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Assessment of spatio-temporal vegetation dynamics in tropical arid ecosystem of India using MODIS time-series vegetation indices

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Abstract

In the present study, we analyzed spatio-temporal vegetation dynamics to identify and delineate the vegetation stress zones in tropical arid ecosystem of Anantapuramu district, Andhra Pradesh, India, using Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), and Vegetation Anomaly Index (VAI) derived from time-series Moderate Resolution Imaging Spectroradiometer (MODIS) 16-day products (MOD13Q1) at 250 m spatial resolution for the growing season (June to September) of 19 years during 2000 to 2018. The 1-month Standardized Precipitation Index (SPI) was computed for 30 years (1989 to 2018) to quantify the precipitation deficit/surplus regions and assess its influence on vegetation dynamics. The growing season mean NDVI and VCI were correlated with growing season mean 1-month SPI of dry (2003) and wet (2007) years to analyze the spatio-temporal vegetation dynamics. The correlation analysis between SPI and NDVI for dry year (2003) showed strong positive correlation ($r = 0.89$). Analysis of VAI for dry year (2003) indicates that the central, western, and south-western parts of the district reported high vegetation stress with VAI of less than -2.0. This might be due to the fact that central and south-western parts of the district are more prone to droughts than the other parts of the district. The correlation analysis of SPI, NDVI, and VCI distinctly shows the impact of rainfall on vegetation dynamics. The study clearly demonstrates the robustness of NDVI, VCI, and VAI derived from time-series MODIS data in monitoring the spatio-temporal vegetation dynamics and delineate vegetation stress zones in tropical arid ecosystem of India.

Keywords SPI · MODIS · NDVI · VCI · VAI · Vegetation stress zones · Tropical arid ecosystem

Introduction

Vegetation plays a pivotal role in the global atmospheric, terrestrial ecosystem, hydrologic, carbon cycles, climate change, and drought monitoring (Peng et al. 2012; De Keersmaecker et al. 2014; Sierra-Soler et al. 2015; Winkler et al. 2017; Measho et al. 2019). Changes occurred in vegetation constitute as good indicators in ecological and environmental assessment from local to global scales (Sobrino and Julien 2011; Schucknecht et al. 2013; Guay et al. 2014).

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Vegetation productivity of arid and semi-arid ecosystems is mostly governed by inter-annual variability in precipitation (Huber et al. 2011; Li et al. 2017), and these ecosystems are highly susceptible to moisture stress condition because of the low annual precipitation (Wilhite and Glantz 1985). In drought assessment, monitoring of vegetation stress is considered to be one of the important indicators (Tadesse et al. 2017). Most often meteorological and agricultural droughts occur in arid and semi-arid regions and their monitoring refers to point-based analyses, which include simple presentations of specific events relative to their long-term historical averages (Zhang et al. 2017). The drought-prone areas in India are confined mostly to arid, semi-arid, and sub-humid regions of western and peninsular India (Nagarajan 2003). Successful monitoring of such vulnerable terrestrial ecosystems requires frequent and internally consistent records of information on range of biophysical variables (Kogan 2001). The traditional methods of mapping and monitoring of large areas mainly based on conventional field surveys are not cost-effective and time-efficient to analyze vegetation changes and drought patterns, but the satellite-based inputs provide consistent and reliable datasets to study the vegetation dynamics and drought patterns in spatio-temporal scale. SPI gives a better depiction of abnormal dryness/wetness in a region (McKee et al. 1993, 1995; Guttman 1999; Hazaymeh and Hassan 2017). Due to its robustness, SPI was widely used to characterize dryness/wetness conditions in many climatic regimes (Moradi et al. 2011; Dutta et al. 2015). Karavitis et al. (2011) studied duration of droughts, their intensity, and spatial extent in semi-arid areas of Greece with the help of SPI. Use of time series remote sensing data presents a number of advantages in determining the impacts of drought on vegetation (Kogan 2002).

In recent years, the use of time series remote sensing datasets and geographic information systems (GIS) is increasing in assessment of spatio-temporal patterns of vegetation dynamics at regional to global scales (Zhou et al. 2001; Cleland et al. 2006; Xie et al. 2015; Cao et al. 2018). Remote sensing provides calibrated, objective, repeatable, and cost-effective information for large areas in monitoring vegetation dynamics (Tucker et al. 2001; Gao et al. 2013). Remote sensing data and methods are critical tools in studying the spatio-temporal dynamics of vegetation and the underlying drivers of droughts in the context of limited availability and inconsistency of drought-related *in situ* data (Naumann et al. 2014; Rojas et al. 2011). Vegetation indices derived from temporal remote sensing data were extensively used for identifying the periods of vegetative stress (Kogan 2001; Rojas et al. 2011; Rhee et al. 2010; Logan et al. 2010; Skakun et al. 2016). The spatial, spectral, and temporal components of the MODIS 250 m data are appropriate for vegetation mapping and monitoring (Tucker et al. 2005; Zambrano et al. 2016). The two bands in the red and near-infrared wavelength intervals of MODIS 250 m data are the important spectral

regions for remote sensing of vegetation (Townshend et al. 1991). This strong contrast between red and near-infrared reflectance helps to generate vegetation indices like NDVI and VCI. NDVI is being widely used in many applications including to study and monitor the spatio-temporal patterns of vegetation at regional and continental scales (Lotsch et al. 2003; Chang et al. 2011; Son et al. 2012) especially in arid and semi-arid lands (Gurgel and Ferreira 2003; Wang et al. 2010). Besides NDVI, globally many researchers have used VCI for assessment of agricultural drought in varied ecological conditions (Kogan 1995; Ji and Peters 2003). VCI was used for drought monitoring over India (Singh and Kogan 2002; Dutta et al. 2015) and Southwest Asia (Thenkabail et al. 2004) and concluded that VCI was found to be sensitive indicator of drought conditions. Furthermore, VCI has the ability to distinguish NDVI fluctuations due to short-term climate changes to long-term ecosystem changes (Kogan 1990). The analysis of indices like SPI and NDVI can generate the best correlation relationships for early detection of drought impacts, drought monitoring, and identification of hot spots at local scales (Linés et al. 2017). Amri et al. (2011) proposed Vegetation Anomaly Index (VAI) and observed high correlation between VAI derived from SPOT-VGT data and precipitation levels in semi-arid region of Kairouan plain, central Tunisia.

In India, about 15.8% (52.0 Mha) of the geographical area is characterized by arid and nearly 35.4% (116.5 Mha) is under semi-arid climatic conditions (Sehgal et al. 1992). The Intergovernmental Panel on Climate Change (IPCC) has estimated an increase in frequency of droughts over the semi-arid regions of India (IPCC 2013). Although the frequency, duration, and intensity of droughts vary, they are being experienced in arid and semi-arid regions of India. There is also a growing concern over change in vegetation dynamics, weather aberrations, and drought patterns with the increasing climate variability, particularly in the semi-arid regions of India (Todmal 2019; Vyas and Bhattacharya 2020). The study area of Anantapuramu district of Andhra Pradesh, India, is located in rain-shadow region of arid to semi-arid and prone to recurring droughts and crop losses. Furthermore, Anantapuramu district has reported to be the second lowest annual rainfall receiving district in the India after Jaisalmer district in Rajasthan state. Hence, the analysis of time series rainfall data and spatio-temporal dynamics of vegetation assumes importance to delineate the vegetation stress zones and devise the combating mechanisms to restore the degraded ecosystems. The objectives of the present study are, firstly, analyze 1-month SPI to assess the spatio-temporal variability of precipitation deficit/surplus conditions, secondly, analyze vegetation indices, such as NDVI, VCI, and VAI derived from time-series MODIS 250 m data for the growing season (June–September) to monitor the vegetation dynamics, and, thirdly, identify the vegetation stress zones

through analysis of spatio-temporal dynamics of vegetation anomalies in tropical arid ecosystem of Anantapuramu district, Andhra Pradesh, India.

Geographical settings

Anantapuramu district is located in the drought-prone Rayalaseema region of Andhra Pradesh between 13° 40′ and 15° 15′ north latitude and 76° 50′ and 78° 30′ east longitude with a total geographical area of 1.91 Mha (Fig. 1). Administratively, the district consists of five revenue divisions and 63 revenue mandals. The mean annual rainfall of the district is 553.0 mm. Besides the low quantum of rainfall, the distribution is highly erratic in the district. The district is located in the arid agro-ecological zone and is characterized by hot arid bioclimatic conditions with dry summers and mild winters. The district is vulnerable to climate extremes like droughts due to its exposure to climate variability with shallow soils. Agro-ecological settings of the district shows that hot arid, hot dry semi-arid, and hot moist semi-arid ecological sub-regions occupy 92.5, 4.9, and 2.6%, respectively, with the

length of growing period of 90 days (Velayutham et al. 1999). The total cropped area of the district is 0.92 Mha, out of which 0.89 Mha is under net sown area and 0.02 Mha is under area sown more than once during the years 2016–17 (DES 2017). The net irrigated area in the district is only 14.13% (0.13 Mha) out of total cultivated area mainly under tube wells and canals. The field crops, like groundnut, chickpea, sunflower, pearl millet, rice, redgram, sorghum, maize, cotton, and finer millets, are grown in the district. The horticulture crops, like sweet orange, mango, grapes, pomegranate, papaya, and banana, and the vegetable crops, like tomato and chillies, were also grown under irrigated conditions in the district.

Materials and methods

Datasets used

The mandal wise monthly rainfall data for the period of thirty years from 1989 to 2018 for 63 rain-gauge stations were obtained from the Agricultural Research Station, Anantapuramu, Andhra Pradesh, India, and the same were
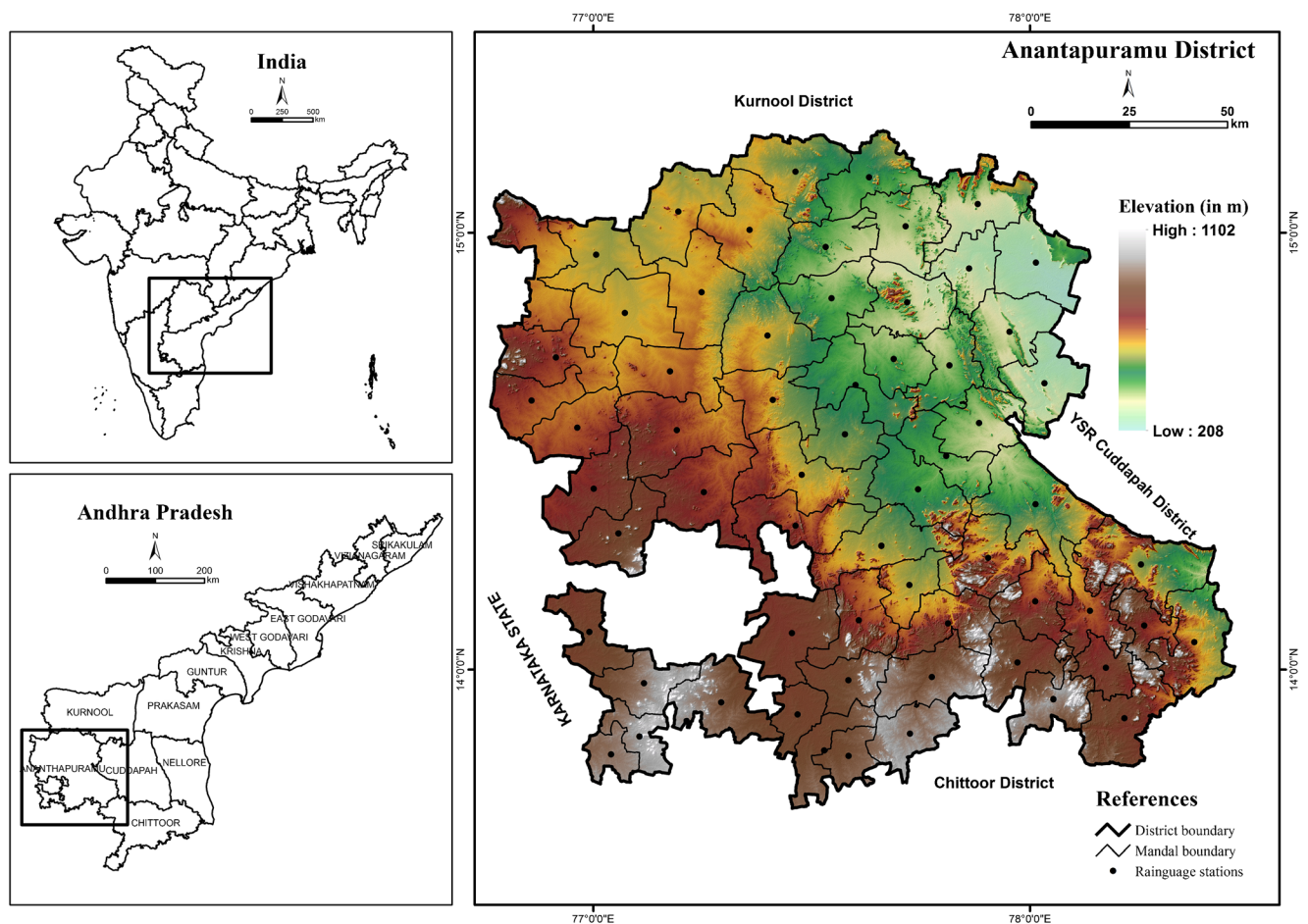

Fig. 1. Location map of the study area with elevation depicted from SRTM DEM of 30 m resolution along with mandal boundaries and locations of rain-gauge stations

used to compute 1-month SPI. MODIS 16-day composites (MOD13Q1) at 250 m spatial resolution for 19 years (2000 to 2018) were downloaded (https://lpdaac.usgs.gov) to develop monthly and then growing season mean (June to September) NDVI products. Subsequently, monthly and growing season mean VCI (Kogan 1997) and VAI (Mongkolsawat et al. 2001) were also computed by using the standard mathematical equations.

Computation of 1-month SPI

McKee et al. (1993, 1995) proposed the SPI as a tool based on the precipitation primarily for defining and monitoring the drought. Computation of SPI is based on the probability of precipitation for any given time scale, and it is a spatially invariant indicator of drought (Guttman 1999). In the study, monthly rainfall data for the period of thirty years from 1989 to 2018 for 63 rain-gauge stations were used to compute 1-month SPI using the software developed by the World Meteorological Organization (WMO 2012). The 1-month SPI was computed by using the following mathematical equation to assess the wet and dry conditions based on precipitation variables.

$$SPI = (Xij - Xi_{mean})/\sigma \qquad (1)$$

where, Xi is the precipitation for the ith station and j^{th} observation, Xi_{mean} is long-term average rainfall of ith station, and σ is standard deviation.

SPI was defined as the number of standard deviations that the observed cumulative rainfall at a given time scale would deviate from the long-term mean for that same time scale over the entire length of the record (McKee et al. 1993). Subsequently, the obatined 1-month SPI values at each rain-gauge station were used to develop 1-month SPI raters' for the growing season (June–September) from the years 2000–2018 by using ordinary kriging interpolation technique in ArcGIS (ESRI 2001). The 1-month SPI rasters were used to develop growing season mean 1-month SPI raster for the period from 2000 to 2018, and the same was used for further analysis with the vegetation indices derived from time series MODIS datasets. The positive SPI values indicate greater than mean precipitation, and negative values indicate less than mean precipitation. Classification of SPI proposed by McKee et al. (1993), i.e., extremely wet ($\geq$ 2.00), very wet (1.50–1.99), moderately wet (1.00–1.49), near normal ($-$ 0.99 to 0.99), moderately dry ($-$ 1.00 to $-$ 1.49), severely dry ($-$ 1.50 to $-$ 1.99), and extremely dry ($\leq -$ 2.00) was adopted to define the wet and dryness intensities of the study area. The analysis of growing season mean 1-month SPI shows that 2003 was the driest and 2007 was the wettest years during the period from 2000 to 2018. The growing season mean NDVI and VAI derived from time series MODIS datasets were validated with growing season mean 1-month SPI of dry (2003) and wet (2007) years.

Pre-processing of time series MODIS NDVI

In the study, MODIS NDVI 16-day composite data (MOD13Q1) (tile h25v7) in HDF format were downloaded (https://earthexplorer.usgs.gov/) from the USGS data gateway (MODIS 1999) for the growing season (June–September) during 2001 to 2018. The characteristics of the datasets used in the study area are shown in Table 1. The acquired products represent a 16-day composite at 250 m spatial resolution in a sinusoidal projection, and these datasets were reprojected to the UTM projection (WGS84, Zone 44N) by using the MRT tool downloaded from LPDAAC (https://lpdaac.usgs.gov/lpdaac/tools) and then clipped with the study area boundary. In the study, maximum value composite (MVC) was generated to select the highest pixel value to represent the composting period (Holben 1986; Huete et al. 2002). To remove the cloud cover and other atmospheric disturbances from the projected time-series MODIS NDVI datasets, Savitzky-Golay filter (Savitzky and Golay 1964) was applied by using Timesat software version 3.2 (http://web.nateko.lu.se/timesat/timesat.asp). The Savitzky-Golay filter is a simplified least-square-fit convolution to smooth and compute the derivatives of a set of consecutive values (Chen et al. 2004). The NDVI is a normalized difference measure comparing the near infrared and visible red bands defined by the following formula:

$$NDVI = \frac{NIR - R}{NIR + R} \qquad (2)$$

where, NIR and Red denote surface reflectance in near infrared and red bands in MODIS image, respectively.

Subsequently, the areas under waterbodies were subtracted from the filtered NDVI datasets by using "IsNull," a condition in ArcGIS to minimize the effect of such features on analysis of time series NDVI products. The atmospherically corrected monthly NDVI products were used to develop growing season mean MODIS NDVI data products for the period from 2001 to 2018 in ArcGIS.

Computation of time series VCI

The VCI derived from NDVI was widely used for detecting the onset of drought, its intensity, duration, and impact (Kogan 1995; Seiler et al. 1998). In the study, atmospherically corrected NDVI products derived from MODIS 250 m time series data of growing season were used to generate monthly VCI and subsequently mean VCI for the growing season during the period from 2000 to 2018. VCI provides the information on the current status of vegetation compared with

Table 1. Characteristics of MOD13Q1 dataset used in the study

Parameters	Characteristics
Collection	Terra MODIS
Temporal coverage	February 18, 2000 – until date
Tile area	~10 × 10 lat/long
File size	~ 92.86 MB
Projection	Sinusoidal
Data format	HDF-EOS
Dimension (rows/columns)	4800 × 4800
Resolution	250 meters
Science Data Sets (SDS HDF Layers)	12
Scale factor	NDVI, EVI, B, R, NIR, MIR: 0.0001
	View Zenith and Sun Zenith: 0.01
	Azimuth angle: 0.1
Temporal interval	16 days
Spectral calibration	12 bits

(Source: earthexplorer.usgs.gov)

the historical maximum and minimum (Kogan 1997). The following equation was used to derive VCI:

$$VCI = \frac{NDVI(x, y) - NDVI_{min}(x, y)}{NDVI_{max}(x, y) - NDVI_{min}(x, y)} \times 100 \qquad (3)$$

where, $NDVI(x,y)$ is the current year growing season, NDVI is value at location (x,y), $NDVI_{min}(x,y)$ is the historically minimum value at location (x,y), and $NDVI_{max}(x,y)$ is the historically maximum value at location (x,y). VCI provides the deviation of each pixel from the historical NDVI values. VCI value is being measured in percentage ranging from 1 to 100. VCI value below 35% indicates severe drought condition, 35 to 50% shows the drought condition, and 50 to 100% indicates above normal condition of vegetation (Kogan 1995). The growing season mean NDVI and VCI profiles were analyzed to assess their spatio-temporal vegetation dynamics during 2000 to 2018. In conjunction with growing season mean 1-month SPI, the detailed analysis of growing season mean NDVI and VCI was carried out for dry (2003) and wet (2007) years.

Computation of time series VAI

In the study, VAI proposed by Amri et al. (2011) was computed to analyze the vegetation anomalies during 2000 to 2018; VAI was computed; and it provides the quantitative illustration of vegetation stress and influence of droughts on vegetation cover (Mongkolsawat et al. 2001). The VAI is defined as follows:

$$VAI_i = \frac{NDVI_i - (NDVI_i)_{mean}}{\sigma_i} \qquad (4)$$

where $NDVI_i$ is the NDVI estimate for a given growing season

i, $(NDVI_i)_{mean}$ is the mean value of the NDVI during growing season i, derived from 19 years of NDVI time series, and σ_i corresponds to the standard deviation of the NDVI values estimated for growing season i, over the same 19-year period. If VAI is greater than zero, it indicates the absence of vegetation stress or drought. Whereas, the VAI is negative, it indicates the vegetation stress as a result of drought or a period with lack of precipitation. To determine the dynamics of VAI, growing season mean VAI was carried out for dry (2003) and wet (2007) years of the study area. The influence of rainfall on VAI was analyzed to understand the variations in vegetation stress. In the study, based on the variations of growing season mean VAI during dry (2003) and wet (2007) years, the vegetation stress zones were identified and delineated.

Validation of NDVI and VCI with SPI during dry and wet years

In the present study, Pearson's correlation analysis was carried out using R software to investigate the relationship between growing season mean 1-month SPI and NDVI as well as growing season mean 1-month SPI and VCI of dry (2003) and wet (2007) years. Galarça et al. (2010) and Figueiredo Filho and Silva Júnior (2009) stated that the Pearson's correlation coefficient (r) has values ranging from -1 to 1, where, values close to 1 ($r = 1$) represent a perfectly positive correlation and values close to -1 ($r = -1$) represent a perfectly negative correlation between two variables. Dancey and Reidy (2006) proposed a classification for the Pearson's correlation coefficient as $r = 0.10$ to 0.30 (weak), $r = 0.40$ to 0.6 (moderate), and $r = 0.70$ to 1 (strong). In the study, the Pearson's correlation coefficient (r) was calculated through scatter plot between growing season mean 1-month SPI and

NDVI for dry (2003) and wet (2007) years to analyze the correlation between rainfall variability and vegetation dynamics. Correlation coefficient was worked out using the growing season mean 1-month SPI on one hand and the growing season mean NDVI on the other hand in the scatter plot. Similarly, Pearson's correlation coefficient (r) was also determined between growing season mean 1-month SPI and growing season mean VCI for dry (2003) and wet (2007) years to analyze the correlation between rainfall and its impact on vegetation condition.

Results and discussion

Spatio-temporal dynamics of growing season mean 1-month SPI

Rainfall, as a key factor, controls active variations in vegetation status especially in arid and semi-arid regions as vegetation health in those regions is vulnerable to the quantity, duration, and frequency of rainfall (Dutta et al. 2015; Kundu et al. 2015). Spatio-temporal dynamics of growing season mean 1-month SPI for the period of thirty years from 1989 to 2019 shows that year 2003 was the driest and year 2007 was the wettest in the study area. The dry (2003) and wet (2007) years were considered to establish the relationship among growing season mean 1-month SPI and growing season mean NDVI and VCI. Analysis of spatio-temporal dynamics of growing season mean 1-month SPI for the dry year (2003) showed that the SPI ranges from extremely dryness (≤ -2.00) to severely dryness (-1.50 to -1.99) conditions prevailed in western, central, southwestern, and northwestern parts of the district. The moderately dry (-1.00 to -1.49) and near normal (-0.09 to 0.09) conditions were observed in northern, northeastern, and southeastern parts of the district (Fig. 2a). However, during the wet year (2007), the SPI ranges from near normal (-0.99 to 0.99) to extremely wet (>2.0) (Fig. 2b), and no region was found under moderately dry (-1.00 to -1.49), severely dry (-1.50 to -1.99), and extremely dry (≤ -2.00) conditions. The near normal (-0.99 to 0.99) conditions were noticed in the western parts of the district. The western and northwestern parts of the district were characterized by moderately wet (1.00 to 1.49) conditions. However, very wet (1.50 to 1.99) conditions were observed in the southwestern parts of the district. Interestingly, during the wet (2007) year, majority of the study area was under extremely wet (>2.0) condition. Analysis revealed that SPI could be used to identify the dryness and wetness, their intensities, and spatio-temporal extent (Dutta et al. 2015; Kundu et al. 2020). Furthermore, growing season mean 1-month SPI was compared with the corresponding vegetation indices, such as growing season mean NDVI and VCI, derived from temporal MODIS 250 m data to assess the impact of rainfall on status of vegetation.

Spatio-temporal dynamics of growing season mean NDVI

Spatio-temporal dynamics of growing season mean NDVI for the dry year (2003) of the district ranges from -0.14 to 0.65. The lowest growing season mean NDVI of -0.14 to 0.05 was found in the western and central parts of the district. The majority area of the district was characterized by low NDVI that ranges from 0.05 to 0.50 in the western, southwestern, and southeastern parts of the district. However, the higher range of NDVI from 0.50 to 0.65 was observed in the southeastern parts of the district (Fig. 3a). The intra-seasonal dynamics of NDVI in dry year (2003) shows low NDVI of less than 0.25 in more than half of the growing season due to deficit rainfall. But at the end of the growing season, NDVI could reach 0.4 due to late monsoon rains received in the season, which clearly indicates the impact of rainfall on vegetation dynamics. On the other hand, in the wet year (2007), the growing season mean NDVI ranges from -0.07 to 0.78. The lowest NDVI of -0.07 to 0.05 was noticed in the western and northwestern parts of the district; these regions normally receive relatively low rainfall and that might be the cause for low vegetative cover during the growing season. Furthermore, the central, western, and south-western parts of the study area are under rain shadow of south-west monsoon and north-east monsoon, which could not reach effectively to this region due to the distance from the east coast of India. However, majority of the area particularly in the eastern parts of the district, is characterized by moderate growing season mean NDVI, and it ranges from 0.05 to 0.50. At the same time, the southeastern parts of the district showed NDVI that ranges from 0.50 to 0.78 (Fig. 3b). However, during the wet year (2007), initially, NDVI trends showed fluctuations around 0.30 but due to above normal rainfall received during middle of the growing season, NDVI could able to increase from 0.30 to 0.50. Though the changes of growing season mean NDVI were mainly attributed to rainfall patterns, the activities like irrigation scheduling, land management practices, cropping systems, and crop harvesting schedules also might have influenced the NDVI patterns to some extent in the study area.

Spatio-temporal dynamics of growing season mean VCI

VCI can be obtained based on temporal NDVI datasets and it reflects the overall status of vegetation growth (Mishra and Singh 2011) and widely used for detecting and monitoring of agricultural drought (Kogan 1995; Du et al. 2013; Quiring and Ganesh 2010). Analysis of spatio-temporal trends of growing season mean VCI for dry year (2003) showed that the majority of the area particularly the central, western, and south-western parts of the district were characterized by low VCI of less than 35% due to below normal rainfall and severe drought
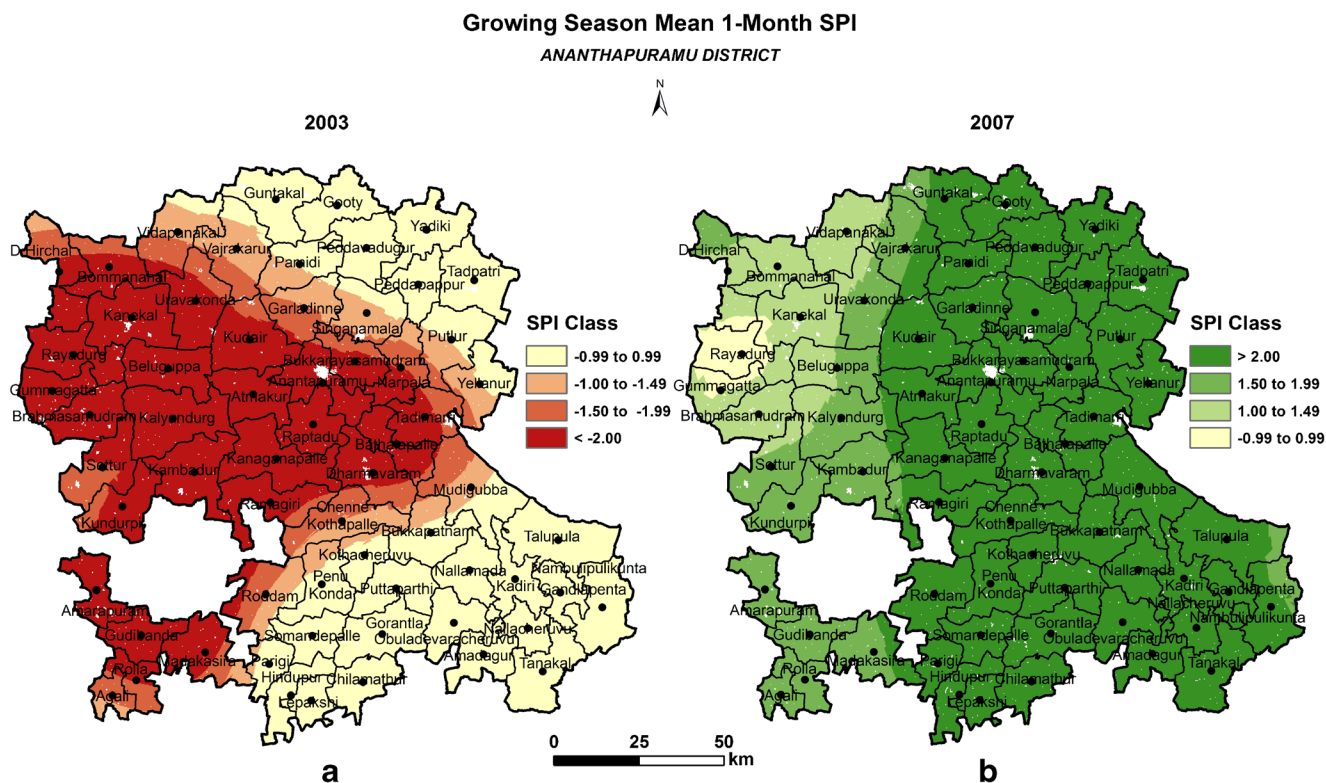
Growing Season Mean 1-Month SPI

ANANTHAPURAMU DISTRICT

Fig. 2. Spatio-temporal dynamics of growing season mean 1-month SPI of dry (2003) (**a**) and wet (2007) (**b**) years

conditions during the dry year 2003. The dismal performance of VCI during the growing season of the dry year (2003) clearly indicates the impact of deficit rainfall on the health of overall vegetation status. VCI ranges from 30 to 50% and
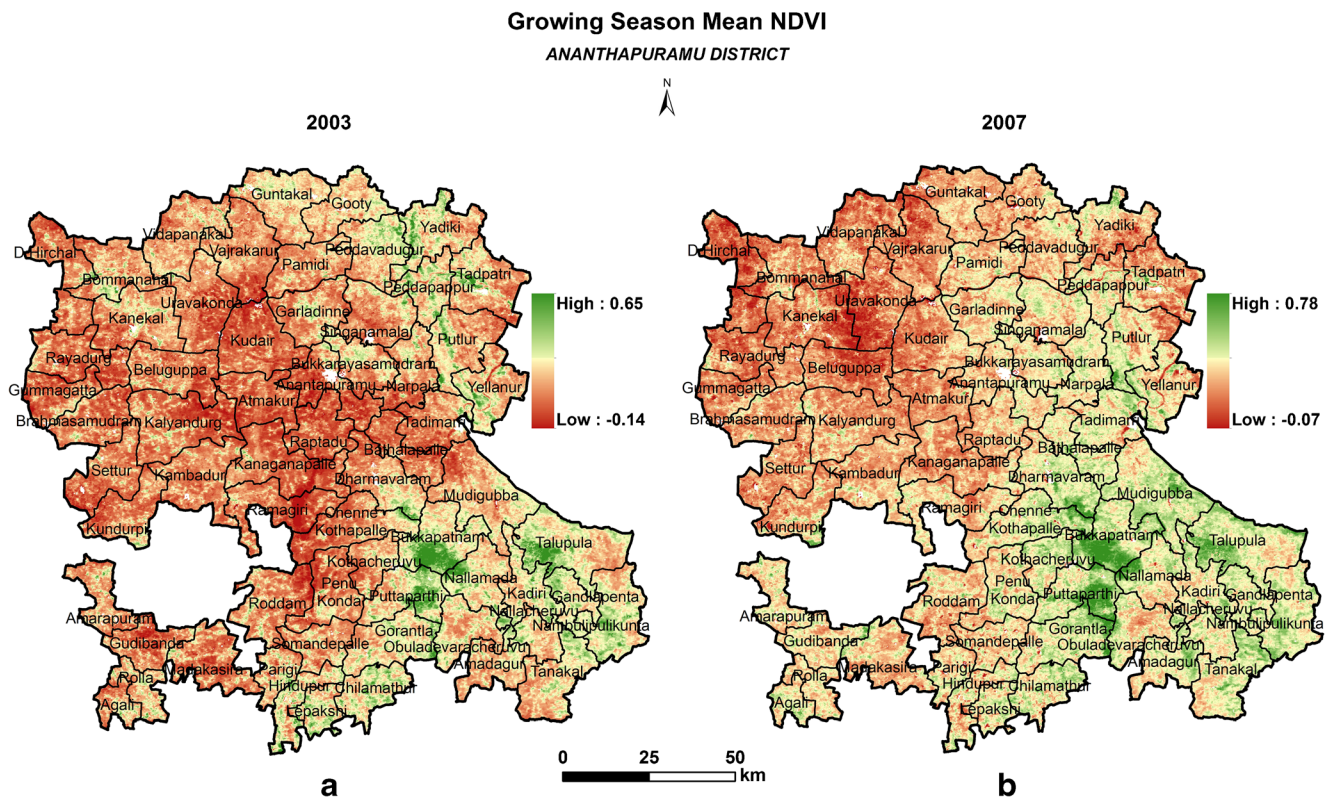
Growing Season Mean NDVI

ANANTHAPURAMU DISTRICT

Fig. 3. Spatio-temporal dynamics of growing season mean NDVI of dry (2003) (**a**) and wet (2007) (**b**) years

above 50% were noticed in the northern and southeastern parts of the district (Fig. 4a). The VCI of less than 30% in the early part of the season and below 50% in the entire season during the dry year (2003) clearly shows the direct impact of deficit rainfall on the status of vegetation. It is also clearly evident that changes in rainfall pattern and its spatio-temporal distribution directly affect the vegetation status in the district. On the other hand, VCI in growing season of wet year (2007) showed that few pockets in the northern parts of the district are characterized by low VCI of less than 35%. In the western, northern, and central parts of the district, the VCI was 35–50%. However, the majority area of the district was characterized by VCI of above 50% (Fig. 4b). The spatio-temporal analysis of growing season mean VCI of dry year (2003) and wet year (2007) clearly indicates the influence of rainfall pattern on vegetation status. The analysis of inter-monthly vegetation dynamics during the growing season clearly shows that the change of vegetation patterns is consistent with the change of rainfall patterns, implying the vegetation growth dynamics within a growing season is more sensitive to the rainfall patterns in the district.
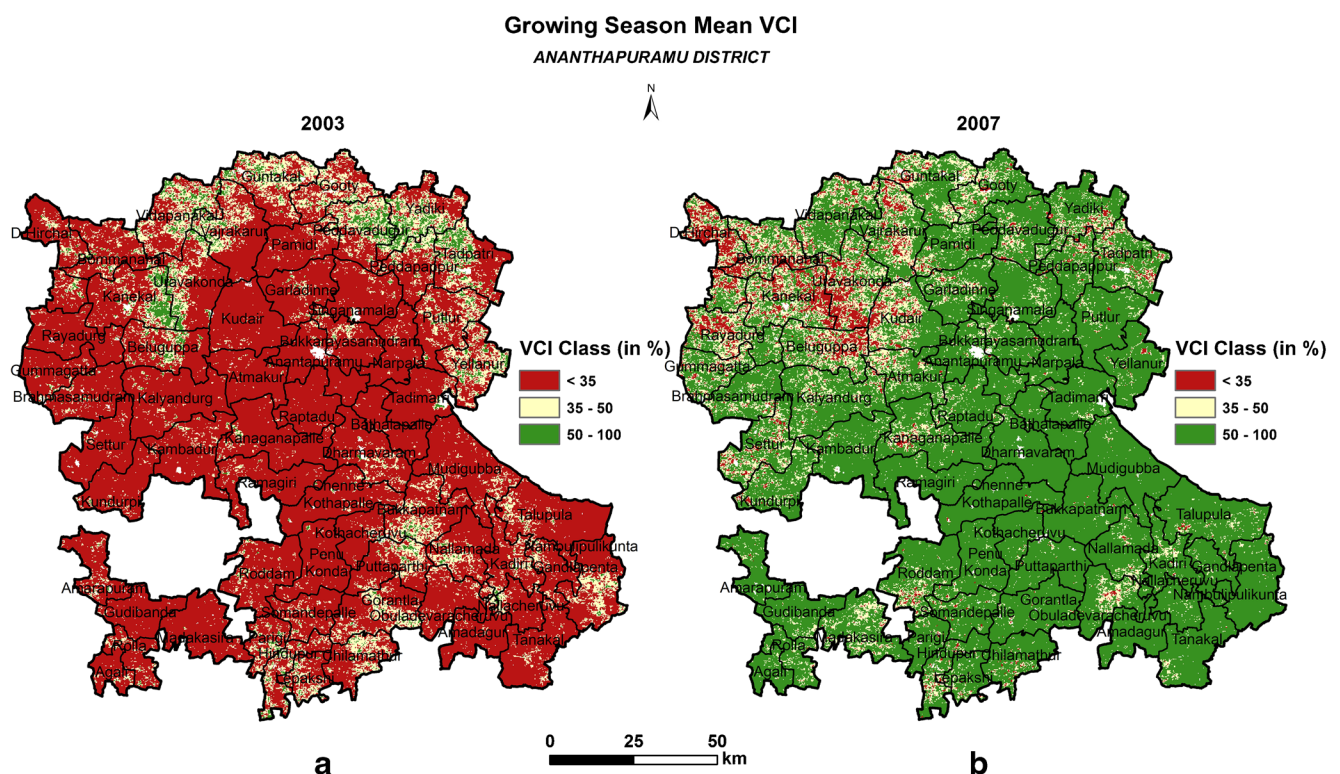
Correlation between SPI and NDVI

The correlation analysis between growing season mean 1-month SPI and growing season mean NDVI during the dry year (2003) shows a strong positive correlation with correlation coefficient (r) of 0.89 (Fig. 5a). It indicates that low rainfall pattern clearly affects the vegetation conditions. Furthermore, the positive correlation between SPI and NDVI also explains the severity of drought conditions during the dry year (2003). Whereas, during the growing season of the wet year (2007), strong positive correlation was observed with correlation coefficient (r) of 0.73 between SPI and NDVI, which indicates the impact of above normal rainfall on the status of vegetation in the district (Fig. 5b). It is evident from the analysis that the spatio-temporal patterns of rainfall has strong positive correlation with vegetation dynamics as it reflects through the NDVI patterns. The analysis showed that NDVI could be used as a robust indicator to assess and monitor the drought conditions in semi-arid and arid regions. The results of the present study are consistent with results reported by Ji and Peters (2003), Dodamani et al. (2015), and Khosravi et al. (2017), who all confirmed the strong positive correlation between NDVI and SPI.
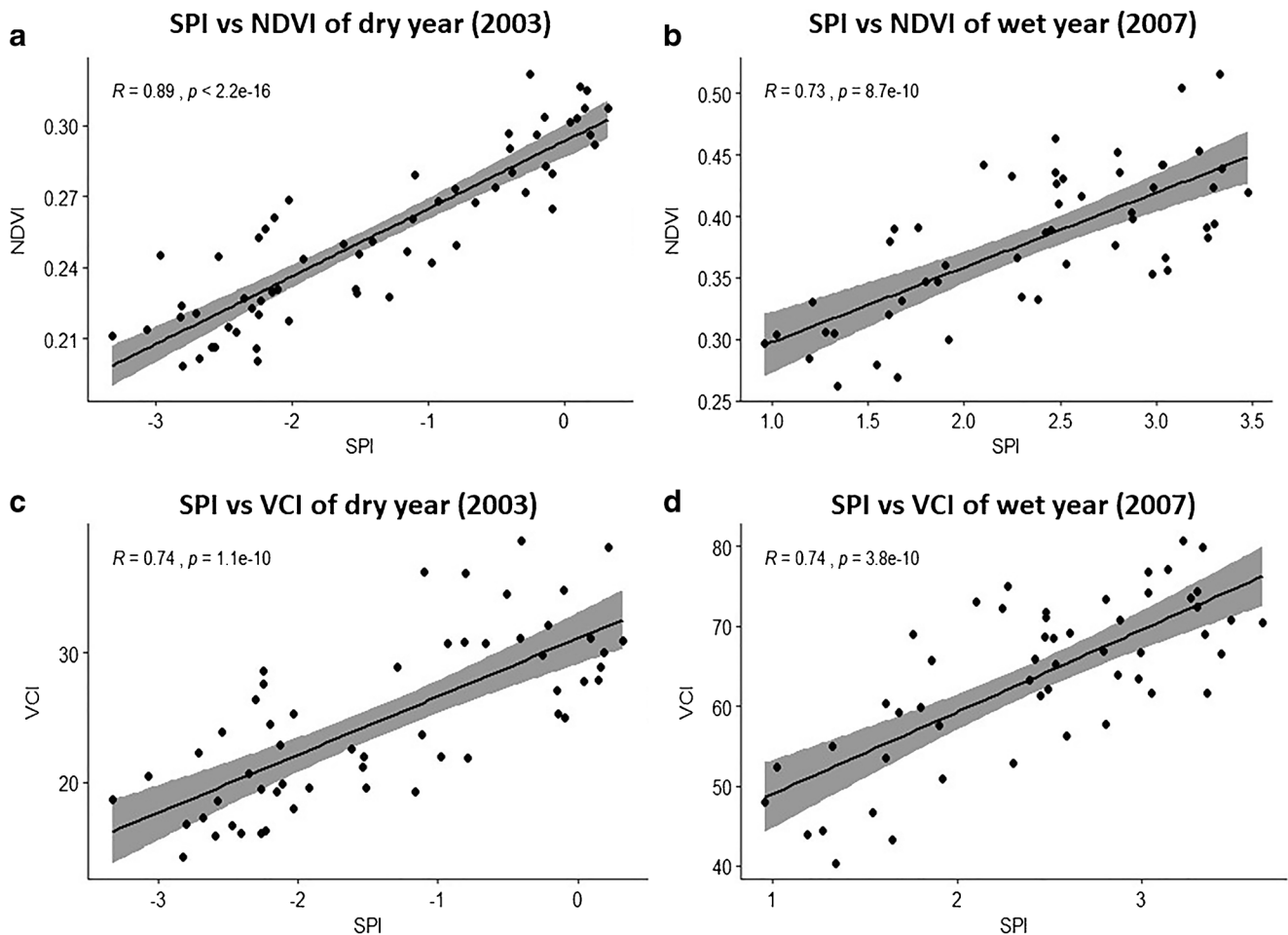
Correlation between SPI and VCI

The correlation analysis between growing season mean 1-month SPI and growing season mean VCI during the dry year (2003) showed a strong positive correlation with correlation coefficient (r) of 0.74 (Fig. 5c). It is evident from the analysis that SPI trends during growing season of the dry year (2003) are in agreement with the VCI patterns. Analysis showed that

Fig. 4. Spatio-temporal dynamics of growing season mean VCI of dry (2003) (**a**) and wet (2007) (**b**) years

a SPI vs NDVI of dry year (2003)

R = 0.89 , *p* < 2.2e-16

b SPI vs NDVI of wet year (2007)

R = 0.73 , *p* = 8.7e-10

c SPI vs VCI of dry year (2003)

R = 0.74 , *p* = 1.1e-10

d SPI vs VCI of wet year (2007)

R = 0.74 , *p* = 3.8e-10

Fig. 5. Scatterplots of Pearson's correlation analysis between (**a**) growing season mean 1-month SPI and growing season mean NDVI in dry (2003) year; (**b**) growing season mean 1-month SPI and growing season mean NDVI in wet (2007) year; (**c**) growing season mean 1-month SPI and growing season mean VCI in dry (2003) year; and (**d**) growing season mean 1-month SPI and growing season mean NDVI in wet (2007) year

VCI was found to be more robust in providing detailed description of the vegetation dynamics with corresponding level of precipitation received during the growing season. Correlation between growing season mean 1-month SPI and growing season mean VCI during the wet year (2007) showed strong positive correlation with correlation coefficient (*r*) of 0.74 (Fig. 5d). Though VCI showed fluctuations in the early part of the season, it was picked up from the middle of the growing season due to above normal rainfall received and reached above 50%. Analysis shows that VCI patterns during the growing season are well in agreement with SPI, and the correlation analysis illustrates the robustness of VCI in explaining the impact of dry and wet conditions on vegetation dynamics in the district. The correlation analysis between the growing season mean 1-month SPI and growing season mean VCI indicates the potential of VCI in measuring the direct impact of rainfall on vegetation dynamics (Thenkabail et al. 2004).

Vegetation anomalies in growing season of dry and wet years

Analysis of vegetation anomalies through VAI for dry year (2003) in the district shows that it ranges from − 3.60 to 2.21. A positive VAI indicates the satisfactory vegetation status, whereas, a negative VAI indicates the presence of vegetation stress in the district. Analysis of VAI in the dry year (2003) indicates that the western, central, and south-western parts of the district are characterized by VAI of less than − 2.0 (Fig. 6a). This might be due to the fact that the western, central, and south-western parts of the district are more prone to dry conditions than the other parts of the district as it reflects through growing season mean 1-month SPI. Majority of the district was characterized by VAI ranges from − 2.0 to − 1.0, and it indicates the proneness to drought conditions and its impact on the status of vegetation. Whereas, the northern, northeast, and south-eastern parts of the district are characterized by VAI

Growing Season Mean VAI

ANANTHAPURAMU DISTRICT

N

2003   2007
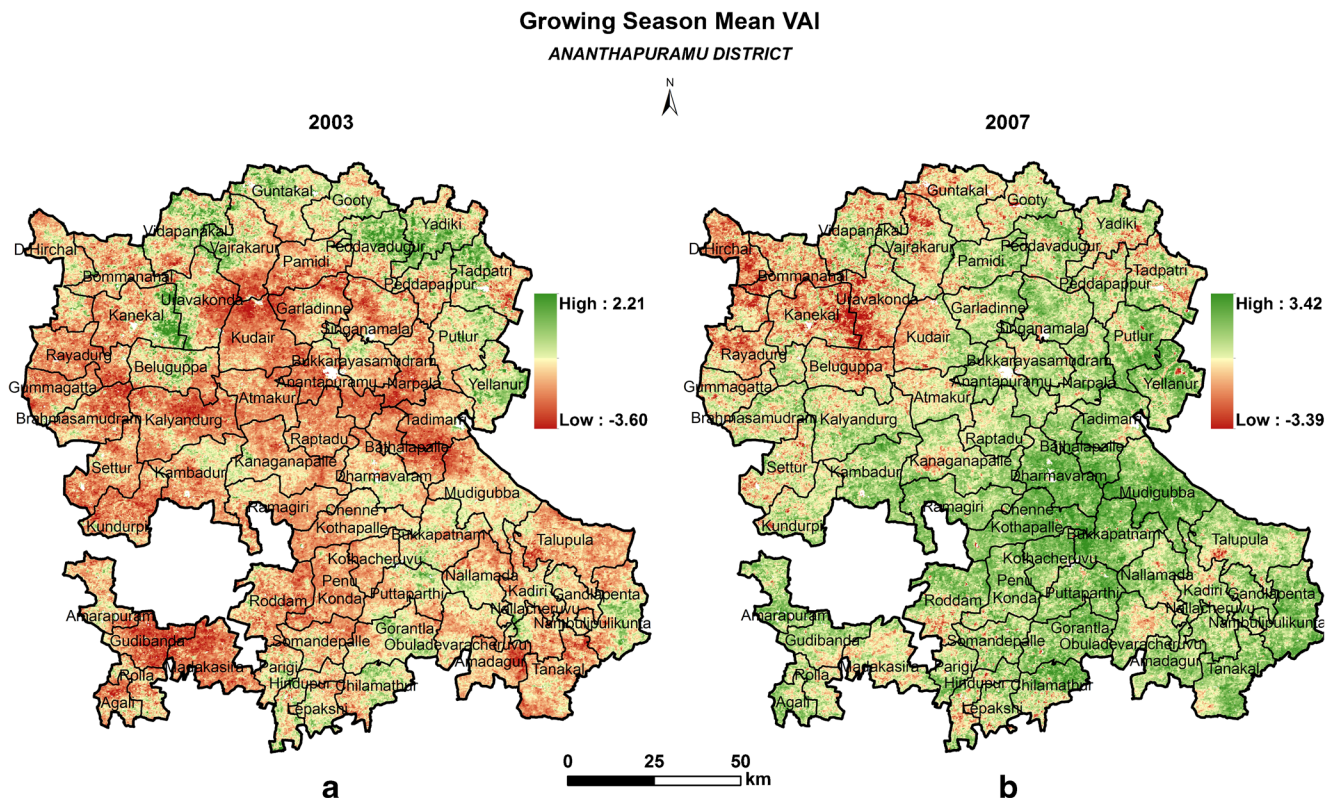
Fig. 6. Growing season mean vegetation anomaly index (VAI) during (**a**) dry year (2003) and (**b**) wet year (2007)

of more than 2.0, which shows that these regions are relatively low in vegetation stress. The analysis of VAI in conjunction with SPI showed large variations in vegetation anomaly during the dry year 2003 due to experience of below normal rainfall and prevailing severe drought conditions in the district. On the other hand, despite of the wet year (2007), the VAI of less than − 2.0 was observed in some pockets of northwestern and northern parts of the district (Fig. 6b), whereas, the majority of the district is characterized by positive VAI of 1.0 to 2.5, clearly indicates the status of low vegetation stress conditions. The higher VAI of more than 2.5 was observed in the eastern and south-central parts of the district. The analysis shows that VAI is found to be strongly correlated with precipitation conditions in the study area.

Identification of critical vegetation stress zones

Analysis of growing season mean VAI patterns in conjunction with the growing season mean 1-month SPI of the district clearly indicates the degree of vegetation stress due to below normal rainfall. The analysis shows that very high and high vegetation stress zones in the district are characterized by low rainfall as compared with the other parts of the district. Based on the analysis of the growing season mean VAI during the dry year (2003), very high vegetation stress zone with VAI of less than − 2.0 was identified predominantly in the central part

of the district covering Kuder, Raptadu, Anantapuramu, Bathalapalli, and Narpala mandals, in the south-western part encompassing Ramagiri, Chennekothapalli, Penukonda, Roddam, Gudibanda, and Madakasira mandals and in the northwestern part covering Kalyandurg, Kundurpi, Bramhasamudram, Gummagutta, Rayadurgam, Kanekar, D.Hirehal, and Bommanahal mandals (Fig. 6a). On the contrary, in the northeastern parts of the study area particularly in mandals like Guntakal, Gooty, Peddavadugur, and Yadiki, in southeastern parts of the district like Bukkapatnam and N.P.Kunta mandals showed the higher VAI of above 2.0, which indicates the stable vegetation condition. Even during the wet year (2007), high vegetation stress zone with VAI of less than − 2.0 was noticed mainly in the north-western parts of the district covering Beluguppa, Uravakonda, Kanekal, Raydurgam, D.Hirehal, Bommanahal, Vidapanakal, and Vajrakarur mandals (Fig. 6b). These mandals received below normal rainfall during the growing season in majority of the years from 2000 to 2018. Analysis of VAI patterns in the district clearly indicates the degree of vegetation stress due to below normal rainfall. The analysis distinctly shows that very high and high vegetation stress zones in the district are associated with low growing season mean 1-month SPI as compared with the other parts of the district. The results of the study could be used by the policy makers and planners to devise appropriate drought-management strategies

particularly in very high and high vegetation stress zones to minimize the vegetation stress and restore the degraded eco-systems in the district.

Conclusions

Spatio-temporal dynamics of growing season mean 1-month SPI during the dry year (2003) showed extremely dry ($\leq -$ 2.00) and severely dry ($-$ 1.50 to $-$ 1.99) conditions in the western, central, and southwestern parts of the district. Analysis of growing season mean NDVI derived from MODIS 250 m data showed fluctuation trends as influenced by the amount and distribution of rainfall received during the growing season. Analysis of SPI and NDVI during the dry year (2003) showed dismal performance of NDVI in the growing season as it is clearly evident that below normal rain-fall affects badly the vegetation growth. Similarly, during the dry year (2003), majority of the area was characterized by growing season mean VCI of less than 35%, which clearly indicates the severity of drought. During the dry year (2003), the study indicates strong positive correlation between SPI and NDVI as well as SPI and VCI with correlation coefficient (r) 0.89 and 0.74, respectively. Analysis of VAI patterns in the district clearly shows its robustness in delineating vegetation stress zones. Based on the correlation analysis between SPI and NDVI and SPI and VCI, this study confirms that below normal rainfall was the main contributing factor for increased drought conditions and vegetation stress in the study area. The study amply demonstrates that SPI can explain the spatio-temporal variability of dry and wet conditions in the district. Furthermore, vegetation indices *viz.*, NDVI, VCI, and VAI, derived from time-series MODIS 250 m data show their ro-bustness in monitoring the spatio-temporal dynamics of veg-etation patterns and identify the vegetation stress zones in tropical arid ecosystem of Anantapuramu district, Andhra Pradesh, India. The SPI in conjunction with vegetation indices of NDVI, VCI, and VHI derived from time series MODIS data was found to be an effective approach in monitoring vegetation stress and drought conditions. The methodology adopted in the study provides reliable scientific information to the planners and policy makers to prepare drought mitiga-tion plans and minimize the risk of droughts on agriculture and livelihoods of people in the district.

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