Association between drought and agricultural productivity using remote sensing data: a case study of Gujarat state of India
Koyel Sur and M. M. Lunagaria

ABSTRACT
Drought is a complex hazard which directly affects the water balance of any region. It impacts agricultural, ecological and socioeconomical spheres. It is a global concern. The occurrence of drought is triggered by climatic phenomena which cannot be eliminated. However, its effect can be well managed if actual spatio-temporal information related to crop status influenced by drought is available to decision-makers. This study attempted to assess the efficiency of remote sensing products from space sensors for monitoring the spatio-temporal status of meteorological drought in conjunction with impact on vegetation condition and crop yield. Time series (2000–2019) datasets of the Tropical Rainfall Measuring Mission (TRMM) were used to compute Standardized Precipitation Index (SPI) and MODIS (MODe rate resolution Imaging Spectroradiometer) was used to compute Vegetation Condition Index (VCI). Association between SPI and VCI was explored. YAI was calculated from the statistical data records. Final observations are that the agricultural crop yield changed as per the climate variability specific to location. The study indicates drought indices derived from remote sensing give a synoptic view because of the course resolution of the satellite images. It does not reveal the precise relationship to the small-scale crop yield. Remote sensing can be an effective way to monitor and understand the dynamics of the drought and agriculture pattern over any region.

Key words | agriculture, association, drought, space sensors, time series

INTRODUCTION
Drought is considered to be a terrestrial ecosystem imbalance, imposing direct influence on the sustainable development of both the socio-physical environment and human economy (Stocker et al. 2014; Liu et al. 2015). It challenges water and food security concerns leading to economic risks, especially in developing nations (Godfray et al. 2010). The occurrence of extreme climate events like drought has significantly increased since the 1970s (Liu et al. 2016). A report released in April 2014 by the Intergovernmental Panel on Climate Change forecasts serious disruptions to agricultural systems due to shifts in weather patterns (Field 2014). Pertaining to this fact, scientific research on drought has attracted the attention of the public and governments worldwide as drought is an impact of change in long-term weather phenomena.

Droughts can be categorized into four main types, namely, meteorological, hydrological, agricultural and socioeconomic drought. All these droughts can be associated with a persistent precipitation deficit in an area (Wilhite 2005). Agricultural drought assessment plays an important role in the agrarian-dominated economies like India where more than 68% of people are dependent directly or indirectly upon agriculture (Dutta et al. 2015). Agricultural drought occurs when soil moisture and rainfall are inadequate during the growing season to support healthy crops resulting in crop stress and wilting (Jain et al. 2009). Around 28% of the geographical area in India is vulnerable to drought and includes arid, semi-arid and sub-humid regions (Gupta et al. 2011). The western regions of India (Rajasthan and Gujarat states) have
suffered from severe droughts many times in the past (Jain et al. 2010). The recurrent occurrence of agricultural drought in these regions is due to poor rainfall and abnormally high temperatures in the summer season. Monitoring and mitigating drought are important to manage the socio-economic adversities of these regions. However, there are several challenges regarding assessment and monitoring of drought. Meteorological ground stations demonstrate good accuracy but the distribution and density of stations is insufficient for the spatial information detection over large extents (Unganai & Kogan 1998; Brown et al. 2008; Eskandari et al. 2016). Moreover, precipitation recordings of several weather stations are most of the time interrupted due to technical disorders and, in some cases, the measurement methodology changes over time, making analysis difficult. Satellite sensor-based information in recent times is thus the most accepted form of meteorological data due to its cost-effectiveness, synoptic view, temporal acquisition and reliability. Satellite data are continuous datasets and consistently available and thus can be used to detect the drought phenomenon and magnitude easily (Thiruvengadachari & Gopal Krishna 1993).

Various drought indices have been developed by researchers all over the world to understand drought intensity of different types. Meteorological drought indices have been developed to describe the drought intensity, namely, Standardized Precipitation Index (SPI), Percent of Normal Index (PNI), Deciles Index (DI), Effective Drought Index (EDI), China-Z index (CZI), Modified MCZI, Rainfall Anomaly Index (RAI) and Z-Score Index (ZSI) (Salehnia et al. 2017). Drought impact on agricultural conditions in different regions with varying climatic conditions is usually done by the Vegetation Condition Index (VCI) based on Normalized Difference Vegetation Index (NDVI) all over the globe (Nicholson & Farrar 1994; Kogan 1995; Wang et al. 2001; Ji & Peters 2003; Anonymous 2016). Remote sensing-based NDVI alone often fails to depict a drought scenario exactly due to the effect of the time lag of 3-4 weeks (Patel & Yadav 2013). In recent times, several algorithms have been developed using support vector regression and artificial neural networks and also a combination of them with wavelet transforms to predict evaporation rates, which can also help to understand drought impacts (Ali Ghorbani et al. 2018; Moazenzadeh et al. 2018; Qasem et al. 2019), but complexity still remains. However, we have chosen a simple methodology so that it can be easily adopted by users to delineate drought-prone regions. This study aims at characterization of agroclimatic conditions based on the association between meteorological drought and agricultural conditions over long-term satellite datasets, agriculture health monitoring in conjunction with crop yield as per climatic variability over Gujarat and further suitability analysis of large-scale satellite datasets for assessing the drought and agriculture relationship. Developing countries like India, in particular, need reliable information and evidence-based decision-making to better adapt to the recurrence of droughts from local to nation level. Thus, this study provides insight into regional level drought monitoring using remote sensing-based spatial information.

MATERIALS AND METHODS

Study area

India is composed of various climatic zones. Drought monitoring over these zones at local level is an important task. Major climatic zones according to Koppen’s classification system over India are: (1) Montane, (2) Humid subtropical, (3) Tropical wet and dry, (4) Tropical wet, (5) Semi-arid and (6) Arid. Since the present study is focused on drought impact analysis on a regional scale, Gujarat was chosen as the study area because this is the state in India which shows three major climatic variations according to the climatic zonation map of India, i.e., arid, semi-arid and tropical wet zones. The state of Gujarat is situated in the westernmost part of India and shares an international border with Pakistan. The state is situated between 20° and 25° north latitudes and 68° and 75° east longitudes (Figure 1). States of India bounding Gujarat are Rajasthan in the northeast, Madhya Pradesh to the east and Maharashtra to the south. The state has an area of 19,6024 km², with the longest coastline in India, running up to 1,600 km (National Institute of Disaster Management (NIDM) 2015). Gujarat state can be divided into three physiographical divisions: (a) Saurashtra peninsula, which is a hilly region with low mountainous terrain; (b) Kutch, located in the
The Gulf of Kutch separates the Saurashtra peninsula from Kutch and the Gulf of Cambay divides Mainland from Saurashtra. The geographical diversity of Gujarat includes hills, desert, forests and rivers. Gujarat has many rivers; the five major rivers are Narmada, Sabarmati, Tapti, Mahi and Aji. Around 59.2% of the total area is under agricultural cultivation in Gujarat (Swain et al. 2012). The state is largely dependent on the southwest monsoon regarding agricultural disparities such as: (i) the northern part of the state has drought-prone areas and the lowest annual rainfall amounts to about 345 mm; (ii) the southeastern region of the state witnesses the highest annual rainfall amounting to about 2,500 mm; (iii) central Gujarat has moderately well distributed rainfall ranging from 287 mm to 1,693 mm; and (iv) the coastal regions are prone to frequent cyclones, floods and locusts.

Datasets

Remote sensing datasets

To assess time series of meteorological drought and agricultural conditions over the long term (2000–2019), the following satellite data products were used:

- Rainfall dataset: The Tropical Rainfall Measuring Mission (TRMM) is a combined programme of National Aeronautics and Space Administration (NASA) of the United States and the National Space Development Agency (NASDA), Japan. A number of sensors related
to precipitation, such as precipitation radar (PR), TRMM microwave imager (TMI) and the visible and infrared radiometer system (VIRS) are on board the TRMM (Kummerow et al. 1998). Level 3 product, 3B43, was produced by the Global Precipitation Climatology Center (GPCC) using a Huffman’s algorithm (Huffman et al. 1995); this contains precipitation rates (mm/h) for each month at a special resolution of 0.25° × 0.25°. In this study, TRMM 3B43 data from 2000 to 2019 were downloaded from the web portal of Goddard Earth Sciences Data and Information Services Center and used for meteorological drought assessment. There are several other satellite datasets such as: CHELSA high resolution land surface temperature and precipitation, CHOMPS high resolution optimally interpolated microwave precipitation from satellites, CMAP (CPC merged analysis of precipitation), CMORPH (CPC morphing technique), COREVE air sea surface fluxes, CPC unified gauge-based analysis of global daily precipitation, GHCN global historical climatology network daily temperature – NOAA/NCEI, global precipitation and temporal, GPCC global precipitation climatology center, GPCC global precipitation climatology center, HOAPS Hamburg ocean atmosphere parameters and fluxes from satellite data, PERSIANN-CDR precipitation estimation from remotely sensed information using ANN-climate data records, SSM/I, SSMIS spatial sensor microwave/imager sounder, Tropical Moored Buoy system: TAO, TRITON, PIRATA, RAMA (TOGA), but most of them do not have suitable temporal and spatial resolution for regional drought monitoring at scale.

- Vegetation index data: MODIS (MDe-rate resolution Imaging Spectroradiometer) is a key instrument on board the Terra and Aqua satellites. Terra’s orbit around the Earth is timed so that it passes from north to south across the equator in the morning, while Aqua passes south to north over the equator in the afternoon. Terra MODIS and Aqua MODIS are viewing the entire Earth’s surface every 1–2 days, acquiring data in 36 spectral bands, or groups of wavelengths between 0.405 μm and 14.385 μm, and it acquires data at three spatial resolutions 250 m, 500 m and 1,000 m (Gallo et al. 2004). In this study, the Terra MODIS monthly composite NDVI with 250 m resolution (MOD13Q1) of the period 2000–2019 was used from the Earth Observing System Data Gateway. Apart from MODIS NDVI, product Climate Data Record (CDR) of NOAA provides NDVI product but at a much coarser spatial resolution (0.5° × 0.5°), therefore these data have not been used and MODIS is preferred.

Agricultural statistics

District-wise crop yield of the Kharif season was collected for the time frame 2001–2016 from the Directorate of Agriculture, Gujarat Government, India for analysis of the impact of drought on agriculture in the state.

METHODOLOGY

Multi-source remote sensing data used for comprehensive drought assessment cannot be directly compared and synthesized. Thus, the data were scaled and deduced into common dimensions. The research flowchart is depicted in Figure 2.

Standard precipitation index (SPI)

The SPI was developed by McKee et al. (1993) to quantify precipitation at multiple scales. Research has shown that SPI has many advantages over other drought indices referred to in the Introduction section. The index is relatively simple, spatially consistent and temporally flexible, thus allowing observation of water deficits at different scales (Guttman 1998; Ji & Peters 2003). It does not require any other information about land surface or atmospheric conditions and is solely a function of the precipitation amount. Therefore, it can be computed from the spatial and temporal rainfall-related satellite data products. Apart from this, most of the international and national drought monitoring institutes use SPI as a more reliable index for detecting emerging drought at state, regional and local level. It assigns a single numerical value to the precipitation that can be compared across regions with marked different climates. The index was calculated using a continuous, long-term 20-year series of historic monthly precipitation records. As rainfall is not normally distributed for
aggregation periods of less than 12 months, a gamma distribution is fitted to the frequency distribution. Its value is given by the precipitation deviation from the mean of an equivalent normally distributed probability distribution function with a zero mean value and a standard deviation of one. The gamma distribution is frequently used to represent precipitation datasets because it provides a flexible representation of a variety of distribution shapes while utilizing only two parameters, the shape and the scale (Wilks 1995). This distribution is a good choice for describing precipitation values because the distribution is always bounded on the left by zero; this is particularly important for precipitation applications because negative rainfall is an impossibility, so a distribution that excludes negative values is readily applicable. This technique is especially important in dry regions or locations with high variability and low mean rainfall. As well as this, the gamma distribution is positively skewed, which means that it has an extended tail to the right of the distribution; this phenomenon matches non-zero probability of extremely high rainfall amounts, even though the typical rainfall may not be very large (Ananthakrishnan & Soman 1989). As the gamma distribution offers a tremendous amount of flexibility in the shape of the rainfall distribution function it allows fitting to any number of rainfall regimes with reasonable accuracy, while other distributions may fit only a single, specific rainfall regime (Husak et al. 2007). Due to the above advantages other alternatives were not preferred. The SPI is expressed as:

$$g(x) = \frac{x^{\alpha - 1} \, e^{-x/\beta}}{\beta^\alpha \, \tau(\alpha)} \quad \text{for } x > 0$$

where $\alpha > 0$ is a shape parameter, $\beta > 0$ is a scale parameter, $\chi$ is precipitation amount, $\tau(\alpha)$ is gamma function.

The SPI values can be classified into seven categories as per Table 1. The computed results are in units of standard deviation. The SPI conditions considered in this study are for the months of June to September, based on a four-month scale. This scale and period were chosen for the study because Gujarat is dependent on monsoon rainfall. After persistent hot weather and dryness during the pre-monsoon months, the southwest monsoon rains arrive over the Indian subcontinent with amazing regularity from the months of June to September every year (Mujumdar
et al. 2015). Understanding the regular pattern of rainfall over these months (June, July, August and September) can help to understand the drought impact over the study area.

**Vegetation condition index (VCI)**

In semi-arid regions, drought is a frequent phenomenon leading to serious problems in agriculture and food security. Drought assessment from a meteorological dataset is not sufficient to ensure spatial drought quantification. Therefore, most studies use the Normalized Difference Vegetation Index (NDVI) to understand the impact of drought on agriculture, since this index has demonstrated good accuracy for the quantification of green vegetation density. However, many researchers have used the VCI at different scales to reveal high potentiality for detection and monitoring of drought rather than NDVI (Kogan 1997; Seiler et al. 2000). Quiring & Ganesh (2010) observed a high correlation between the VCI and agricultural production in different regions of the globe. Therefore, the VCI was preferred in the study. The VCI is an indicator of vegetation density as a function of NDVI minima and maxima over many years. It is an attempt to separate the short-term signal from the long-term signal. Thus, it is regarded as a better indicator of drought stress condition than the NDVI (Kogan & Sullivan 1993). The VCI is expressed as:

$$VCI = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \times 100$$

where NDVI is smoothed pixel values of NDVI based on Savitzky-Golay filter (Chen et al. 2004). NDVI$_{max}$ and NDVI$_{min}$ are maximum NDVI and minimum NDVI, calculated by the corresponding pixels in the same month from the entire NDVI values (of years 2001–2019). The VCI scale ranges from 0 to 100, corresponding to the changes in vegetation condition from extreme to optimal. VCI can be classified as per Table 2.

**Correlation between meteorological drought and agricultural condition**

Correlation between meteorological drought and agricultural condition is conducted spatially over the study area. This analysis is used to determine the effect of time lag between meteorological drought and agricultural drought over the region and its impact analysis over the crop yield. This spatial relationship also helps to understand the effect of the above types of drought in the agroclimatic zones which exhibit high to low correlation between them.

**Correlation between agricultural condition and crop yield anomaly**

Any scientific result needs validation with its other related factors so as to understand the certainty of its findings. Satellite-derived meteorological and vegetation dataset analysis needs to be validated on the ground. Thus, long-term crop yield anomaly analysis of the predominant crops over each of the districts in the study area was performed. In this study, crop statistics of the major rainfed crops castor, cotton, paddy and groundnut from 2001 to 2016 in different districts of Gujarat were considered for validation.

The crop yield anomaly technique was used to identify deviation of yield for a particular year from its long-term trend. Yield anomalies of these crops were calculated as follows:

**Table 1 | SPI classification (McKee et al. 1993)**

<table>
<thead>
<tr>
<th>SPI Value</th>
<th>Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt;2.0</td>
<td>Extremely wet</td>
</tr>
<tr>
<td>1.5–1.99</td>
<td>Very wet</td>
</tr>
<tr>
<td>1.0–1.49</td>
<td>Moderately wet</td>
</tr>
<tr>
<td>–0.99 to 0.99</td>
<td>Near normal</td>
</tr>
<tr>
<td>–1.0 to –1.49</td>
<td>Moderately dry</td>
</tr>
<tr>
<td>–1.5 to –1.99</td>
<td>Very dry</td>
</tr>
<tr>
<td>≤2.0</td>
<td>Extremely dry</td>
</tr>
</tbody>
</table>

**Table 2 | VCI classification**

<table>
<thead>
<tr>
<th>VCI Value</th>
<th>Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt;90</td>
<td>Extremely wet</td>
</tr>
<tr>
<td>75–90</td>
<td>Very wet</td>
</tr>
<tr>
<td>60–75</td>
<td>Moderately wet</td>
</tr>
<tr>
<td>45–60</td>
<td>Near normal</td>
</tr>
<tr>
<td>30–45</td>
<td>Moderately dry</td>
</tr>
<tr>
<td>15–30</td>
<td>Very dry</td>
</tr>
<tr>
<td>&lt;15</td>
<td>Extremely dry</td>
</tr>
</tbody>
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the Yield Anomaly Index (YAI) using the following formula:

\[
YAI = \frac{(\gamma - \mu)}{\sigma}
\]

where \(\gamma\) is crop yield, \(\mu\) is long-term average yield and \(\sigma\) is standard deviation. However, due to advances in global civilization, modern technique implementation often impacts the crop yield to a larger extent so before YAI calculation we need to use a detrending method to ignore the artificial impacts. Detrending is a widely used technique for obtaining stationary time series data. Several detrending models have been proposed in the literature such as linear regression model, locally weighted regression model, second order polynomial regression model, smoothing spline model, empirical mode decomposition model and central moving average model (CMAM). CMAM (Bashan et al. 2008) is one of the popular detrending methods. This model was used for detrending the data and smoothening the irregular roughness and high-frequency variation to the overall pattern and trend in the time series. This model is data self-adaptive and detects local trends that simple linear regression models cannot. CMAM averages both before and after the current time values. As the time span of the moving average increases, the trend becomes smoother giving better results. In this study, CMAM at time spans of 15 years is calculated to identify the trend because agricultural statistics are available for the years 2000–2016. The formula used in this case is as follows:

\[
mY_t = \frac{1}{15} \sum_{j=-7}^{7} Y_{t+j}
\]

where \(Y_t\) is the original crop yield at time \(t\), and \(mY_t\) is the moving averaged crop yield at time \(t\).

RESULTS AND DISCUSSION

Meteorological drought monitoring using SPI

The drought condition prevailing in Gujarat state during 2001–2019 was assessed using the SPI. Results show that the SPI can reflect the duration, extent and severity of drought in accordance with the historical observation of rainfall datasets in Gujarat. Spatial distribution of drought from 2001 to 2019 is shown in Figure 3. Prominent drought is clearly visible in the year 2016 over Gujarat state. Apart from this, 2001, 2004, 2009, 2012 and 2017 exhibit dry conditions over certain districts of Gujarat. On the other hand, 2002, 2005, 2007, 2012 and 2018 witnessed wet conditions over almost the entire state. The remaining years show that the conditions are near to normal. Satellite datasets used to monitor drought are very coarse, therefore the spatial view obtained picks up only the pattern of the drought in each year.

Vegetation condition

The VCI shows the health of vegetation condition over the area with respect to the long-term vegetation index over the region. Often, VCI has been considered as an equivalent to the cover of agriculture in India, over any region, because maximum green cover spread is in agricultural regions and that is why VCI is preferred (Mondal et al. 2015). Long-term VCI for the rainfed season (July–September) of each year (2001–2019) was used in the present study. The VCI over Gujarat ranged from 0 to greater than 95.33% (Figure 4). The Kutch district of Gujarat is mostly devoid of vegetation due to the natural presence of a vast salt desert in the northern part of Gujarat. This is very well picked up by the algorithm used in the study since almost every year shows poor vegetation condition in this area due to the moderately to very dry moisture stress conditions present. The years 2001 and 2002 show moisture stress conditions in many places of Gujarat. The VCI thus in one way helps to bring out the drought impact over a region. The year 2003 was difficult to assess as there was constant cloud cover present and no values were recorded by the satellite sensor in most instances, therefore spatial distribution was unable to be computed. The years 2004–2010 and 2012–2019 show good vegetation condition revealing that this region did not face any agriculture drought scenarios over this period. This also proves that meteorological drought does not always affect the agriculture condition because irrigation facilities like canals, check dams, bunds, etc., which are very well adopted in Gujarat, can help to cope with water stress conditions.
Association of meteorological drought and vegetation condition

Spatial depiction of correlation coefficients between SPI and VCI provides a drought proneness map of the state during the monsoon season. Correlation varied spatially and ranged between −0.3 and 0.6 and shows poor to good association at different parts of the state (Figure 5(a)). It is clear that the meteorological drought highly influences the vegetation in the central part of Gujarat, including Surendranagar, Ahmedabad, Mahesana, Gandhinagar and Kheda. This also determines that these regions are highly dependent during the monsoon rainfall regarding the agricultural cropping pattern and its yield. Parts of Ahmedabad, Kheda and Surendranagar fall in Bhal region. Bhal is a marine ingressed and flooded coastal plain near the Gulf of Kambhat. Agriculture in Bhal region depends on flooding during the monsoon and conserved soil moisture during winter. High evaporation during summer produces salt, and mostly drought prevails. Thus, the association between the SPI and VCI in these districts is typical of the Bhal ecosystem. The Kutch region and certain parts of the coastal gulf region and coast near Khambat show a very poor relationship due to the major influences of its terrain like the salt desert of Kutch and the sandy marsh area along the coast. These regions have contrasting behaviours under heavy rainfall. Most of the Kutch region is waterlogged and becomes a land of salt marsh during the rainy season and therefore it has no association with the vegetation cover over the region. However, moderate correlation exists between the other parts of Gujarat like the southern coastal part. A significance test has been carried out to assess the relationship of SPI and VCI at significance level 0.01 and 0.05. The reason for the comparatively weaker significance impact seen throughout the area may be due to the reason that the probability curve fitted on the period of the SPI calculation. Since the availability of TRMM data was just
20 years to be used for SPI computation, results show a shifted drought condition. However, to assess the true condition, apart from the correlation between SPI and VCI, the association between cumulative rainfall and VCI was also studied. Figure 5(b) depicts a high significance level in both 0.01 and 0.05 and the correlations are positive, ranging between 0 and 0.9. Moreover, it is very clear that central Gujarat is very much dependent on agricultural water resources like ground water or different irrigation sources like canals and the Kutch region has very poor association between the amount of water received and the vegetation grown over this area, due to salt deposits. The cumulative rainfall pattern gives a better interpretation because it helps to pick up the effect of drought on the agriculture pattern. A spatial correlation map also helps us to understand the broader agroclimatic zonation which finally helps with understanding the cropping pattern of the state based on soil moisture availability in Kharif season. The agroclimatic zonation map can be of great help to planners for analysing and planning crop production areas.

**Correlation between VCI and YAI**

Correlation between VCI and YAI is important to analyse and find the impact assessment of drought on agriculture because this helps with ground reality verification. Thus, in order to relate VCI and YAI, some Kharif crops like castor, paddy, groundnut and cotton were considered for the selected districts, which are delineated by Lunagaria *et al.* (2017) as the primary zones for cultivation of these crops. Table 3 shows VCI and YAI have positive correlation for all the districts except Ahmedabad and Rajkot. Negative correlation between VCI and YAI in these two districts might be due to the fact that they are highly urbanized areas. Therefore, crop yield is affected over this region due to the scarcity of proper farmlands devoted to farming. Urban sprawl has often led to encroachment on agricultural...
land, especially in the developing nation of India. Therefore, total yield in these regions may be affected over time.

Years which show a YAI positive relationship demonstrate that agriculture did not face any moisture stress condition, whereas a negative relationship clearly shows that there are moisture stress conditions affecting the agricultural yield. Figure 6(a) and 6(b) show the YAI of castor in Mehesana and Banaskantha district. Castor is a deep-rooted crop so usually considered as drought resistant. In the case of Mehesana, the year 2001 shows maximum drought affected condition over other years. The years 2002, 2003 and 2004 show a gradual reduction in drought impact, but drought significantly affected the region for other years. In Banaskantha, the years 2002, 2004, 2006 and 2013 reveal drought impact. Drought conditions have been well picked up by both the VCI and YAI for Banaskantha district except during the year 2004, which may be due to some impact of socioeconomic policies; however, SPI over Banskantha district during all these years was near to normal. Paddy is one of the most important crops of the Kharif season in Gujarat. Figure 6(c)–6(f) show the YAI of paddy in the four districts of Ahmedabad, Kheda, Mehesana and Anand, which are the main paddy growing areas. Ahmedabad shows drought stressed conditions for paddy in the years 2001, 2014 and 2016, which are directly comparable with the spatial extension of drought expressed

### Table 3 | Correlation between VCI and YAI

<table>
<thead>
<tr>
<th>Crop</th>
<th>District</th>
<th>Correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Castor</td>
<td>Banaskantha</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>Mehesana</td>
<td>0.42</td>
</tr>
<tr>
<td>Paddy</td>
<td>Ahmedabad</td>
<td>-0.27</td>
</tr>
<tr>
<td></td>
<td>Kheda</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>Anand</td>
<td>0.29</td>
</tr>
<tr>
<td></td>
<td>Mehesana</td>
<td>0.46</td>
</tr>
<tr>
<td>Groundnut</td>
<td>Jamnagar</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td>Junagadh</td>
<td>0.26</td>
</tr>
<tr>
<td>Cotton</td>
<td>Rajkot</td>
<td>-0.18</td>
</tr>
<tr>
<td></td>
<td>Bhavnagar</td>
<td>0.17</td>
</tr>
</tbody>
</table>

Figure 5 | (a) Spatial association between SPI and VCI during monsoon in Gujarat and (b) spatial association between cumulative rainfall and VCI during monsoon in Gujarat.
by the SPI and VCI. This might be due to the fact that Ahmedabad is a growing city facing water stress with a high demand for water from the industrial sectors and urban demand. An urban heat trap can have a major effect in this region which may be affecting its crop yield. The YAI in Kheda shows drought impact in the years 2001, 2002, 2006; although only 2001 and 2002 were drought years in Kheda. In Mehesana, the years 2001, 2003 and 2011 suffered drought conditions and in Anand the years 2001, 2002 and 2006 were drought years. Spatial statistics of these cases pick up the years 2001, 2002 and 2003 as dry, but 2011 and 2006 as wet years. Figure 6(g) and 6(h) show the YAI values of groundnut in Jamnagar and Junagadh. Junagadh was affected by drought conditions during the years 2001, 2002, 2004, 2006 and 2012, while for Junagadh it was the years 2001, 2004, 2006, 2012 and 2015. Groundnut is also affected by rainfall if it is not well distributed during flowering, pegging and pod formation phases, and its productivity becomes affected. Figure 6(i) and 6(j) show the YAI of cotton. In Rajkot, cotton was affected by drought for most years from 2001 to 2016, except for 2002, 2005, 2006, 2007, 2010 and 2016. However, it is observed that in most of the cases all three indices match quite well except in the case of cotton. This might be because cotton is very sensitive to cold, soil salinity, heat and drought stress. The YAI of Bhavnagar was not in agreement with spatially generated SPI and VCI which might be because the district has a salinity affected area, and also part of Bhal, which governs crop production in this region.

CONCLUSIONS

Gujarat state has seen association of VCI with SPI and cumulative rainfall in the recent past. There was a clear
correlation between SPI and VCI according to the agroclimatic conditions in different parts of Gujarat state. Cumulative rainfall and VCI show a prominent and strong correlation. The VCI and yield of major rainfed crops show positive correlations. The findings signify the usefulness of remote sensing data and spatial analysis technique for identifying drought stress and cropping pattern prediction for Kharif season. Longer time series availability in future may produce better results and accuracy. Apart from this improved spatial resolution, satellite datasets can result in better understanding for ground validation. This study has a broad future scope, and time series satellite database generation should be focused on the same scale so that this algorithm can be operationalized for the entire globe.
Further, apart from rainfall other climatic factors like temperature, solar flux, evaporation rate, etc. need to be explored to refine this study.

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