIs became significant when the time scale was larger than 3 months (i.e., 3, 6, 9, 12, 15, 18, 21, and 24 months). This means that the remote-sensing indices can better reflect the rainfall deficiency in previous (≥ 3) months rather than the current month during the dry season. The fact that the remote-sensing indices performed badly in the dry-to-wet season may be due to an insignificant correlation with the SPIs in May when the leaves

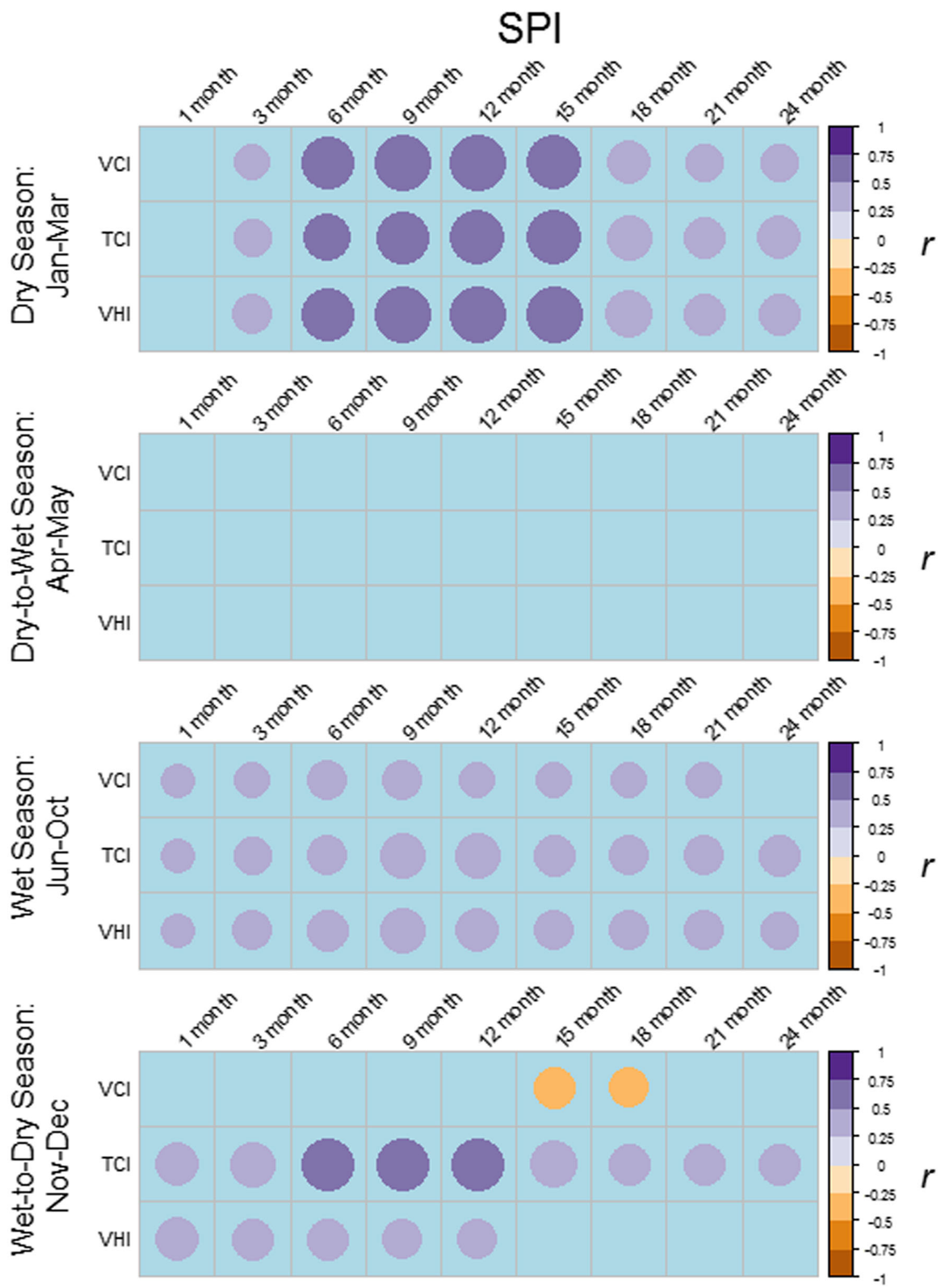
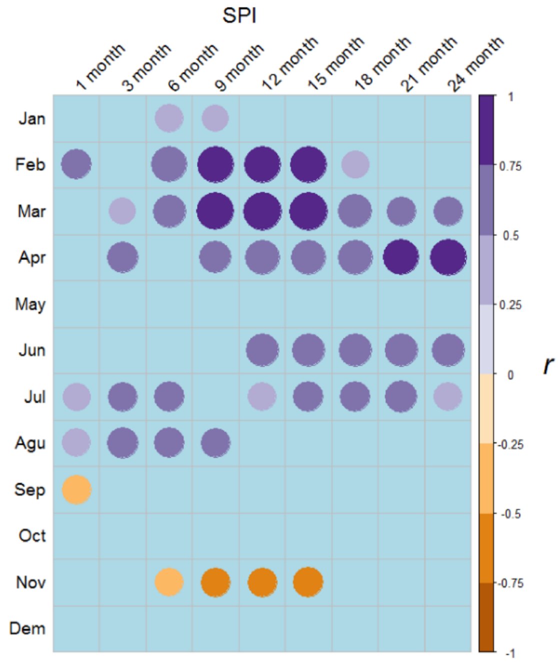
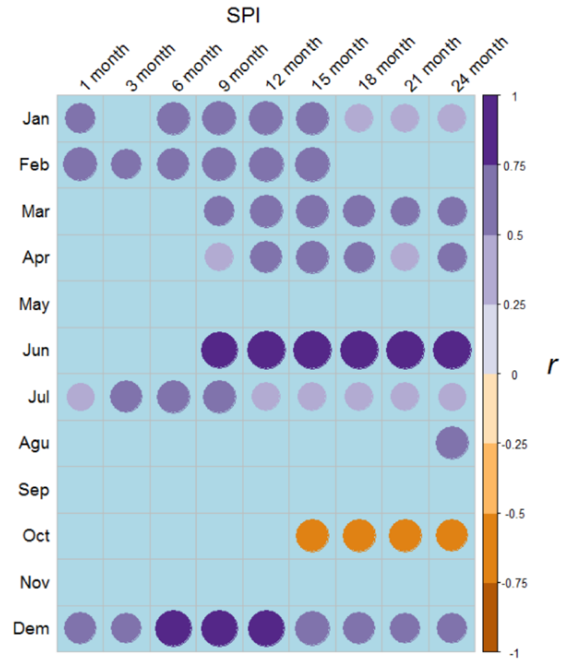


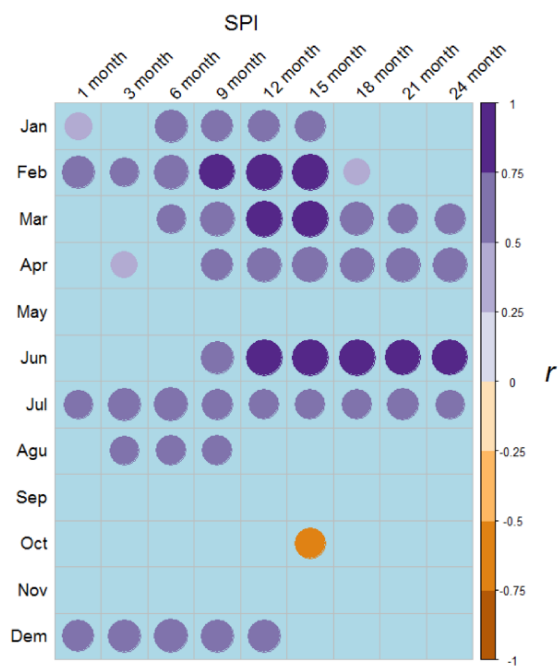
Fig. 4 The correlation coefficients (r) between remote-sensing-based drought indices (the VCI, TCI, and VHI) and multiple-scale SPIs in four seasons at the SRNP-EMSS. Blank places represent p values that are not significant (significance level = 0.05). Purple circles indicate significantly positive relationships and yellow circles indicate significantly negative relationships. The darker and bigger circles stand for higher absolute r values



(a). the VCI-SPIs correlation



(b). the TCI-SPIs correlation



(c). the VHI-SPIs correlation

Fig. 5 The correlation coefficients (r) between the remote-sensing-based drought indices (the VCI, TCI, and VHI) and the multiple-scale SPIs for each month at the SRNP-EMSS. Blank places represent p values that are not significant (significance level = 0.05). Purple circles indicate significantly positive relationships and yellow circles indicate significantly negative relationships. The darker and bigger circles stand for higher absolute r values

of TDFs develop quick fast (Fig. 3). The remote-sensing indices moderately reflected meteorological condition in the wet season, probably associated with the water content in the root regions. In the early stage of wet season (June, July, and August), significant correlations between remote-sensing-based indices, the VCI, TCI and VHI, and the SPIs were found

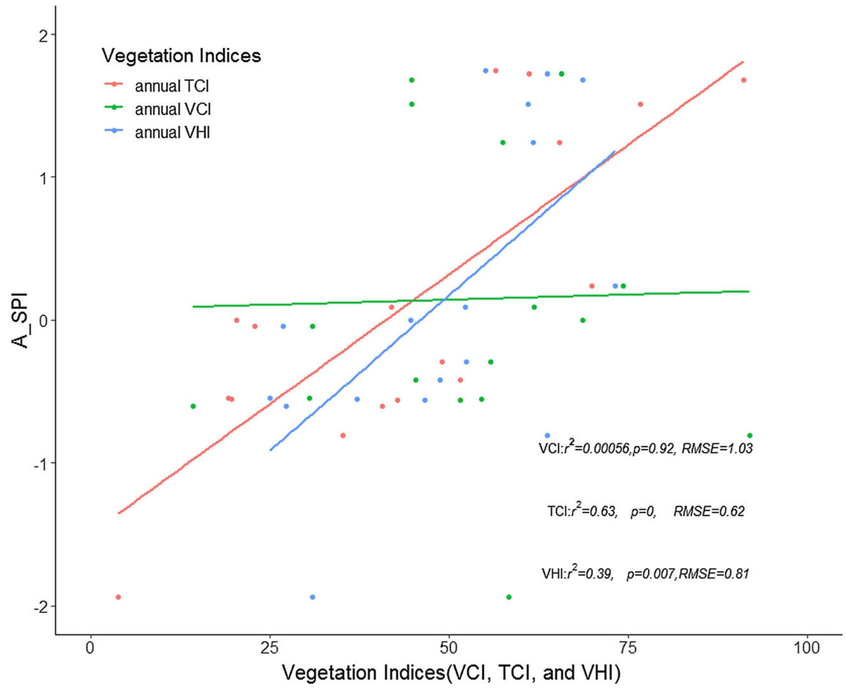


Fig. 6 The correlation coefficients between the annual satellite-based drought indices (the VCI, TCI, and VHI) and the A_SPI which indicates annual mean meteorological drought condition

when the soil moisture was not much high; when the water content in the root regions was much abundant (September and October), the remote-sensing indices could no longer reflect the meteorological condition probably because TDFs, with sufficient water content in the root regions, were resistant to meteorological drought. Ji and Peters (2003) found similar patterns in areas of northern Great Plain where high correlations between the NDVI and the SPIs occurred in the middle (June, July, and August) of the growing season and low correlations occurred at the start (May) and end (September and October) of the same season.

Observed significant differences for the VCI, TCI, and VHI reflected meteorological drought in the wet-to-dry season. We found that remote-sensing indices could not reflect the meteorological drought condition at the early stage of the wet to dry season (November), because the water content in the root regions was still saturated though its leaves started falling. But in the late stage of the wet-to-dry period (December) when falling leaves dramatically and water content being not saturated, the TCI reflected all the time-scale meteorological drought conditions. Moreover, the VHI described the precipitation deficiency within 1 year, and the VCI did not respond to the rainfall.

The varying performances of the VCI, TCI, and VHI are a result of reflecting the seasonal and monthly dynamics of TDFs in different biochemical or biophysical manners. The VCI detected the canopy greenness, leaf vigor, and the deciduousness during the growing season (Kogan 1995, 1997). The TCI is more sensitive to the soil moisture when the leaf falls during the dry season and is more sensitive to the water content in the canopy when the leaf is saturated during the wet season (Karnieli et al. 2010). The VHI, which indicates the vegetation health condition, inherits characteristics of the VCI and TCI. These indices performed similarly to reflect meteorological drought conditions except for the wet-to-dry season in terms of seasonal scales. The variation of precipitation regime triggered the changes in the canopy greenness and leaf vigor, in the evapotranspiration of the canopy and soil, and in the health conditions of TDFs. Thus, the VCI, TCI, and VHI have the potential to detect meteorological drought indirectly. The biophysical and biochemical parameters responding to the VCI, TCI, and VHI in the dry seasons were associated with the rainfall in previous (≥ 3) months because the precipitation in the current dry season was pretty low. In the dry-to-wet season, the variabilities of the biophysical and biochemical parameters were related to the rapid growth of TDFs in May (Fig. 3) which was driven by the precipitation regime in previous months rather than in the current month, although the rainfall in May was pretty much (Fig. 2).

In the wet season, meteorological droughts can lower VCI by altering the leaf reflectance at both the red and near-infrared wavelength (Carter et al. 1996). In detail, when a leaf is in the water-stressed condition, the chlorophyll concentration would decrease and results in higher reflectance in the red band; meanwhile, spaces within the spongy mesophyll would be enlarged and lead to an increase of the scattering effect for near-infrared photons at the cell wall-air interface and eventually increase the near-infrared reflectance (Carter et al. 1996; Asner 1998). The sensitivity of red reflectance to decreased water content in the leaf was much more than near-infrared reflectance, resulting in lower values of the VCI while suffering from meteorological droughts. At the same time, meteorological droughts can trigger the closure of the leaf stomata and weaken the transpiration process, leading to an increase in the surface temperature at the canopy (Carter et al. 1996). As such, the TCI also decreased under water stress. As a linear combination of VCI and TCI, VHI declined with VCI and TCI when suffering from drought. During the wet-to-dry period, the role of precipitation was no longer to sustain the canopy greenness (because phenologically falling leaves) but to promote evapotranspiration of plants and soil (Karnieli et al. 2010). As a result, the VCI did not reflect the precipitation deficiency (SPIs) in December while TCI was able to depict the evapotranspiration process in TDFs and thus well responded to variations in precipitation and soil moisture (Cao et al. 2016).

The remote-sensing-based drought indices performed significantly different to reflect annual meteorological drought condition. The annual mean TCI and VHI explained 63% and 39% variability of the A_SPI, respectively, and annual mean VCI was a poor indicator to account for the change in the A_SPI. This was because the evapotranspiration of TDFs was more sensitive than canopy greenness to the inter-annual precipitation deficiency.

The performance of a specific remote-sensing-based drought index for the early, intermediate, and late stage of TDFs should be similar. This is because time-series of leaves intensity for intermediate and late are very close during the whole period, and three stages of TDFs have similar leaves intensity during May and November. The changes in leaf intensity for early, intermediate, and late stages of TDFs, driven by the effect of phenology, are simultaneous (no time lag) and have the same direction (Lopezaraiza-Mikel et al. 2013). The remote-sensing drought indices (e.g., VCI and TCI) emphasize the relative changes in the biophysical parameters (NDVI and LST) through time. As a result, the values of a specific remote-sensing-based drought index for three stages of TDFs should be similar in each month, under the assumption that the difference in leaf intensity between early and intermediate/late stage in a certain month (from December to April) does not vary with a given year. Furthermore, the element of vegetation heterogeneity is buffered by the available MODIS satellite information (250 m and 1 km), which prevents to fully consider differences between the different levels of successional stages present in our study area.

Conclusion

In this study, we evaluated the use of three popular remote-sensing-based vegetation indices, i.e., the Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and Vegetation Health Index (VHI), calculated on MODIS the NDVI and LST products, towards the monitoring of the meteorological drought in a TDF at SRNP-EMSS. Multiscale Standard Precipitation Index (SPIs) calculated on precipitation data from a meteorological station was used to evaluate satellite-based indices. Pearson correlation analysis was performed between remote-sensing indices and SPIs. We concluded that the ability of these remote-sensing-based drought indices to monitor meteorological drought varied with timing, and TCI outperformed VCI and VHI in terms of seasonal and annual scale. They performed similarly in the dry, dry-to-wet, and wet season while TCI performed best to monitor meteorological drought in the wet-to-dry period, followed by VHI, and VCI did worst. These remote-sensing indices performed well in monitoring meteorological drought in the dry season, poorly in the dry-to-wet season, and moderately reflected rainfall deficiency in the wet season. However, these remote-sensing indices were not suitable to reflect meteorological drought in the dry-to-wet season.

The utility of remote-sensing indices was also assessed in terms of the monthly scale. The varying performance of remote-sensing indices can be mostly explained by their nature in describing the biophysical and biochemical properties in TDFs. All of them failed to well monitor the drought in May when the leaf flushed sharply and in September, October, and November when the water content in the root region was abundant. Besides, the inter-annual analysis showed that the evapotranspiration of TDF was more sensitive than canopy greenness to precipitation deficiency. Our study effectively increased the ability to provide real-time drought monitoring and early warning of drought in the TDF.

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