Earth Systems and Environment
https://doi.org/10.1007/s41748-018-0055-9

ORIGINAL ARTICLE

Using Drought Indices to Model the Statistical Relationships Between Meteorological and Agricultural Drought in Raya and Its Environs, Northern Ethiopia

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Received: 10 October 2017 / Accepted: 4 June 2018

Abstract

The aim of this study was to model the relationship between Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), Temperature Condition Index (TCI), Vegetation Health Index (VHI), and Standardized Precipitation Index (SPI) at 3-month timescale in Raya and its environs, Northern Ethiopia. This study answered how NDVI and LST, VCI and TCI, SPI and VHI are related. It also explained better drought indices for meteorological and agricultural drought monitoring. MOD11A2 LST Terra, eMODIS NDVI, and monthly rainfall data of the tropical applications of meteorology using satellite and ground-based observations (TAMSAT) were used. The data were analyzed using a simple linear regression model. The results revealed that the mean LST was high (i.e., between 39.6 and 41.29 °C), while NDVI was poor and unhealthy (i.e., below 0.27) in the lowland area due to unfavorable moisture condition than the mid and highland areas. The regression result indicated that NDVI and LST have a relatively strong negative and significant relationship ($R^2/P=0.40/0.01$ to $R^2/P=0.62/0.00$) in all districts of the study area. This study also reported that there is a positive and significant relationship between VCI and TCI ($R^2/P=0.38/0.02$ to $R^2/P=0.63/0.00$) in all districts of the study area. Furthermore, this study found that the relationship between SPI and VHI is positive and significant ($R^2/P=0.36/0.02$ to $R^2/P=0.60/0.00$) in all districts of the study area. The SPI and VHI indices are suitable for monitoring the incidence of meteorological and agricultural drought. This study may help to improve the understanding of both meteorological and agricultural drought indices relationships.

Keywords NDVI · LST · VCI · TCI · SPI · VHI · Raya · Ethiopia

1 Introduction

Drought is mainly triggered by the El Niño phenomena (Sholihah et al. 2016) in the majority of southern and eastern African countries. This causes an increase in the surface temperature (Wolde-Georgis 1997) and a stress in soil moisture. As a result, the incidence of meteorological and agricultural droughts intensified in the majority part of the continent (e.g., Ethiopia, Somalia, South Sudan, Kenya, Tanzania, Zimbabwe, South Africa and others). Both meteorological and agricultural drought are among the four types of drought: meteorological, agricultural, hydrological, and socio-economic. Meteorological drought is caused by the seasonal or annual precipitation reduction over an extended period of time, usually a season or more in length, while agricultural drought is due to a shortage of soil moisture in the crop root zone and it significantly affects vegetation as well as crop growth (Zhang et al. 2017; Zhang and Jia 2013; Choi et al. 2013;

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Published online: 15 June 2018

Wilhite 2000). Hydrological drought is caused by the decline in the amount of surface and subsurface water supplies such as stream flow, inflow to lakes, ponds, and reservoirs (Wilhite 2000). Zhang and Jia (2013) reported that socio-economic drought is largely associated with the supply to meet the demand of economic goods. Kogan et al. (2013) showed that the climatic phenomenon depresses vegetation greenness and vigor due to the diminution in chlorophyll and water content and rising of temperature. The Land Surface Temperature (LST) represents the interface between the incoming radiation fluxes and other terms of the energy balance such as the ground heat fluxes (Frey et al. 2012; Sruthi and Aslam 2015). Drought is a reality that many governments in Sub-Saharan Africa (SSA) have to deal with on a regular basis. Often, many governments fail to prepare for and respond appropriately to mitigate negative consequences of drought. Choi et al. (2013) reported that geo-spatial technologies (e.g., remote sensing and GIS) provide an alternative approach to effectively monitor drought based on vegetation stress as well as moisture status over large areas. Currently, we have a number of drought indices based on remote sensing data with various time scales, application, and methods of estimation. Each of these indices reflects diverse drought conditions, characteristics or severity and has their own strength and weaknesses (Marufah et al. 2017; Zhang et al. 2017).

This study considered only six important drought indices such as Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), Land Surface Temperature (LST), Temperature Condition Index (TCI), Standardized Precipitation Index (SPI), and Vegetation Health Index (VHI) based on their applications, characteristics, and data availability. Studying drought phenomena using various drought indices can help us not only to understand the drought event better, but also to comprehensively analyze their relationships (Zhang et al. 2017). For instance, the World Meteorological Organization (WMO) approved the Standardized Precipitation Index (SPI) developed by McKee et al. (1993) to use for monitoring meteorological drought conditions at any location in a different time scales (e.g., 1, 3, 6, 12, or 24 months). The index requires only time-series precipitation data. Similarly, the Vegetation Health Condition (VHI) developed by Kogan (2001) has been universally used in agricultural drought assessment based on the remote sensing (satellite) data because the index incorporates both the Vegetation Condition Index (VCI) and Temperature Condition Index (TCI) to measure the stress of crops. The VCI and TCI are estimated from the multi-temporal Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST). Drought monitoring based on vegetation condition indices only (e.g., NDVI and VCI) has certain limitations. However, this limitation can be resolved by incorporating surface temperature (LST). Therefore, VHI would be a better choice in agricultural drought monitoring if only NDVI and LST data are available (Mu et al. 2006; Zhang et al. 2017). However, the major challenge in studying drought is developing statistically tested and proven methods and techniques to acquire timely drought information (e.g., meteorological and agricultural) for improving the existing drought preparedness and response (Panu and Sharma 2002; Brown et al. 2008).

Wang et al. (2003) reported that the relationship among NDVI, precipitation, and temperature require detailed analyses to comprehend the temporal variation of precipitation and temperature as they influence vegetation growth. Most scholars have focused on the relationship between precipitation, NDVI and soil water (Zhou et al. 2012). The relationships between vegetation vigor and available soil moisture, especially in arid and semiarid areas, NDVI and LST data sets have been used to monitor drought conditions (Sun and Kafatos 2007). Zhou et al. (2010) reported that the relationship between vegetation condition and precipitation is complex and not adequately examined with LST, VHI, TCI, and SPI. This affects the ability to recognize the strengths of each drought index. Raghavendra (2012) stated that understanding the relationship among the TCI, VCI, and terrain factors (e.g., elevation, slope, and aspect) is significant to conserve natural and environmental resources. For example, few scholars determine the relationships between SPI and VHI (Marufah et al. 2017) in Indonesia, VCI and TCI (Singh et al. 2003; Raghavendra 2012) in India. However, in Ethiopia, there are no known studies dealing with the relationships among NDVI and LST, VCI and TCI, SPI and VHI at a 3-month time scale. Therefore, there is a need to conduct in-depth empirical analysis on each index (Karnieli et al. 2010). The novelty of this study is that for the first time we are able to determine the statistical relationships of six major drought indices (i.e., both meteorological and agricultural drought) in Africa in general and Ethiopia in particular. This study, therefore, aims to examine the relationships among NDVI and LST, VCI and TCI, SPI and VHI at 3-month timescale from the year 2001–2015. The relationships were determined using the seasonal mean values of each index. This study is a useful addition to advance the existing drought monitoring, early warning systems and mitigation carried out in Ethiopia in general and the study area particular. Further, the study conducted a pairwise matrix correlation analysis among all drought indices for verification and/or validation of the relationships.

2 Materials and Methods

2.1 Study Area

This study was conducted in Raya and its environs (Northern Ethiopia) which is an intermountain plain area located at 39°24′40″ and 40°25′20″ longitude East and 12°7′20″ and 13°8′0″ latitude North (Fig. 1) (Gidey et al. 2017). It consists

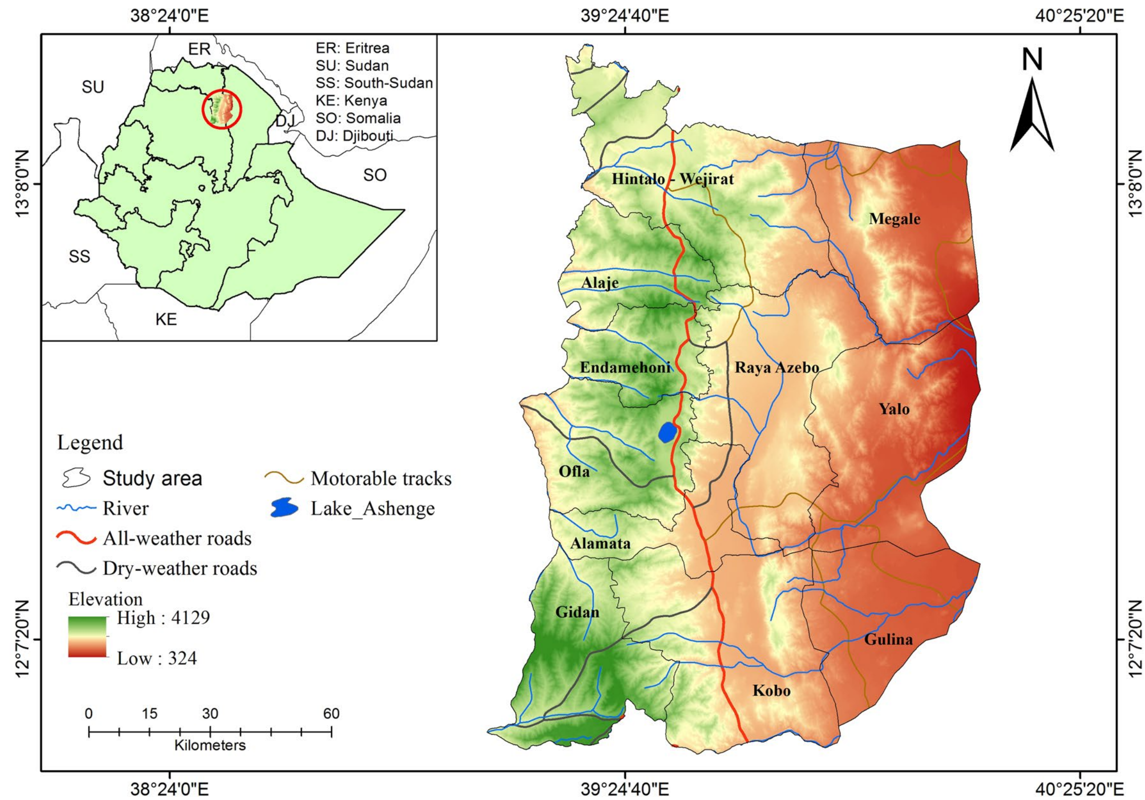

Fig. 1 Map of the study area. Source: Gidey et al. (2017)

of 11 districts, namely, Megale, Yalo, Gulina, Gidan, Kobo, Alaje, Alamata, Hintalo Wejirat, Ofla, Endamehoni, and Raya Azebo. The total area coverage of the study area is estimated 14,532 km^2 of which 48% fall in the southern Tigray region, 22% in Amhara and 30% in the Afar region (Gidey et al. 2017). The study area receives up to 558 mm of rainfall annually (Gidey et al. 2017). Rainfall is erratic and bimodal (Ayenew et al. 2013) in the area. During the last 33 years, the maximum (T_{max}) and minimum temperatures (T_{min}) were 30.5 and 15.9 °C, respectively. The study area consists of four river basins such as Danakil Basin, which covers about 10,265.8 km^2 (70.64%), Lake Ashinge 16.0 km^2 (0.11%), Abay (Blue Nile) 13.2 km^2 (0.09%), and Tekeze 4237.0 km^2 (29.16%) (Gidey et al. 2017). The mean elevation value of the area is 1762 meters above sea level (m.a.s.l). Similarly, the slope of the study area ranged from 0% (flat) to 395.3% (very steep slope). In the study area; eutric cambisols are the predominant soil type covering about 4667.1 km^2 or 32.1%, while dystric gleysols cover only a small portion, i.e., 1.1 km^2 (0.001%), respectively (Gidey et al. 2017).

2.2 Data Acquisition

The Moderate Resolution Imaging Spectroradiometer (MODIS) instrument has been developed to enhance the studies on land, ocean, and atmosphere (Justice et al. 1998). Bisht et al. (2005) reported that the MODIS product has 36 spectral bands ranging from 0.405 to 14.385 µm. The sensor gives near-daily imaging capability globally, complementing the spectral, spatial, and temporal coverage (Justice et al. 1998). The spatial resolution of the product ranges from 250 to 1000 m. Tucker et al. (2005) reported that vegetation indices derived from the MODIS or SPOT (Satellite Pour l'Observation de la Terre) instruments represent improved measurements of surface vegetation conditions, spatially, spectrally, and radiometrically. In this study, moderate spectral and spatial resolution monthly LST Terra (MOD11A2), and eMODIS NDVI data were obtained from the National Aeronautics and Space Administration (NASA) and United States Geological Survey (USGS) Land Process Distributed Active Archive Center (LP DAAC) and Famine Early Warning System Network (FEWS-NET) from the year 2001 to 2015. The spatial resolutions of the images were 1 km by 1 km (LST) and 250 m by 250 m (eMODIS NDVI). However, the resolutions of all images were adjusted to 250 m to correspond with the entire images using the MODIS Re-projection Tool (MRT) v 4.1. Mu et al. (2006) reported that observation data alone are not enough for monitoring of different drought (e.g., meteorological, agricultural and/or hydrological) because there is a difference between the result and the fact since the distribution of station is a lack of rationality. However, in this study hybrid monthly rainfall, i.e., the Tropical Applications of Meteorology using Satellite data and ground-based observations (TAMSAT) rainfall data were collected from 19 existing rain gauge stations from the National Meteorological Agency of Ethiopia (NMA) for the period 2001–2015. These data sets were used to estimate the seasonal precipitation deficit using the SPI 3-month timescale and correlate with the other drought indices. The MOD11A2 LST Terra, eMODIS NDVI, and TAMSAT are distinct datasets and are an important input in real-time drought monitoring. For instance, the MOD11A2 LST Terra provides information about surface temperature or moisture status, eMODIS NDVI shows the overall vegetation health status, and TAMSAT gives satellite-based rainfall estimates at high resolution.

2.3 Data Processing and Analysis

2.3.1 eMODIS NDVI

NDVI is a very good parameter for studying vegetation greenness or health status, and mapping vegetation cover dynamics. This index consists of two important components (i.e., ecology and weather) (Singh et al. 2003). However, it is not effective to characterize drought or non-drought epochs. In this study, NDVI was applied to evaluate the impacts of weather on vegetation from the eMODIS products. The row eMODIS NDVI data were rescaled to find out the real NDVI value in ArcGIS 10.4.1 as follows (Eqs. 1, 2):

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{RED})/(\mathrm{NIR} + \mathrm{RED}) \tag{1}$$

where NIR = near-infrared reflectance and RED = visible-red reflectance

$$\mathrm{eMODIS\ NDVI} = \mathrm{Float\ (eMODIS\ NDVI}_i - 100)/100. \tag{2}$$

The value of eMODIS NDVI ranges from − 1.0 to + 1.0. The standard unit of eMODIS NDVI is NDVI ratio. The negative NDVI ratio shows less vigorous or unhealthy vegetation cover mainly occurred in a barren rock (rock outcrop), and sand, while the positive NDVI value depicts the healthy vegetation cover. High NDVI values depend on the density, canopy architecture, and vegetation moisture (Zhang and Jia 2013). Studies showed that in arid and semi-arid regions the values of NDVI are low due to moisture stress. In this study, the eMODIS NDVI value was interpreted based on Table 1.

The eMODIS NDVI data were used as input to compute VCI. This index is highly applicable for assessing the vegetation stress and/or to examine the response of vegetation. In this study, VCI was estimated as follows (Eq. 3):

$$\mathrm{VCI} = 100 \times (\mathrm{NDVI}_i - \mathrm{NDVI}_{\mathrm{min}})/(\mathrm{NDVI}_{\mathrm{max}} - \mathrm{NDVI}_{\mathrm{min}}), \tag{3}$$

Table 1 Vegetation health and density value interpretation

Vegetation health and density status	NDVI value
Very good	0.72 to 1.00
Good	0.42 to 0.72
Normal	0.22 to 0.42
Poor	0.12 to 0.22
Very poor	− 0.10 to 0.12

http://endeleo.vgt.vito.be/dataproducts.html#ndvi

where NDVI_i = the current smoothed NDVI value of *i*th month, $\mathrm{NDVI}_{\mathrm{min}}$, and $\mathrm{NDVI}_{\mathrm{max}}$, is a multi-year (2001–2015) absolute minimum and maximum NDVI value for every pixel at a particular period.

VCI is measured in percentile ranged from 0 to 100. The value shows how much the vegetation has advanced or deteriorated in response to weather. A high value of VCI signifies healthy and/or unstressed vegetation condition. VCI value of 50–100% shows above normal or wet condition. This means that there is no drought, while values between 35 and 50% show areas under the incidence of moderate drought (MD) and VCI value between 20 and 35% shows severe drought (SD) prevalence. Furthermore, the seasonal and/or annual VCI value 0–20% is showing very severe agricultural drought event (VSD). Studies indicated that VCI model based on NDVI alone is not sufficient for agricultural drought monitoring (Kogan 1995; Sholihah et al. 2016). The combination of TCI derived from MOD11A2 LST Terra is good to assess agricultural droughts effectively.

2.3.2 Temperature Condition Index (TCI)

2.3.2.1 Land Surface Temperature (LST) 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 process on regional and global scales (Parviz 2016). The Terra MODIS collection 005-based temperature product (i.e., MOD11A2) LST measures the ground temperature of the Earth's surface. The Terra-based MOD11A2 LST data were computed by averaging all the valid pixels under clear-sky and it was rescaled by 0.02 to get the correct LST value in Kelvin unit. In this study, the values of LST were rescaled and converted into degree celsius (°C) unit to measure TCI. TCI is a thermal stress indicator used to determine temperature-related drought situations. This satellite-derived index assumes that during the drought event soil moisture diminished significantly and cause high vegetation stress. The TCI assumed that higher temperature has a tendency to cause deterioration or drought during the vegetative growth period, while low temperatures are largely favorable for vegetation during its development. Both the LST and TCI were estimated as follows (Eqs. 4, 5):

$$\mathrm{LST} = (\partial \times 0.02) - 273.15, \tag{4}$$

where LST = land surface temperature in degree celsius (°C), ∂ = row scientific data (SDS)

$$\mathrm{TCI} = 100 \times (\mathrm{LST}_{\max} - \mathrm{LST}_i)/(\mathrm{LST}_{\max} - \mathrm{LST}_{\min}), \tag{5}$$

where LST_i = LST value of ith month, $\mathrm{LST}_{\max}$ and $\mathrm{LST}_{\min}$ are the smoothed multi-year maximum and minimum land surface temperature (LST).

2.3.3 Vegetation Health Index (VHI)

The Vegetation Health Index (VHI) consist both the VCI and TCI and it shows the availability of moisture and temperature in the vegetation. In this study, the VHI was analyzed by computing both VCI and TCI derived from the eMODIS NDVI and MOD11A2 Terra 8-day LST data as follows (Eq. 6):

$$\mathrm{VHI} = a \times \mathrm{VCI} + (1 - a) \times \mathrm{TCI}, \tag{6}$$

where VHI = Vegetation Health Index, $a = 0.5$ (contribution of VCI and TCI), VCI = Vegetation Condition Index, TCI = Temperature Condition Index.

The lower VHI value indicated that the high incidence of agricultural drought whereas a higher VHI value show wet or non-drought conditions (Table 2).

Table 2 Agricultural drought classes by VHI. Source: Kogan (2001)

Level of severity	VHI values
Extreme drought	< 10
Severe drought	10–20
Moderate drought	20–30
Mild drought	30–40
No drought	> 40

2.3.4 Standardized Precipitation Index (SPI)

In this study, the SPI 3-month timescale was computed based on McKee et al. (1993) algorithm to evaluate the condition of meteorological drought as follows (Eq. 7):

$$\mathrm{SPI} = (p_i - \bar{p})/\sigma, \tag{7}$$

where p_i = seasonal precipitation, $\bar{p}$ = long-term mean, σ = standard deviation of the long-term rainfall record.

Meteorological drought event begins any time when the SPI value is negative and reaches close to −1 or less (Table 3). The negative SPI value shows periods of drought, while the positive value is wet or non-drought conditions.

Table 3 Meteorological drought characteristics by SPI. Source: McKee et al. (1993)

SPI values	Drought category	
	Severity	Symbol
SPI < −2.0	Extreme drought	ED
−1.5 < SPI < −1.99	Severe drought	SD
−1.0 < SPI < −1.49	Moderate drought	MD
−0.99 < SPI < 0	Mild drought	MiD

2.3.5 Regression Analysis

A simple linear regression model was applied to examine how the LST–NDVI, VCI–TCI and VHI–SPI relate to each other to ascertain drought. Besides, the Pearson correlation matrix was applied to evaluate the relationships of each index. Minitab v. 17 advanced statistical software package was used to assess the strengths of the relationships and level of significance. The linear regression model was computed as follows (Eq. 8):

$$Y_i = b_0 + b_1 X_i + e_i, \tag{8}$$

where Y_i = VCI, NDVI, VHI for the ith period, X_i = LST, SPI, TCI, $b_0 + b_1 X_i$ = linear relationships between Y_i and X_i, b_0 = mean of Y_i when $X = 0$ (intercept), b_1 = change in mean of Y when X increases by 1 (slope), e_i = random error term.

The results of simple linear regression or Pearson correlation can be positive or negative. This ranges between 0 and +1 (Table 1). Regression or Pearson correlation values close to zero indicate no relationship between the indices. However, if one index (e.g., LST) increases as the other index (e.g., NDVI) decreases, then the relationship is negative. The Evans standard (1996) was adopted to determine the level of Pearson correlation matrix and coefficient of determination (R^2) strengths (Table 4).

Table 4 Strengths of Pearson correlation matrix and linear regression model (R^2). Improved: Evans (1996)

Level of statistical strength (s)	Pearson correlation matrix (r)	Coefficient of determination (R^2)
Very strong (perfect)	0.80–1.00	0.64–1.00
Strong	0.60–0.79	0.36–0.63
Moderate	0.40–0.59	0.16–0.35
Weak	0.20–0.39	0.04–0.15
Very weak	0.00–0.19	0.00–0.036

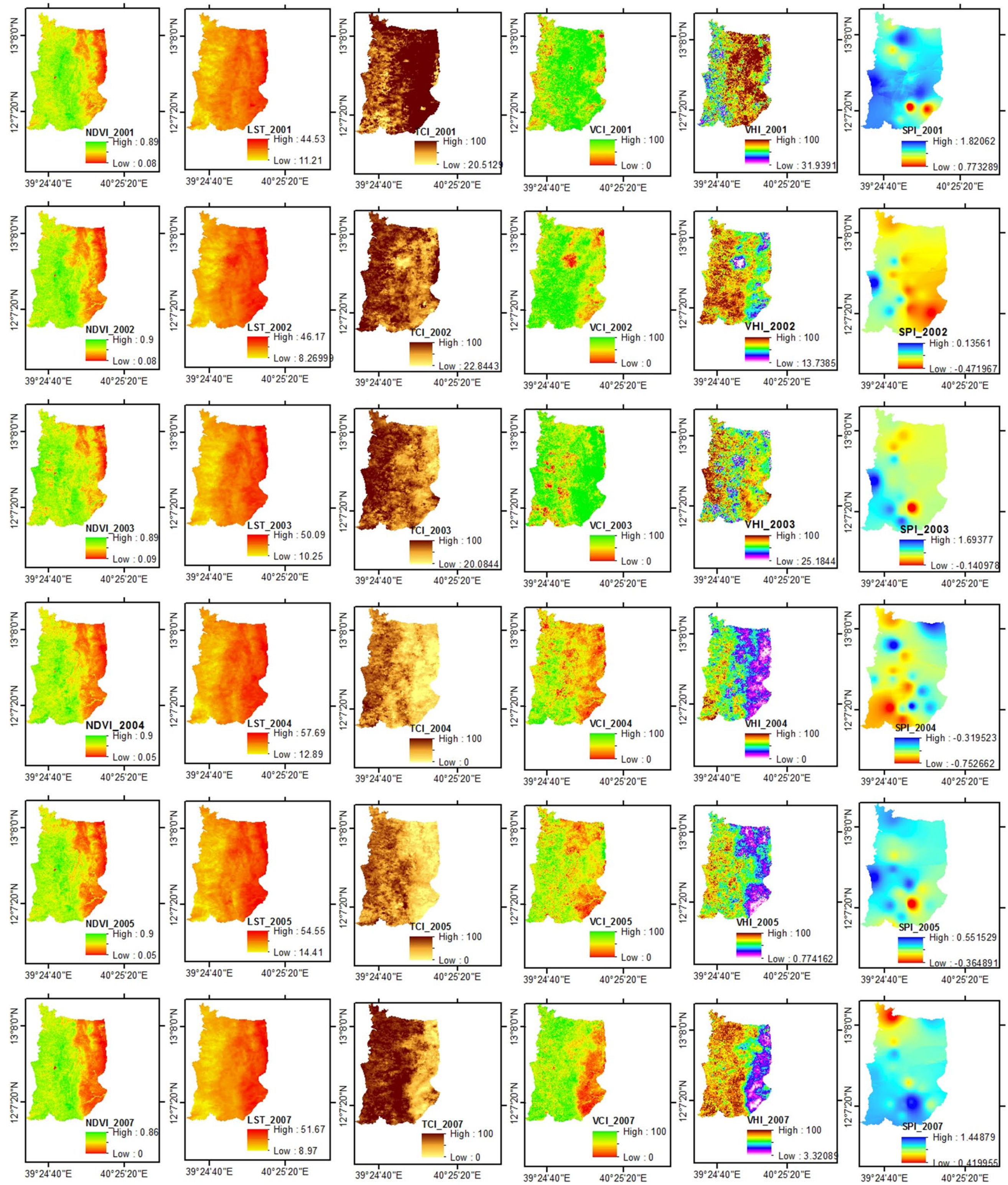

Fig. 2 Spatio-temporal analysis of NDVI, LST, TCI, VCI, SPI and VHI over Raya and its environs for the period 2001–2015

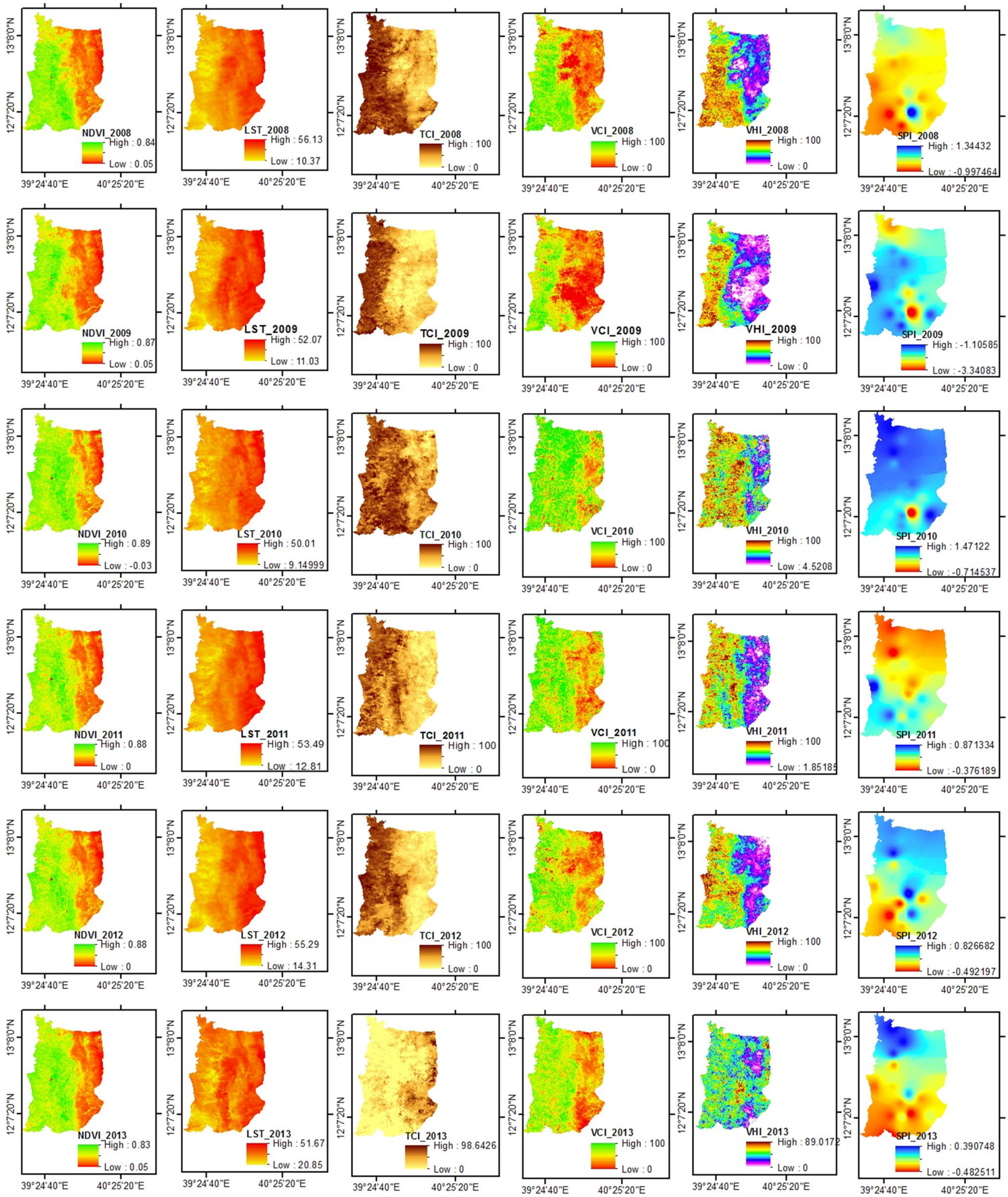

Fig. 2 (continued)

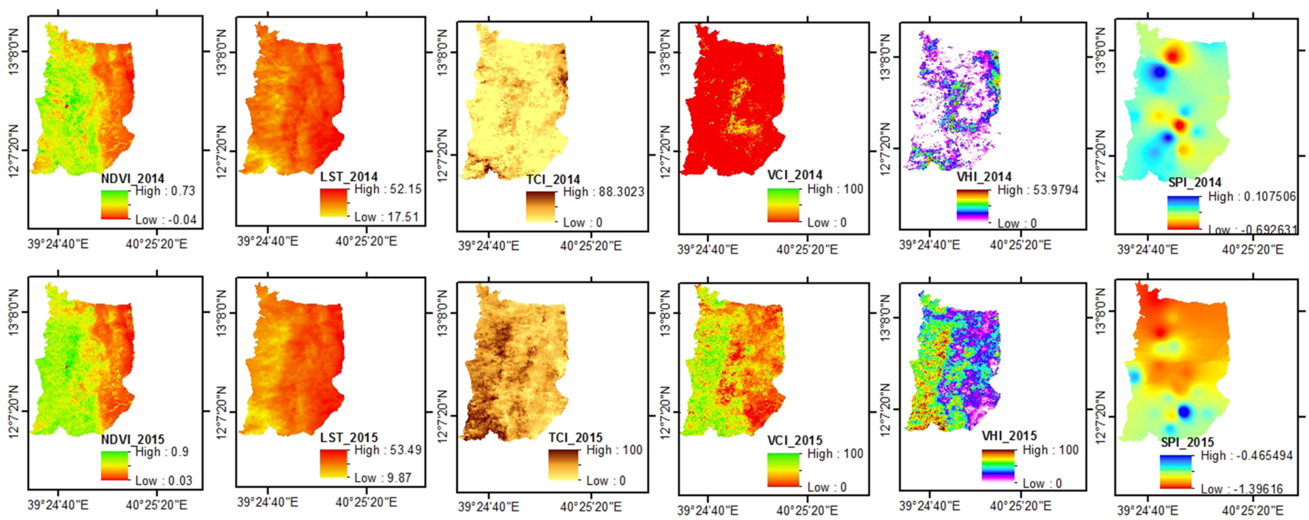

Fig. 2 (continued)

3 Results and Discussion

3.1 Analysis of Major Drought Indices

This study analyzed the spatio-temporal meteorological and agricultural drought indices such as NDVI, LST, TCI, VCI, SPI and VHI to assess the relationships of each drought index (Fig. 2) during the main rainy seasons. The results indicated that the long-term (2001–2015) mean NDVI values in the lowland area (e.g., Yalo, Megale, and Gulina districts) were below 0.27, while LST value was between 39.6 and 41.29 °C. LST was high in the lowland area, while NDVI was poor and unhealthy vegetation greenness due to unfavorable moisture condition. Singh et al. (2003) reported that NDVI is largely controlled by weather parameters (e.g., rainfall, and temperature among others) to reflect the vegetation greenness. For example, Cunha et al. (2015) stated that during the dry season, the values of NDVI are becoming low, whilst during the rainy seasons the values are largely higher due to optimal soil water moisture. However, in the lowland of the study area, NDVI was continuously low even during the main rainy seasons due to poor moisture resulting from the unfavorable climate conditions. Besides, the VCI values of the same area were between 37.18 and 44.48. This identifies areas where vegetation is more or less dense than usual condition (Choi et al. 2013). The TCI value of the lowland area was between 38.54 and 39.58. This determines the temperature-related vegetation stress due to moisture stress (Singh et al. 2003; Choi et al. 2013). Furthermore, the VHI value was from 38.35 to 43.58, while the SPI value was less than 0.19. In the midland area (e.g., Raya Azebo, Alamata, Hintalo Wejirat, and Kobo), NDVI was relatively better and the mean value was between 0.44 and 0.57, while LST ranged from 30.30 to 34.97. Similarly, the VCI ranged between 58.45 and 62.65, while TCI was between 52.57 and 64.40. Singh et al. (2003) reported that both VCI and TCI are found to be dependent on weather and ecological conditions. Moreover, VHI ranged between 53.17 and 60.89, while the SPI was less than 0.19. In the highland area (e.g., Endmehoni, Ofla, Alaje, and Gidan districts), good NDVI or vegetation greenness was observed. In this area, the long-term mean NDVI value was between 0.53 and 0.57, while LST value ranged between 23.58 and 24.60. Low LST and high NDVI values were observed in the area. Besides, the VCI value was between 63.94 and 67.87, while TCI was 66.09–68.88. Furthermore, VHI value ranged between 66.47 and 69.85, while SPI was less than 0.23. Choi et al. (2013) stated that VHI reflects both vegetation cover and temperature anomalies. The statistical relationship of each index is presented in Figs. 3, 4 and 5.

3.2 NDVI and LST Relationships

Figure 3 and Table 5 show the statistical relationships between NDVI and LST. The result revealed that LST is negatively related to NDVI ($R^2/P = 0.40/0.01$ to $R^2/P = 0.62/0.00$) and statistically significant across all districts of the study area (such as Yalo, Megale, Gulina, Raya Azebo, Alamata, Kobo, Hintalo Wejirat, Endamehoni, Ofla, Alaje, and Gidan). Zhang and Jia (2013) and Karnieli et al. (2006) also reported similar findings (i.e., an inverse relationship) between NDVI and LST in the Brazilian semi-arid region and Mongolia. In this study, higher regression results were observed in the district of Kobo (Fig. 3f) and were relatively lower in Alaje (Fig. 3j). This relationship exploited as an indicator of spatial–temporal characteristics of water stress conditions (Abbas et al. 2014). The NDVI and LST relationship results show that when the LST increases at

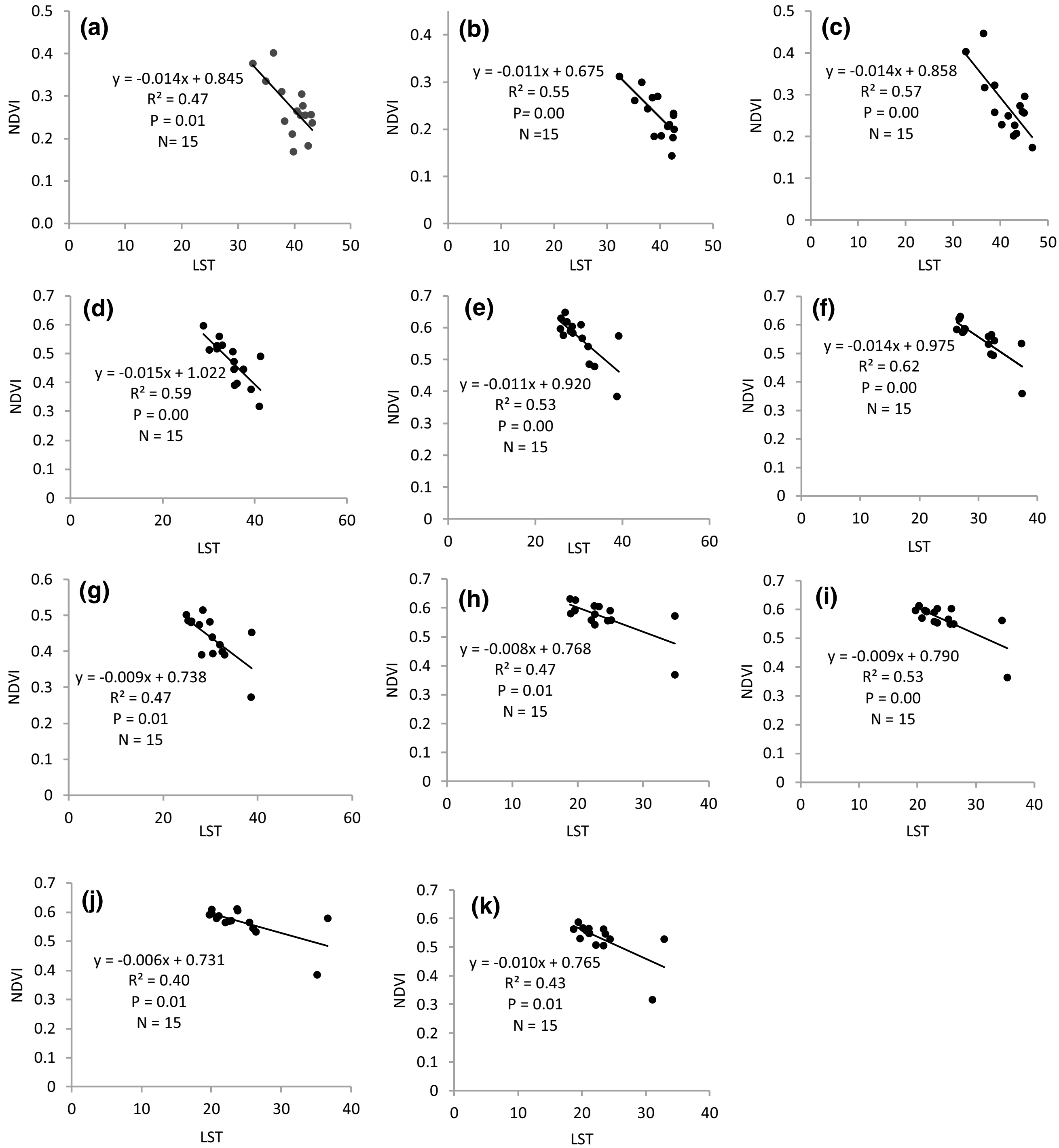

Fig. 3 NDVI and LST relationships over Raya and its environs for the period 2001–2015. **a** Yalo, **b** Megale, **c** Gulina, **d** Raya Azebo, **e** Alamata, **f** Kobo, **g** Hintalo Wejirat, **h** Endamehoni, **i** Ofla, **j** Alaje, **k** Gidan

a certain value, NDVI tends to decrease because LST is stronger during the day time than night time. This causes a higher level of vegetation stress that can lead to the incidence of drought (Zhang and Jia 2013). Another important reason, the increases in evaporation along with a decrease in soil moisture caused by higher temperatures affect the NDVI (Karnieli et al. 2006). Therefore, this study noted that there is a strong negative relationship between NDVI and LST and is corroborated by the study conducted by Sun and Kafatos (2007) in North America. A few unusual severe and frequent droughts that covered a large area have occurred during the warmest period after the year 2000 (Kogan et al.

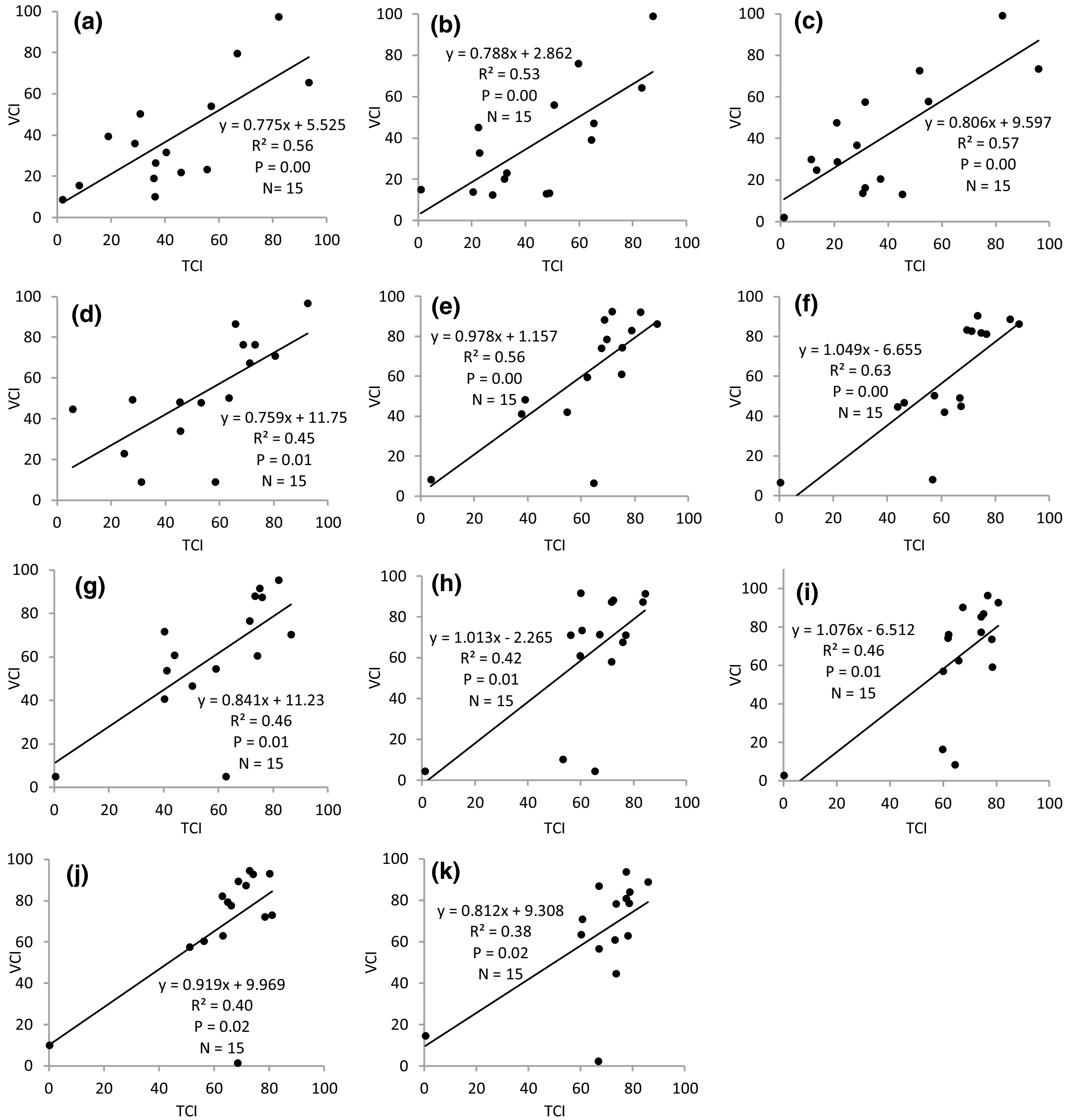

Fig. 4 VCI and TCI relationships over Raya and its environs for the period 2001–2015

2013). Sruthi and Aslam (2015) reported that when the LST correlated with the NDVI, the agricultural drought could be monitored effectively by integrating additional drought indicators (e.g., VCI, TCI, and VHI). Anbazhagan and Paramasivam (2016) investigated the relationships between NDVI and LST and found a correlation of −0.21, −0.14 and −0.19 using the Landsat Thematic Mapper (TM) products for the periods of 1992, 2001 and 2010, respectively, in Egypt. The correlations are largely weak and are not statistically significant. Hence, it is difficult to draw a conclusion on the cause–effect relationship of the two indices, but the results can only show us how much the two indices were related to each other. Similarly, Sruthi and Aslam (2015) also examined the relationships of NDVI and LST in Karnataka, India, and found a relatively better correlation (*r*) −0.64, and −0.59 for the year 2002 and 2012. However, this

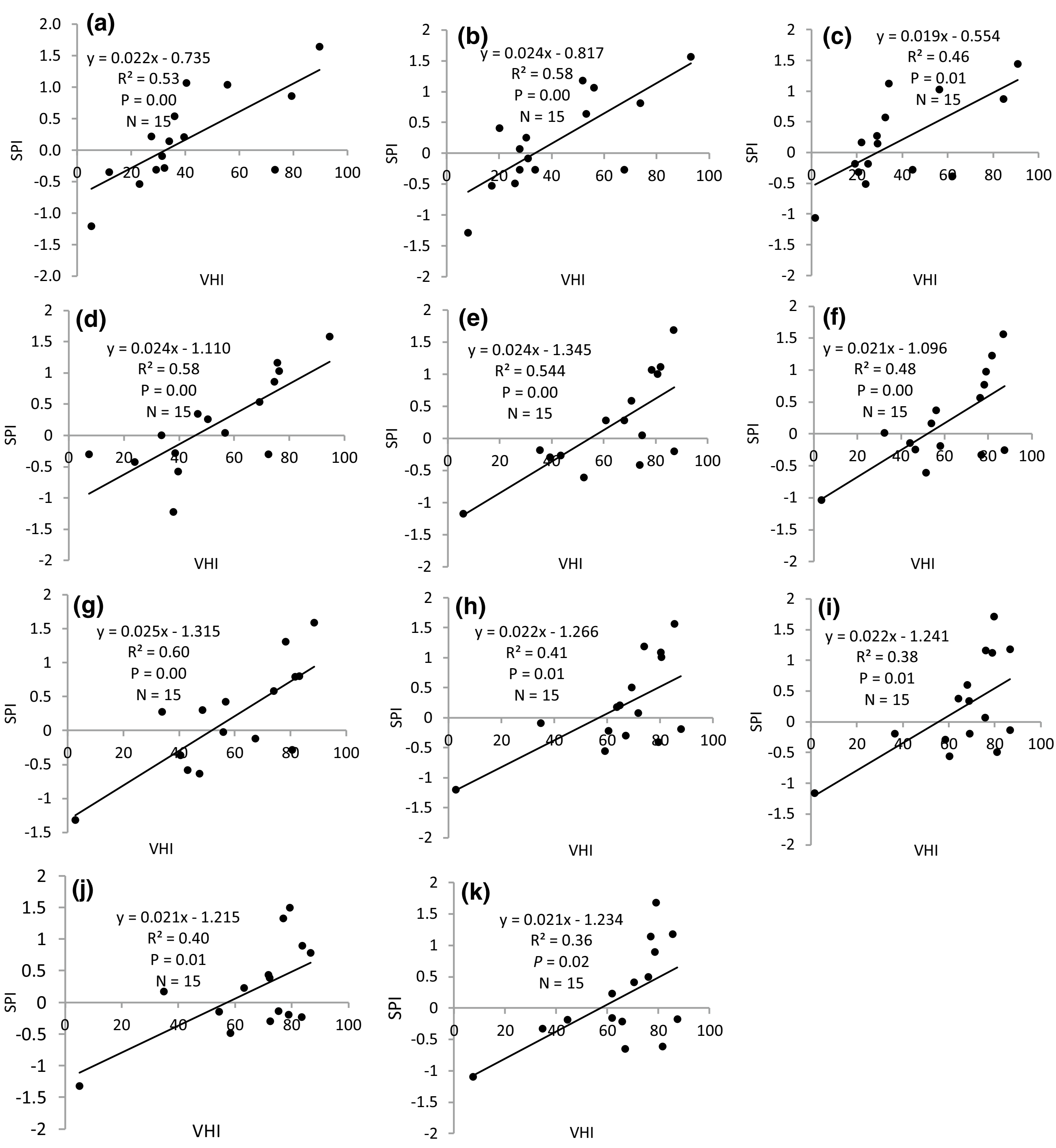

Fig. 5 SPI and VHI relationships over Raya and its environs for the period 2001–2015

study found better regression results using the MOD11A2 Terra 8-days LST and eMODIS NDVI data sets (Fig. 3). Furthermore, Sruthi and Aslam (2015) reported that NDVI and LST increase during the event of drought. This study, however, found out that during drought, only LST increased while NDVI significantly decreased due to poor moisture availability and rising surface temperature. This is a result of low precipitation in the area. Some scholars (e.g., Kumar and Shekhar 2015) suggested that the statistical relationship between NDVI and LST during drought is negative. However, in low-temperature areas the relationship between NDVI and LST might be positive (Karnieli et al. 2010). For example, during the winter or cold season, the regression between NDVI and LST is positive (Sun and Kafatos 2007).

Table 5 Pearson correlation matrix between meteorological and agricultural drought indices based on remote sensing and gauge observation data over Raya and its environs for the period 2001–2015

District	Indices	NDVI	LST	VCI	TCI	SPI	VHI	District	Indices	NDVI	LST	VCI	TCI	SPI	VHI
Raya Azebo	NDVI	1						Endamehoni	NDVI	1					
	LST	− 0.77	1						LST	− 0.70	1				
	VCI	1.00	− 0.78	1					VCI	0.99	− 0.67	1			
	TCI	0.67	− 0.87	0.67	1				TCI	0.63	− 0.92	0.65	1		
	SPI	0.85	− 0.79	0.85	0.69	1			SPI	0.55	− 0.44	0.55	0.47	1	
	VHI	0.84	− 0.83	0.84	0.95	0.77	1		VHI	0.89	− 0.95	0.87	0.87	0.54	1
Ofla	NDVI	1						Hintalo Wejirat	NDVI	1					
	LST	− 0.74	1						LST	− 0.69	1				
	VCI	1.00	− 0.72	1					VCI	1.00	− 0.69	1			
	TCI	0.68	− 0.93	0.69	1				TCI	0.68	− 0.99	0.69	1		
	SPI	0.50	− 0.46	0.52	0.50	1			SPI	0.73	− 0.49	0.74	0.49	1	
	VHI	0.90	− 0.95	0.90	0.89	0.52	1		VHI	0.90	− 0.93	0.90	0.92	0.66	1
Alamata	NDVI	1						Alaje	NDVI	1					
	LST	− 0.73	1						LST	− 0.64	1				
	VCI	1.00	− 0.74	1					VCI	1.00	− 0.63	1			
	TCI	0.73	− 1.00	0.75	1				TCI	0.63	− 1.00	0.63	1		
	SPI	0.69	− 0.69	0.68	0.68	1			SPI	0.57	− 0.34	0.58	0.337	1	
	VHI	0.91	− 0.95	0.92	0.95	0.73	1		VHI	0.86	− 0.94	0.86	0.938	0.48	1
Kobo	NDVI	1						Gidan	NDVI	1					
	LST	− 0.77	1						LST	− 0.62	1				
	VCI	0.99	− 0.80	1					VCI	1.00	− 0.65	1			
	TCI	0.79	− 1.00	0.79	1				TCI	0.65	− 1.00	0.65	1		
	SPI	0.64	− 0.60	0.64	0.60	1			SPI	0.38	− 0.42	0.38	0.42	1	
	VHI	0.93	−0.96	0.93	0.96	0.65	1		VHI	0.88	− 0.93	0.88	0.93	0.44	1
Gulina	NDVI	1						Yalo	NDVI	1					
	LST	− 0.78	1						LST	− 0.71	1				
	VCI	1.00	− 0.76	1					VCI	1.00	− 0.76	1			
	TCI	0.75	− 1.00	0.78	1				TCI	0.76	− 0.92	0.78	1		
	SPI	0.63	− 0.57	0.64	0.57	1			SPI	0.73	− 0.59	0.72	0.66	1	
	VHI	0.93	− 0.94	0.93	0.94	0.65	1		VHI	0.94	− 0.86	0.93	0.94	0.74	1
Megale	NDVI	1													
	LST	− 0.75	1												
	VCI	1.00	− 0.73	1											
	TCI	0.75	− 1.00	0.73	1										
	SPI	0.81	− 0.57	0.81	0.57	1									
	VHI	0.93	− 0.94	0.93	0.94	0.74	1								

On the other hand, a strong negative relationship between NDVI and LST was only observed in the warm periods (Sun and Kafatos 2007). In this section, we are interested in depicting the cause–effect relationships between NDVI and LST in each part of the study area (Fig. 3).

3.3 VCI and TCI Relationships

Both the VCI and TCI were successfully used in recent years to detect drought and vegetation stress because they are highly dependent on weather and ecological conditions (Singh et al. 2003). It is, therefore, imperative to verify the relationship between these two prominent agricultural drought indicators. Raghavendra (2012) reported that VCI has a high positive correlation with elevation (0.78), low positive correlation with a slope (0.39) and no correlation with terrain aspect (− 0.13). The same author noted that TCI has no significant relationship with elevation (− 0.04), slope (− 0.06) and aspect (− 0.03). Furthermore, Singh et al. (2003) reported that there is no direct relationship between VCI and TCI. However, this study has proven that there is a positive, relatively strong relationship between

VCI and TCI ($R^2/P = 0.38/0.02$ to $R^2/P = 0.63/0.00$) and statistically significant across all districts of the study area (Fig. 4 and Table 5). When the TCI increases, VCI also tends to increase. Better regression coefficient ranged from ($R^2/P = 0.53/0.00$ to $R^2/P = 0.57/0.00$) and significance level observed in the lowland area (Fig. 4a–c). The highest regression coefficient was observed in Gulina district ($R^2 = 0.57$) and comparatively lower regression coefficient ($R^2/P = 0.53/0.00$ and $R^2/P = 0.56/0.00$) found in the district of Megale and Yalo. In the midland area (Fig. 4d–g), the regression result ranges from ($R^2/P = 0.45/0.01$ to $R^2/P = 0.63/0.00$). The highest regression coefficient ($R^2 = 0.63$) was observed in the district of Kobo, while in other districts such as Raya Azebo, Hintalo Wejirat, and Alamata, the relationships between VCI and TCI were ($R^2 = 0.45$, $R^2 = 0.47$ and $R^2 = 0.55$), respectively. Further, in the highland area (Fig. 4h–k), the regression coefficient was largely between ($R^2 = 0.38$ and $R^2 = 0.46$). In this agro-ecology, the highest regression value was observed in the district of Ofla ($R^2/P = 0.46/0.01$). However, in the districts of Endamehoni, Alaje, and Gidan, the coefficient was ($R^2 = 0.42$, $R^2 = 0.40$ and $R^2 = 0.38$), respectively. This study, therefore, found that the relationship between VCI and TCI is positive, relatively strong and statistically significant in all agro-ecological zones as well as districts of the study area.

3.4 SPI and VHI Relationships

The statistical relationship between SPI and VHI depicted how the agricultural drought monitored by VHI associate with the meteorological drought measured by SPI. The regression analysis result shows that the relationship between SPI and VHI in the 3-month timescale is positive, strong ($R^2/P = 0.36/0.02$ to $R^2/P = 0.60/0.00$) and statistically significant at in all districts of the study area (such as Yalo, Megale, Gulina, Raya Azebo, Alamata, Kobo, HintaloWejirat, Endamehoni, Ofla, Alaje, and Gidan) (Fig. 5 and Table 5). The results indicated that when the SPI increases, VHI also tends to increase. This may lead to more frequent and intense droughts incidence (Kogan et al. 2013). Yan et al. (2016) and Wang et al. (2014) reported the statistical relationship between SPI and VHI has strong correlation during a drought period in Southwest China. This study has also observed similar findings in Raya, Northern Ethiopia.

The regression results in the lowland area (Fig. 5a–c) range from ($R^2/P = 0.46/0.01$ to $R^2/P = 0.58/0.01$). A high regression result (R^2) was observed in the district of Megale ($R^2 = 0.58$), while in the areas of Yalo and Gulina, the regression value was ($R^2 = 0.53$ and $R^2 = 0.46$), respectively. Similarly, in the midland area (Fig. 5d–g) such as Raya Azebo, Alamata, Kobo and Hintalo Wejirat, an $R^2 = 0.58$, $R^2 = 0.54$, $R^2 = 0.48$ and $R^2 = 0.60$ was examined. Furthermore, in the highland area (Fig. 5h–k) the relationship between SPI and VHI ranges from ($R^2/P = 0.36/0.02$ to $R^2/P = 0.41/0.01$). Therefore, this study found a higher degree of regression result, which is statistically significant. Owrangi et al. (2011) reported that the spatial correlation through visual comparison gives more meaningful information than quantitative correlation. However, this study argues the idea suggested by Owrangi et al. (2011) because regression results provide more statistical information on how the VHI (derived from the multi-temporal mean VCI, TCI) and the SPI measured from the long-term precipitation relate each other. In addition, it helps to measure the strength of the relationship between VHI and SPI. Therefore, the relationships between the two indices cannot prove through visual comparison. Further, SPI and VHI clearly explain the relationship between meteorological and agricultural drought (Marufah et al. 2017). Hence, these two indices are suitable for monitoring the incidence of agricultural and meteorological drought.

3.5 Pearson Correlation Analysis of the Major Drought Indices

Pearson correlation analysis was applied to summarize the statistical relationships of NDVI and LST, VCI and TCI, SPI and VHI (Table 5). Zhang and Jia (2013) applied Pearson correlation analysis between the major meteorological and agricultural drought indices for the period 2003–2010 over northern China. The same authors reported that VCI had a lower correlation with SPI, but TCI showed relatively better correlation with SPI during the vegetation growing period. In the present study, the Pearson correlation matrix result revealed that LSI and NDVI was negatively correlated and ranged between ($r = -0.62$ and $r = -0.78$). The highest and lowest correlation were also observed in the district of Gulina and Gidan. The relationships between VCI and TCI were positive and it ranges between ($r = 0.63$ and $r = 0.79$). Furthermore, SPI and VHI were positively correlated ($r = 0.44$ to $r = 0.77$). The highest correlation was observed in Raya Azebo and lowest in Gidan (Table 5). Table 5 provides a detailed summary of each drought index relationships.

4 Conclusions

This study determines the statistical relationships among the NDVI and LST, VCI and TCI, SPI and VHI at 3-month timescale in Raya and its environs, Northern Ethiopia. The analysis revealed that the mean LST is high (i.e., between 39.6 and 41.29 °C) in the lowland areas (e.g., Yalo, Megale, and Gulina districts), while NDVI is poor with unhealthy vegetation greenness (i.e., below 0.27) due to unfavorable moisture condition than the mid (e.g., Raya Azebo, Alamata, Hintalo

Wejirat, and Kobo) and highland areas (e.g., Endmehoni, Ofla, Alaje, and Gidan districts). The study found a better regression and Pearson correlation results using the MOD11A2 Terra 8-days LST, eMODIS NDVI and hybrid TAMSAT data sets. The statistical relationship between NDVI and LST turned out negative and ranged from ($R^2/P=0.40/0.01$ to $R^2/P=0.62/0.00$) and statistically significant across all districts of the study area. The results reveal that when the LST increases, NDVI tends to decrease because LST is stronger during day time than night time. The study also showed that there is a positive, relatively strong relationship between VCI and TCI ($R^2/P=0.38/0.02$ to $R^2/P=0.63/0.00$) and statistically significant across all districts of the study area. When the TCI increases, VCI also tends to increase. Likewise, the relationship between SPI and VHI ($R^2/P=0.36/0.02$ to $R^2/P=0.60/0.00$) is found to be positive, relatively strong and statistically significant in all agro-ecologies as well as districts of the study area. This regression result signifies that when SPI increases, VHI also tends to increase. Therefore, the study noted that the main factor that causes drought in the study area is due to rising of LST because of poor rainfall, moisture and less vegetation cover availability in the area.

Acknowledgements The main author is thankful for the Ph.D. scholarship offered by the TreccAfrica II project. The financial support of Mekelle University, and OSF-ACCAI project of Mekelle University for conducting the research was highly commendable. The National Aeronautics and Space Administration (NASA), United States Geological Survey (USGS), Famine Early Warning System Network (FEWS-NET), and National Meteorological Agency (NMA) of Ethiopia are highly appreciated for the provision of all necessary data. We are grateful for the constructive feedback of the four anonymous reviewers and the editor.

Compliance with Ethical Standards

Conflict of Interest The authors state no conflict of interest.

References

Abbas S, Nichol JE, Qamer FM, Xu J (2014) Characterization of drought development through remote sensing: a case study in central Yunnan, China. Remote Sens 6(6):4998–5018

Anbazhagan S, Paramasivam CR (2016) Statistical correlation between land surface temperature (LST) and vegetation index (NDVI) using multi-temporal landsat TM data. Int J Adv Earth Sci Eng 5(1):333

Ayenew T, GebreEgziabher M, Kebede S, Mamo S (2013) Integrated assessment of hydrogeology and water quality for groundwater-based irrigation development in the Raya Valley, northern Ethiopia. Water Int 38(4):480–492

Bisht G, Venturini V, Islam S, Jiang LE (2005) Estimation of the net radiation using MODIS (Moderate Resolution Imaging Spectroradiometer) data for clear sky days. Remote Sens Environ 97(1):52–67

Brown JF, Wardlow BD, Tadesse T, Hayes MJ, Reed BC (2008) The Vegetation Drought Response Index (VegDRI): a new integrated approach for monitoring drought stress in vegetation. GISci Remote Sens 45(1):16–46

Choi M, Jacobs JM, Anderson MC, Bosch DD (2013) Evaluation of drought indices via remotely sensed data with hydrological variables. J Hydrol 476:265–273

Cunha APM, Alvalá RC, Nobre CA, Carvalho MA (2015) Monitoring vegetative drought dynamics in the Brazilian semiarid region. Agric For Meteorol 214:494–505

Evans JD (1996) Straight forward statistics for the behavioral sciences. Brooks/Cole, Pacific Grove

Frey CM, Kuenzer C, Dech S (2012) Quantitative comparison of the operational NOAA-AVHRR LST product of DLR and the MODIS LST product V005. Int J Remote Sens 33(22):7165–7183

Gidey E, Dikinya O, Sebego R, Segosebe E, Zenebe A (2017) Modeling the spatio-temporal dynamics and evolution of land use and land cover (1984–2015) using remote sensing and GIS in Raya, Northern Ethiopia. Model Earth Syst Environ 3(4):1285–1301

Justice CO, Vermote E, Townshend JR, Defries R, Roy DP, Hall DK et al (1998) The moderate resolution imaging spectroradiometer (MODIS): land remote sensing for global change research. IEEE Trans Geosci Remote Sens 36(4):1228–1249

Karnieli A, Bayasgalan M, Bayarjargal Y, Agam N, Khudulmur S, Tucker CJ (2006) Comments on the use of the vegetation health index over Mongolia. Int J Remote Sens 27(10):2017–2024

Karnieli A, Agam N, Pinker RT, Anderson M, Imhoff ML, Gutman GG et al (2010) Use of NDVI and land surface temperature for drought assessment: merits and limitations. J Clim 23(3):618–633

Kogan FN (1995) Application of vegetation index and brightness temperature for drought detection. Adv Space Res 15(11):91–100

Kogan FN (2001) Operational space technology for global vegetation assessment. Bull Am Meteorol Soc 82(9):1949

Kogan F, Adamenko T, Guo W (2013) Global and regional drought dynamics in the climate warming era. Remote Sens Lett 4(4):364–372

Kumar D, Shekhar S (2015) Statistical analysis of land surface temperature–vegetation indexes relationship through thermal remote sensing. Ecotoxicol Environ Saf 121:39–44

Marufah U, Hidayat R, Prasasti I (2017) Analysis of relationship between meteorological and agricultural drought using standardized precipitation index and vegetation health index. In: IOP conference series: earth and environmental science, vol 54, no 1. IOP Publishing, Bristol, p 012008

McKee TB, Doesken NJ, Kleist J (1993) The relationship of drought frequency and duration to time scales. In: Proceedings of the 8th conference on applied climatology, vol 17, no 22. American Meteorological Society, Boston, pp 179–183

Mu L, Wu B, Yan N, Dong L (2006) An adaptation analysis of drought index in Shanxi province of China. In: IEEE international conference on geoscience and remote sensing symposium, 2006. IGARSS 2006. IEEE, Piscataway, pp 290–293

Owrangi MA, Adamowski J, Rahnemaei M, Mohammadzadeh A, Sharifan RA (2011) Drought monitoring methodology based on AVHRR images and SPOT vegetation maps. J Water Resour Prot 3(5):325

Panu US, Sharma TC (2002) Challenges in drought research: some perspectives and future directions. Hydrol Sci J 47(S1):S19–S30

Parviz L (2016) Determination of effective indices in the drought monitoring through analysis of satellite images. Agric For/Poljoprivreda i Sumarstvo 62(1):305–324. https://doi.org/10.17707/AgricultForest.62.1.34

Raghavendra BR (2012) The influence of terrain factors on VCI and TCI of Jogimatti Forest, Chitradurga District, Central University of Karnataka, India, Department of Geology, Gulbarga 585311, Karnataka, India, pp 1–8

Sholihah RI, Trisasongko BH, Shiddiq D, La Ode SI, Kusdaryanto S, Panuju DR (2016) Identification of agricultural drought extent based on vegetation health indices of landsat data: case of Subang and Karawang, Indonesia. Procedia Environ Sci 33:14–20

Singh RP, Roy S, Kogan F (2003) Vegetation and temperature condition indices from NOAA AVHRR data for drought monitoring over India. Int J Remote Sens 24(22):4393–4402

Sruthi S, Aslam MM (2015) Agricultural drought analysis using the NDVI and land surface temperature data; a case study of Raichur district. Aquat Procedia 4:1258–1264

Sun D, Kafatos M (2007) Note on the NDVI-LST relationship and the use of temperature-related drought indices over North America. Geophys Res Lett. https://doi.org/10.1029/2007GL031485

Tucker CJ, Pinzon JE, Brown ME, Slayback DA, Pak EW, Mahoney R et al (2005) An extended AVHRR 8-km NDVI dataset compatible with MODIS and SPOT vegetation NDVI data. Int J Remote Sens 26(20):4485–4498

Wang J, Rich PM, Price KP (2003) Temporal responses of NDVI to precipitation and temperature in the central Great Plains, USA. Int J Remote Sens 24(11):2345–2364

Wang H, Lin H, Liu D (2014) Remotely sensed drought index and its responses to meteorological drought in Southwest China. Remote Sens Lett 5(5):413–422

Wilhite DA (ed) (2000) Drought as a natural hazard: concepts and definitions. In: Drought: a global assessment, vol 69. Routledge, London, pp 3–18

Wolde-Georgis T (1997) El Nino and drought early warning in Ethiopia. Internet J Afr Stud 2. https://ssrn.com/abstract=1589710

Yan N, Wu B, Boken VK, Chang S, Yang L (2016) A drought monitoring operational system for China using satellite data: design and evaluation. Geomat Nat Hazards Risk 7(1):264–277

Zhang A, Jia G (2013) Monitoring meteorological drought in semiarid regions using multi-sensor microwave remote sensing data. Remote Sens Environ 134:12–23

Zhang L, Jiao W, Zhang H, Huang C, Tong Q (2017) Studying drought phenomena in the Continental United States in 2011 and 2012 using various drought indices. Remote Sens Environ 190:96–106

Zhou L, Wu J, Zhang J, Zhao F, Liu M, Zhao L (2010) Assessing the drought monitoring characteristic of time series NDVI indices in crop growing season. In: 2010 IEEE international geoscience and remote sensing symposium (IGARSS). IEEE, Piscataway, pp 2063–2066

Zhou L, Zhang J, Wu J, Zhao L, Liu M, Lü A, Wu Z (2012) Comparison of remotely sensed and meteorological data-derived drought indices in mid-eastern China. Int J Remote Sens 33(6):1755–1779

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