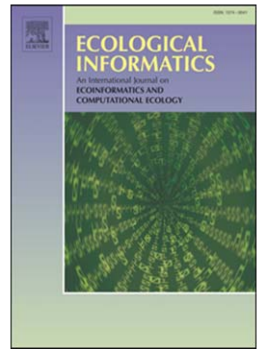

Spatio-temporal variation in terminal drought over western India using dryness Index derived from long-term MODIS data

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PII: S1574-9541(15)00203-4
DOI: doi: 10.1016/j.ecoinf.2015.12.007
Reference: ECOINF 649

To appear in: *Ecological Informatics*

Received date: 31 July 2015
Revised date: 12 December 2015
Accepted date: 20 December 2015

Spatio-temporal variation in terminal drought over western India using dryness Index derived from long-term MODIS data

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ABSTRACT: Drought has always been one of the major hazards in semi-arid and arid regions of the world. This study was undertaken to investigate spatial trends in terminal drought over western India comprising the states of Rajasthan and Gujarat which are characterized by semi-arid to arid climate. These two states have been always vulnerable to drought since they receive highly variable moderate to scanty rainfall. Leaf Area Index (LAI)-based Temperature Vegetation Dryness Index (TVDI) for the period 2002-2012 was computed using 8-day composites of Moderate-Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature (LST) and LAI data sets with 1-kilometer spatial resolution. TVDI maps were prepared for all Days of Year (DOY) of the months September and October which facilitated understanding of the spatial extent of drought during different 8-day periods. Based on the analysis it was found that the LAI-based TVDI could captured drought condition over space and time. Temporal evolution of observed Crop Moisture Index (CMI) against and TVDI reveals that that the TVDI exhibits increasing trend as the CMI decreases or become negative during 2002 drought year. A significant and negative relation relationship (R^2 = 0.23) with TVDI and CMI indicates more sensitivity of TVDI to soil moisture in sparse vegetation canopies under drought conditions. Spatial trends in terminal drought intensity were analysed using linear regression and Mann-Kendall trend test. It was revealed that majority of the northern part of the study area witnessed increase in terminal drought intensity and the southern portion registered negative trends. With 80% of confidence, it can be stated that the terminal drought intensity increased at scattered locations over south-western and central Gujarat. However, over central and south-western Rajasthan decreasing trends were registered.

Keywords: Terminal Drought, TVDI, CMI, MODIS, India, Trend Analysis

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1. Introduction

Drought is one of the most recurrent natural hazards in arid and semi-arid regions of the world, and India is not an exception to it. In a general sense drought can be defined "as a lack of rainfall so large and so long continued to adversely affect all established human activities of the area" (Warrick, 1975). Another definition of drought is "scarcity of water for ecosystems, land and human use, resulting in failing crops, livestock, livelihoods and human health" (Gupta et al., 2011). Based on the timing of rainfall deficiency, Kumar et al. (2009) have classified agricultural droughts in India into three categories: early, mid and late season droughts. Early season drought occurs because of delay in beginning of monsoon rains which results either in delay in sowing of crops or no sowing. Breaks in monsoon lead to mid-season drought, which corresponds with vegetative growth stage of crops. Late season drought is also termed as terminal drought which corresponds with reproductive stage of crop and leads to forced maturity. Droughts lead to severe socio-economic consequences as they affect people more than any other natural hazards (Gupta et al., 2011), and offset the gains obtained in the preceding years.

Some regions in India experience droughts more frequently than other regions. On an average 28% of the geographical area of India is vulnerable to droughts (Samra, 2004). This study focuses on western India including the states of Rajasthan and Gujarat. West Rajasthan has a drought frequency of 2 years, whereas Gujarat and East Rajasthan experience drought every 3 years (National Rainfed Area Authority (NRAA), 2013). These two states have semi-arid to arid type of climate with low and erratic rainfall. Traditionally, the people in Rajasthan have been practicing water harvesting and conservation, but with increase in population and agricultural land they have not succeeded in quelling the ever increasing water demand.

Since drought is directly related to the nation’s food security it’s monitoring and assessment becomes imperative. The complex phenomenon of drought, can be simplified into a drought index, which is a single number that incorporates a large amount of water supply data (Ji and Peters, 2003). Such an index permits researchers to quantify irregularities in climate in terms of intensity, spatial and temporal extent, making it simpler to communicate the information to different users (Wilhite et al., 2000). Numerous indices based on both meteorological and remote sensing (satellite-based) approach have been developed to monitor drought. Normalized Difference Vegetation Index (NDVI), a remote sensing based index has been widely used for drought monitoring (Kogan, 1997; Mcvicar and Bierwirth, 2001; Prathumchai and Honda, 2001; Ji and Peters, 2003; Bayarjargal et al., 2006; Vicente-Serrano et al., 2006, Murali Krishna et al., 2009). Weather and ecosystem components contribute to variations in NDVI, and therefore, to measure the impact of weather on vegetation Kogan (1995a, b) developed Vegetation Condition Index (VCI). This index is useful for identifying onset of vegetation drought as well as measuring the intensity, duration, and impact of drought, and analysing crop response to water availability (Nicholson and Farrar, 1994; Kogan, 1995b; Unganai and Kogan, 1998; Seiler et al., 2000; Wang et al., 2001; Dharkar et al., 2013). Temperature Vegetation Dryness Index (TVDI) is another index than can be employed for monitoring short and long-term changes in soil moisture and its effect on vegetation condition. This index is built on parameterization of the relationship between Land surface temperature (LST) and a vegetation index (Sandholt et al., 2002). It is computed using remote sensing data, exclusive of ancillary data and can be applied to moderately or partially vegetated regions. Several researchers (Wan et al., 2004; Li et al., 2008; Sun et al., 2008; Mallick et al., 2009; Wang et al., 2010; Chen et al., 2011; Son et al., 2012) have utilized TVDI for assessing surface moisture condition. Using this index Huan et al. (2013) investigated spatio-temporal variation in drought in the Huang-Huai-Hai region of China. Soil moisture in a sub-humid area of India was assessed by Patel et al. (2009) with this index. Holzman et al. (2014) estimated regional crop yield using TVDI, which was derived using LST and Enhanced Vegetation Index (EVI) data from MODIS.

The present study uses MODIS LST and LAI data for monitoring terminal drought over western India covering the states of Rajasthan and Gujarat. Satellite data from MODIS have been extensively used for such studies (Wan et al., 2004; Li et al., 2008; Mallick et al., 2009; Patel et al., 2009; Patel et al., 2012; Rhee et al., 2010; Son et al. 2012; Saeid et al. 2015). The principal objective of this study is to detect terminal drought and its long-term variation over western India using TVDI derived from LST and LAI data sets of MODIS. Ground observations on crop moisture index for selected locations were added advantage to test capability of TVDI in capturing short-term drought stress. Earlier works have used NDVI datasets to derive different dryness indices but, one of the major contributions of this work is to demonstrate the use and applicability of LAI datasets for deriving such indices.

2. Material and Methods

2.1 Study Area

The area selected for this study covers western India comprising the two states of Rajasthan and Gujarat. This region forms the part of arid and semi-arid landscape of western India. The latitudinal extent of this area is from 20^{o} 06′ N to 30^{o} 09′ N and longitudinal extent is from 68^{o} 10′ E to 78^{o} 18′ E (Fig. 1). In the north this area shares it’s boundary with the states of Punjab, Haryana and Uttar Pradesh, in the east with Madhya Pradesh, in the south with Maharashtra. To west of Gujarat is Arabian Sea, whereas the western boundary of Rajasthan is an international boundary shared with Pakistan. The northern boundary of Gujarat is also shared with Pakistan. The state of Gujarat has a geographical area of 1.96 lakh square kilometers (0.196 million square kilometers) and comprises of 25 districts. Geographical area of Rajasthan is 3.42 lakh square kilometers (0.342 million square kilometers). Together these two states cover 5.38 lakh square kilometers (0.538 million square kilometers) of area. The western part of the area (west Rajasthan) covers part of Thar Desert also called as the Great Indian Desert. The area is characterized by varying topographic features. The extensive landscape in the north consists of rocky terrain, sand dunes, wetlands, land with thorny scrubs and barren tracts, plateaus, river-drained plains, wooded regions and ravines. In the south, the area encompassing Gujarat is also topographically diverse. Aravali Mountains with altitude of more than 400 meters are located in the east. The Runn of Kutch in the west is a barren surface with almost no vegetation. In the north, over Rajasthan, during winter temperatures range from 8^{o} to 28^{o} C and summer temperatures range from 25^{o} to 46^{o} C. Temperatures over Gujarat are moderate, particularly over coastal area. Rainfall is scanty over northwestern part of the area compared to southern and eastern areas. The western arid areas of Rajasthan get rainfall of about 100 mm annually. Over Gujarat rainfall varies between 330 and 1520 mm. Overall the area receives less rainfall which is highly variable over space and time, and therefore, is vulnerable to drought.

2.2 Data Used

In this study two MODIS products from satellite Terra have been used: MOD11A2 and MOD15A2. These products were downloaded using USGS Global Visualization Viewer (GloVis), an online search and order tool for satellite data (https://lpdaac.usgs.gov/data_access/glovis). MOD11A2 datasets are level-3 MODIS global Land Surface Temperature (LST) and Emissivity 8-day composites. They are derived from daily 1-kilometer resolution LST product (MOD11A1). These derived products are stored on 1-km Sinusoidal grid as the average values of clear-sky LSTs during a 8-day period. MOD15A2 is a level-4 MODIS global Leaf Area Index (LAI) and Fraction of Photosynthetically Active Radiation (FPAR) product. It is also a 8-day composite with 1-kilometer resolution which is stored on Sinusoidal grid. This data product can also be downloaded through GloVis, but the product used in this study is the improved version of this data set downloaded from the website (http://globalchange.bnu.edu.cn/research/lai/) of Land-Atmosphere Interaction Research Group at Beijing Normal University. This improved version of the dataset was prepared by Yuan et al. (2011) to overcome the problem of spatial and temporal discontinuity of MODIS LAI products. The researchers found that the improved MODIS LAI data were closer to the LAI reference maps in magnitude and also more continuous and consistent in both time-series and spatial domains. Both of the above-mentioned products were downloaded for five months (i.e. June to October) spanning over the period 2002-2012.

2.3 Methods

The downloaded images were reprojected to Albers Conical Equal Area Projection keeping datum as WGS 84. Since this is an equal area projection each pixel in the study area now had equal size which made further pixel level analysis easier. This was followed by preparing subsets of the images for the study area. Once the subset images were ready these images and the scaling factor for LST and LAI were used to derive LST and LAI images. First band of subset images obtained from MOD11A2 data (temperature/emissivity) was multiplied by 0.02, which is the scaling factor to convert pixel values into LST (in Kelvin). Only this band was saved in the ouput image. Similarly second band of MOD15A2 data (LAI) images was multiplied by 0.1 (the scaling factor for converting pixel values into LAI) to obtain LAI images. Only the LAI band was saved in the output image. Thus the LAI and LST images were ready for the analysis.

Usually TVDI is computed by analyzing LST and NDVI space. The LST vs NDVI relationship space diagram defined by Sandholt et al. (2002) was modified to define LST vs LAI relationship (Fig. 2). In this study instead of NDVI, LAI has been considered for deriving TVDI. LAI is usually considered as total one-sided leaf area per unit ground surface area. This approach has been used because Sandholt et al. (2002) pointed out that the uncertainties would influence TVDI computation at higher NDVI values. TVDI was computed using following equation.

$$\mathrm{TVDI} = \frac{\mathrm{LST} - \mathrm{LST}_{min}}{\mathrm{LST}_{max} - \mathrm{LST}_{min}}$$

where LST is the observed surface temperature in Kelvin of the given pixel, LST_{min} is the minimum temperature in the LST-LAI space triangle, defining wet edge, LST_{max} = a + b*LAI is the maximum temperature for a given value of LAI, a and b are surface parameters of the image defining the dry edge, modelled as a linear fit to the data. 8-day composite TVDI images of Julian days referred here as Day of Year (DOY) for the months of September and October during all years (2002-2012) were prepared to assess terminal drought. Drought condition during 2002 and 2003 was assessed for all DOY from June-October

TVDI images of the months of September and October were stacked separately for these months and a new image for maximum TVDI representing terminal drought intensity was prepared for every year. Trend analysis of terminal drought intensity was then carried out using linear regression and Mann-Kendall trend test. Linear regression has been widely used across the globe to find long-term tendency in a variable (Englehart and Douglas, 2003; Malmgren et al., 2003; Qian and Lin, 2004; Rio et al., 2005; Gadgil and Dhorde, 2005; Dhorde et al., 2014). Statistical significance of the trends was tested by t-test (for linear regression) and Z-statistic (for Mann-Kendall trend test). More details of application of linear regression can be found in Gadgil and Dhorde (2005) and for Mann-Kendall trend test in Hamed and Rao (1998) and Mondal et al. (2012).

3. Results and Discussion

3.1 Spatial Pattern of TVDI during the year 2002 and 2003

TVDI maps were prepared for the whole season for the years 2002 and 2003. 2002 was a severe drought year, and therefore, TVDI images for all DOY were prepared for this year (Fig. 3). TVDI images were also prepared for the year 2003 (Fig. 4). During the year 2002, on DOY 153 severe drought conditions prevailed over eastern Rajasthan and southern Gujarat, covering Rajkot and surrounding districts (Fig. 3). On DOY 161 conditions worsened over eastern Rajasthan. The images from DOY 169 to 241 are blurred because of cloud cover, but the stressed conditions prevailing over western Rajasthan are clearly seen. On DOY 265 and 273 severe drought conditions prevailed over south-western Rajasthan. Drought spread from this area towards southern Gujarat during DOY 273 to 365. This change is very well picked up by TVDI.

The drought of 2002 was quite severe and the TVDI images showed how this drought spread from south-western Rajasthan to southern Gujarat. Similar pattern is observed in 2003 (Fig. 4) but the severity of drought is less on DOY 265 and 273, which can be clearly understood from by the two figures. During 2002, on these two DOY, severe drought conditions covered major part of the region. The conditions were comparatively less severe in 2003 over eastern Gujarat as compared to 2002. The analysis signifies the importance of such images for real-time monitoring of drought. TVDI image on DOY 249 displays similar conditions over Gujarat observed by Patel et al. (2012) using VTCI.

3.2 Relationship of TVDI with Crop Moisture Index (CMI)

Since drought situation occurs out of moisture deficit it is expected that TVDI values should increase under stressful conditions, that is when the moisture level goes down. This has to be investigated by comparing TVDI values with the available moisture index values. Weekly CMI values were available for some selected locations over Gujarat state for the years 2002 and 2003. The geographic co-ordinates for these locations were known from which a point shape file for these locations was prepared in ArcGIS software. Using spatial modeler in ERDAS TVDI values for corresponding weeks during September and October were extracted for these locations.

For standard meteorological weeks TVDI and CMI values were plotted for each locations for the years 2002 and 2003 and are displayed in figure 5 and 6. In Fig. 5, TVDI and CMI values for weeks between 33 and 40 have been plotted for locations at

Anand, Khedbrama, Rajkot, Mahuva, Amrelli, Mangrol, Baroda, Navsari, Broach, Radhanpur, Dhanduka, Vijyapur and Gandevi. A uniform pattern observed from weeks 35 to 40 is that: as CMI values decrease the TVDI values tend to increase. At some locations fluctuations in TVDI are very well associated with the variations in CMI. For example at Navsari, Vijyapur, Mangrol, Rajkot, Anand, Mahuva. To some extent similar relationship is observed at Dhanduka. Low CMI indicates reduced water availability to meet crop water requirement as crop experiences drought stress. On other hand, less evapotranspiration will lead to higher temperatures and stressed vegetation which in turn manifested as lower LAI values. So the TVDI value of 0 indicates 'well-watered conditions' and the value of 1 represents 'No moisture conditions' The CMI and TVDI depicts drought stress on reverse order of their increments and thus give rise to inverse relationship

In the year 2003 TVDI values were extracted for all stations except Anand for which TVDI values were not available (Fig. 6). In this year too, similar association is observed at some locations. A close look at the graphs in figure 5 and 6 revealed that TVDI values are sensitive to CMI values when CMI values are below 2. For example, in Fig. 6 at Rajkot the CMI values fall below 2 from week 37 onwards, after which there is a sudden rise in the TVDI values. Similar trend is observed at Mangrol and Radhanpur. Moreover once the CMI value falls below 2 the TVDI values tend to increase even when the CMI values again increase beyond 2. Examples of these are Vijyapur, Dhanduka and Broach (Fig. 6). This relationship has to be investigated in future research. Patel et al. (2012) using VTCI have observed that, when CMI values increase VTCI values also increase. Though VTCI values also range from 0 to 1, the higher VTCI values indicate normal conditions and lower VTCI values indicate stressed conditions. Positive relationship between VTCI and CMI values means that when CMI values are higher the conditions are normal (VTCI values near 1) and when CMI values are lower the conditions are stressful (VTCI values near 0). In case of TVDI the values range from 0 to 1, but 0 indicates normal conditions and 1 denotes stressed conditions. Thus, in this case there is a negative relationship between CMI and TVDI, indicating that the results are in agreement with the results obtained by Patel et al. (2012). In both the studies lower (higher) CMI values indicate drought (normal) conditions. Figure 7 illustrates the negative relationship between TVDI and CMI. Correlation Coefficient (CC) was also computed between these two variables. During 2002 the CC between TVDI and CMI was -0.47 and during 2003 it was -0.22. For the years 2002 and 2003 CMI values were available for more number of stations. 2002 was a drought year whereas 2003 was a normal year. From the slope of the regression line and CC value it is evident that a strong relationship between TVDI and CMI exists during drought year (2002). On the contrary the relationship is not strong during normal years. This also suggests that LAI-based TVDI can efficiently capture drought signature over a region.

3.4 Year-to-Year Variation in TVDI

Mean TVDI values were computed for the months of September and October over the whole region for each year. Yearly variations of TVDI values are represented in Fig. 8. The figure also indicates whether the year was El Nino year. During September in the years 2002 and 2009 TVDI mean was higher than the preceding year. Among the 11 years that have been analyzed TVDI mean for the year 2002 was highest. TVDI mean was more than 0.6 during the years 2002-2004 and also between 2006 and 2009. 2009 was also an El Nino year. During October TVDI mean varies less from year-to-year but again it was observed that TVDI mean was highest in 2002. By October southwest monsoon completely withdraws from this area, which may be attributed to less variation in TVDI mean. But, during September, thought the monsoon starts withdrawing there are intermittent rain spells frequency of which depends on monsoon's vigour during a particular year. This may be the reason behind higher fluctuations in September. The graphs of September and October follow similar pattern indicating drought conditions were more severe during 2002-2004 and 2006-2009 over the region.

3.5 Spatial Trends in Terminal Drought

To find trends in terminal drought intensity, all DOY images of TVDI belonging to a particular month of an individual year were stacked together. These stacked images were used to extract maximum value of TVDI for each pixel using STACK MAX function in spatial modeller of ERDAS IMAGINE. In this way a new image containing highest values of TVDI for every pixel was generated for the months of September and October for each year. The maximum TVDI value represented maximum dryness observed in terminal drought during a particular month for a particular year, which indicated terminal drought intensity. Trends in terminal drought intensity were computed for every pixel using spatial modeller. Two statistical methods were used for computing trends: linear regression and Mann-Kendall trend test. Thus, both parametric and non-parametric approaches were used to compute trend. The results of linear regression were tested for statistical significance using t-test, while those of Mann-Kendall test were tested with Z-statistic. During the month of September spatial trends in terminal drought intensity indicated positive tendencies over southern, eastern, central and south-western Gujarat (Fig. 9). With t-test it was found that, at scattered locations over south-western and central Gujarat the trends were significant for 80% confidence level. Over central and south-western Rajasthan decreasing trends were registered, with some tendencies decreasing with 80% confidence. Similar trends were observed with Mann-Kendall rank test, but the Z-statistic test did not find them to be statistically significant. Though the trends were not significant, a general tendency was revealed. Increasing tendencies are observed over eastern Rajasthan, northern most regions of Rajasthan, over most of Gujarat except Kutch and some parts in southern Gujarat. Over central and southwestern Rajasthan decreasing tendencies were observed.

In October increasing trend in terminal drought intensity is observed over northern and most of western Rajasthan and southern Gujarat (Fig. 10). Negative trends were observed over western and southwestern Gujarat. In Rajasthan declining trends were registered over eastern and southern Rajasthan.

In general for the whole region it can be said that terminal drought intensity is increasing in the north and decreasing in south (except Surat and adjoining area).

4. Conclusion

TVDI is an efficient index to comprehend vegetation condition which is based on two vital parameters: land surface temperature and vegetation index. Normally NDVI is taken as the vegetation index. But, in this study LAI has been considered to compute TVDI, therefore it is referred to as LAI-based TVDI. It has been observed that LAI-based TVDI can also give similar information that we get from an index based on NDVI. It can distinguish between healthy vegetation and stressed vegetation. The TVDI maps generated brought out the spatial pattern in normal and stressful conditions quite well so as to understand the spread of drought from one week to other and also know year-to-year variations in conditions on each DOY. During the year 2002 the

TVDI maps illustrated that how drought slowly migrated from south-western Rajasthan to western and southwestern Gujarat. This also indicates that LAI-based TVDI can also be one of the alternatives for drought monitoring. By comparing TVDI and CMI values, it was observed that TVDI values have negative relation with CMI values. That is, with increase in CMI values, TVDI values decrease and tend to approach towards normal. It was also observed that TVDI values are very sensitive when CMI values drop below 2. Having said this, it is necessary that the relationship has to be studied in detail by taking more samples.

In the contemporary world it has been observed that the human population and human activities have been increasingly threatened by natural hazards and disasters. Therefore, there is a growing interest in the researchers to investigate temporal trends in the occurrence of these hazards. In this study, an attempt was made to analyze spatial trends in terminal drought intensity observed during the study period (2002-2012). Parametric as well as non-parametric statistical methods were used to compute temporal trends. It was revealed by the tests that during September positive trends in terminal drought intensity were observed over eastern Rajasthan (particularly northern regions of Rajasthan) and over most of the Gujarat excluding Kutch and some parts of southern Gujarat. Negative trends prevailed over central and southwestern Rajasthan. During October terminal drought intensity increased over northern part of the region and decreased over south, excluding Surat.

Acknowledgements

We would like to acknowledge Land Processes Distributed Archive Centre (LP DAAC), USGS and Land-Atmosphere Interaction Research Group at Beijing Normal University for providing MODIS data sets. The authors are also grateful to the anonymous reviewers for their suggestions which helped in improving the quality of this manuscript.

References

Bayarjargal, Y., Karnieli, A., Bayasgalan, M., Khudulmur, S., Gandush, C., Tucker, C.J., 2006. A comparative study of NOAA-AVHRR derived drought indices using change vector analysis. *Remote Sen. Environ.* 105, 9-22.

Chen, C.F., Son, N.T., Chang, L.Y., Chen, C.C., 2011. Monitoring of soil moisture variability in relation to rice cropping systems in the Vietnamese Mekong Delta using MODIS data. *App. Geogr*. 31, 463–475.

Dhakar, R., Sehgal, V.K., Pradhan, S. 2013. Study on inter-seasonal and intra-seasonal relationships of meteorological and agricultural drought indices in the Rajasthan State of India. *J. Arid Environ.* 97, 108-119.

Dhorde A.G., Zarenistanak, M., Kripalani, R.H., Preethi, B., 2014. Precipitation analysis over southwest Iran: trends and projections. *Meteorol. Atmos. Phys.* 124, 205–216. doi 10.1007/s00703-014-0313-9

Englehart, P.J., Douglas, A.V., 2003. Urbanization and seasonal temperature trends: observational evidence from a data-sparse part of North America. *Int. J. Climatol.* 23, 1253-1263.

Gadgil, A., Dhorde, A., 2005. Temperature trends in twentieth century at Pune, India. *Atmos. Env.* 35, 6550-6556.

Hamed, K.H., Rao, A.R., 1998. A modified Mann-Kendall trend test for auto-correlated data. *J. Hydrol.* 204, 182-196.

Holzman, M. E., Rivas, R., Piccolo, M.C., 2014. Estimating soil moisture and the relationship with crop yield using surface temperature and vegetation index. *Int. J. App. Earth Obs.* 28, 181-192.

Huang, Y., Tian, Q., Du, L., Sun, S., 2013. Analysis of Spatial Temporal Variation of Agricultural Drought and Its Response to ENSO over the Past 30 Years in the Huang-Huai-Hai Region, China. *Terr. Atmos. Ocean Sci.* 24, 745-759.

Ji, L., Peters, A.J., 2003. Assessing vegetation response to drought in the northern great plains using vegetation and drought indices. *Remote Sen. Environ.* 87: 85-98.

Kogan F.N., 1995a. Application of vegetation index and brightness temperature for drought detection. *Adv. Space Res.* 15, 91–100.

Kogan, F.N., 1995b. Droughts of the late 1980 in the United States as derived from NOAA polar-orbiting satellite data. *B. Am. Meteorol. Soc.* 76, 655–668.

Kogan, F.N., 1997. Global drought watch from space. *B. Am. Meteorol. Soc.* 78, 621-636.

Li, Z., Wang, Y., Zhou, Q., Wu, J., Peng, J., Chang, H., 2008. Spatiotemporal variability of land surface moisture based on vegetation and temperature characteristics in Northern Shaanxi Loess Plateau, China. *J. Arid Environ.* 72, 974–985.

Mallick, K., Bhattacharya, B.K., Patel, N.K., 2009. Estimating volumetric surface moisture content for cropped soils using a soil wetness index based on surface temperature and NDVI. *Agr. Forest Meteorol.* 149, 1327–1342.

Malmgren Bjǒrn, A., Ranatunge, H., Hayashi, Y., Mikami, T., 2003. Precipitation trends in Sri Lanka since the 1870s and relationships to EL Nino-Southern Oscillation. *Int. J. Climatol.* 23, 1235-1252.

Mcvicar TR, Bierwirth PN. 2001. Rapidly assessing the 1997 drought in Papua New Guinea using composite AVHRR imagery. *Int. J. Remote Sens.* 22: 2109-2198.

Mondal, A., Kundu, S., Mukhopadhyay, A., 2012. Rainfall trend analysis by Mann-Kendall Test: a case study of north-eastern part of Cuttack district, Orissa. *International Journal of Geology, Earth and Environmental Sciences*. 2, 70-78.

Murali Krishna, T., Ravikumar, G., Krishnaveni, M., 2009. Remote sensing based agricultural drought assessment in PalarBasin of Tamil Nadu State, India. *Journal of the Indian Society of Remote Sensing* 37, 9–20.

Nicholson, S.E., Farrar, T.J., 1994. The influence of soil type on the relationships between NDVI, rainfall, and soil moisture in semiarid Botswana: I. NDVI response to rainfall. *Remote Sen. Environ.* 50, 107-120.

Patel N. R., Parida, B., Venus, V., Saha, S. K., Dadhwal, V. K., 2012. Analysis of agricultural drought using Vegetation temperature condition index (VTCI) from Terra/MODIS satellite data. Environmental monitoring and assessment, 184:7153–7163.

Patel, N. R., Anapashsha, R., Kumar, S., Saha, S.K., Dadhwal, V.K., 2009. Assessing potential of MODIS derived temperature/vegetation condition index (TVDI) to infer soil moisture status. *Int. J. Remote Sens.* 30: 23–39.

Prathumchai, K., Honda, K., 2001. Drought risk evaluation using remote sensing and GIS: a case study in Lop Buri Province. In: 22nd Asian Conference on Remote Sensing, 5-9 November 2001, Singapore.

Qian, W., Lin, X., 2004. Regional trends in recent temperature indices in China. *Clim. Res.* 27, 119-134.

Rhee, J., Im, J., Carbone, G.J., 2010. Monitoring agricultural drought for arid and humid regions using multi-sensor remote sensing data. *Remote Sen. Environ.* 114, 2875–2887.

Río, S.D., Penas, Á., Fraile, R., 2005. Analysis of recent climatic variations in Castile and Leon (Spain). *Atmos. Res.* 73, 69-85.

Saeid, R., Sefidkouhi, M.A.G., Raeini-Sarjaz., M., Valipour, M. 2015. Estimation of actual evapotranspiration by using MODIS images (a case study: Tajan catchment). *Archives of Agronomy and Soil Science*, 61, 695-709, doi:10.1080/03650340.2014.944904

Sandholt, I., Rasmussen, K., Andersen, J., 2002. A simple interpretation of the surfacetemperature/vegetation index space for assessment of surface moisture status. *Remote Sen. Environ.* 79, 213–224.

Seiler, R.A., Kogan, F., Wei, G., 2000. Monitoring weather impact and crop yield from NOAA AVHRR data in Argentina. *Adv. Space Res.* 26, 1177-1185.

Son N.T., Chen, C.F., Chen, C.R., Chang, L.Y., Minh, V.Q., 2012. Monitoring agricultural drought in the Lower Mekong Basin using MODIS NDVI and land surface temperature data. *Int. J. App. Earth Obs.* 18, 417–427.

Sun, W., Wang, P.X., Zhang, S.Y., Zhu, D.H., Liu, J.M., Chen, J.H., Yang, H.S., 2008. Using the vegetation temperature condition index for time series drought occurrence monitoring in the Guanzhong Plain, PR China. *Int. J. Remote Sens.* 29: 5133–5144.

Unganai, L.S., Kogan, F.N., 1998. Southern Africa's recent droughts from space. *Adv. Space Res.* 21, 507-511.

Vicente-Serrano, S., Cuadrat-Prats, J.M., Romo, A., 2006. Early prediction of crop productivity using drought indices at different time scales and remote sensing data: application in the Ebro valley (north east Spain). *Int. J. Remote Sens.* 27, 511-518.

Wan, Z., Wang, P., Li, X., 2004. Using MODIS land surface temperature and normalized difference vegetation index products for monitoring drought in the southern Great Plains, USA. *Int. J. Remote Sens.* 25, 61–72.

Wang, H., Li, X., Long, H., Xu, X., Bao, Y., 2010. Monitoring the effects of land use and cover type changes on soil moisture using remote-sensing data: a case study in China's Yongding River basin. *Catena* 82, 135–145.

Wang, J, Price, K.P., Rich, P.M., 2001. Spatial patterns of NDVI in response to precipitation and temperature in the central Great Plains. *Int. J. Remote Sens.* 22, 3827-3844.

Yuan, H., Dai, Y., Xiao, Z., Ji, D., Shangguan, W., 2011. Reprocessing the MODIS leaf area index products for land surface and climate modelling. *Remote Sen. Environ.* 115, 1171-1187. doi:10.1016/j.rse.2011.01.001.

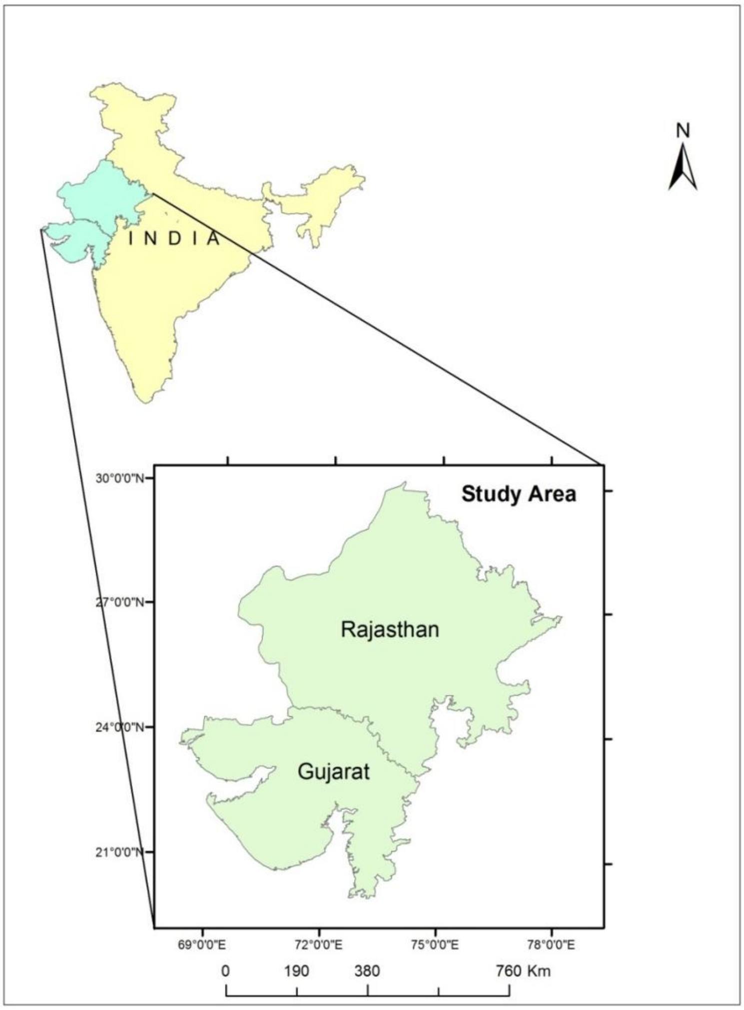

Figure 1: Location Map of the Study Area

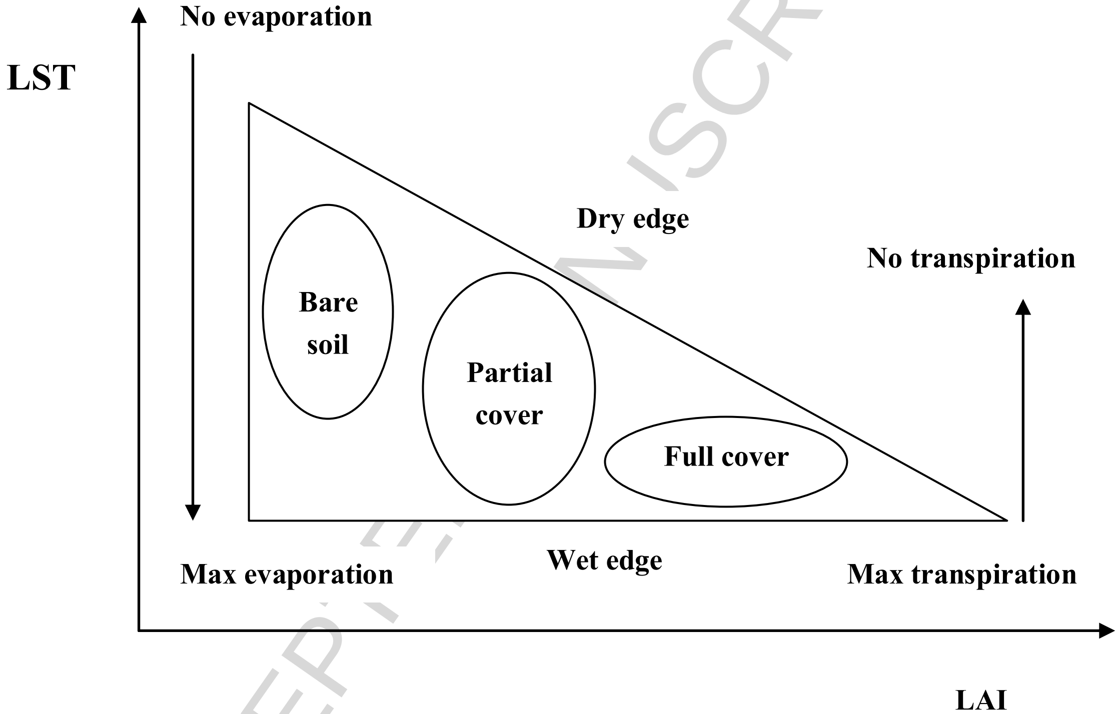

Figure 2: LST-LAI space modified from Sandholt et al. (2002)

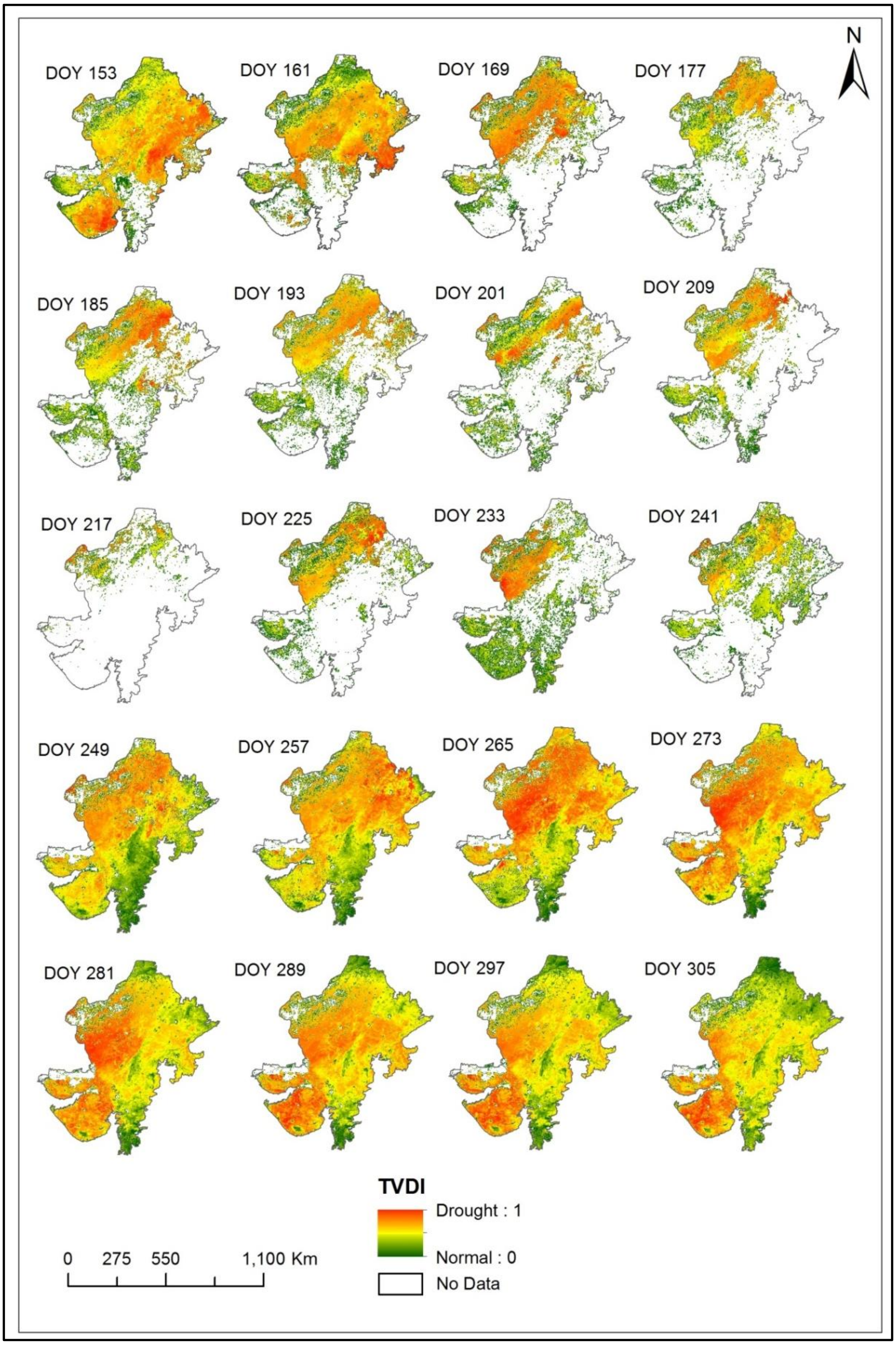

Figure 3: Spatial Pattern of TVDI on All DOY in the Year 2002

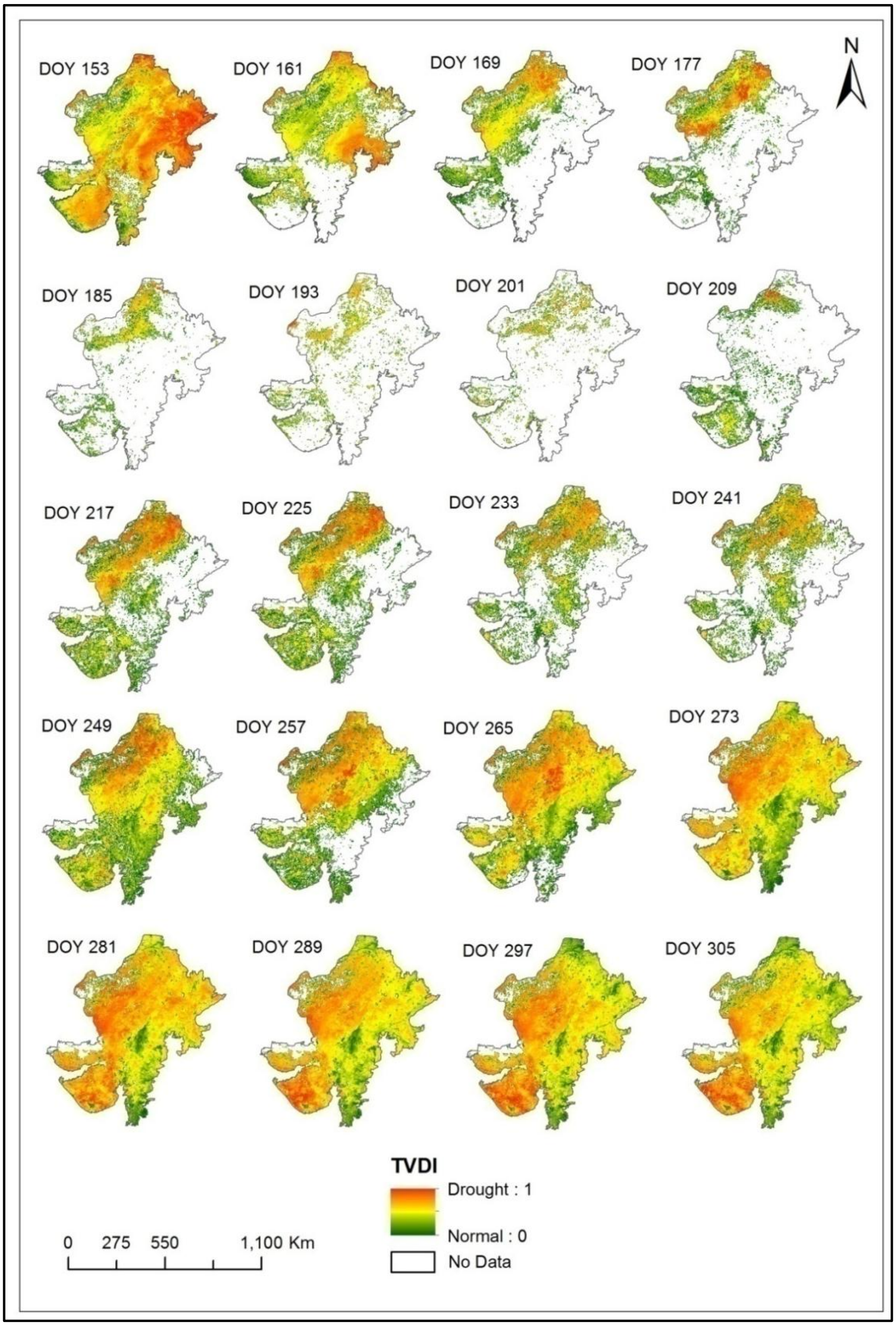

Figure 4: Spatial Pattern of TVDI on all DOY of the year 2003

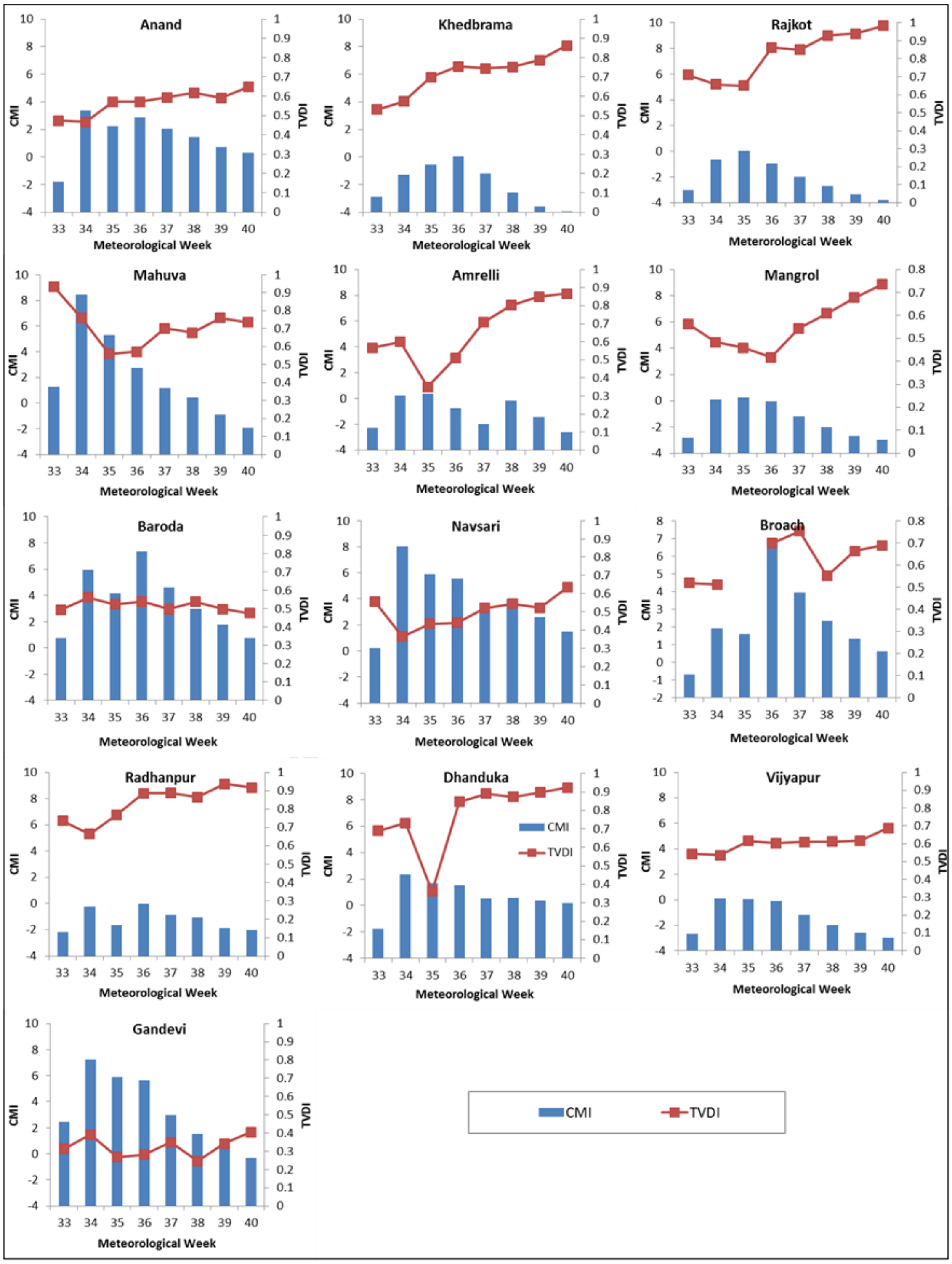

Figure 5: Weekly CMI and TVDI Values at Some Selected Locations in the Year 2002

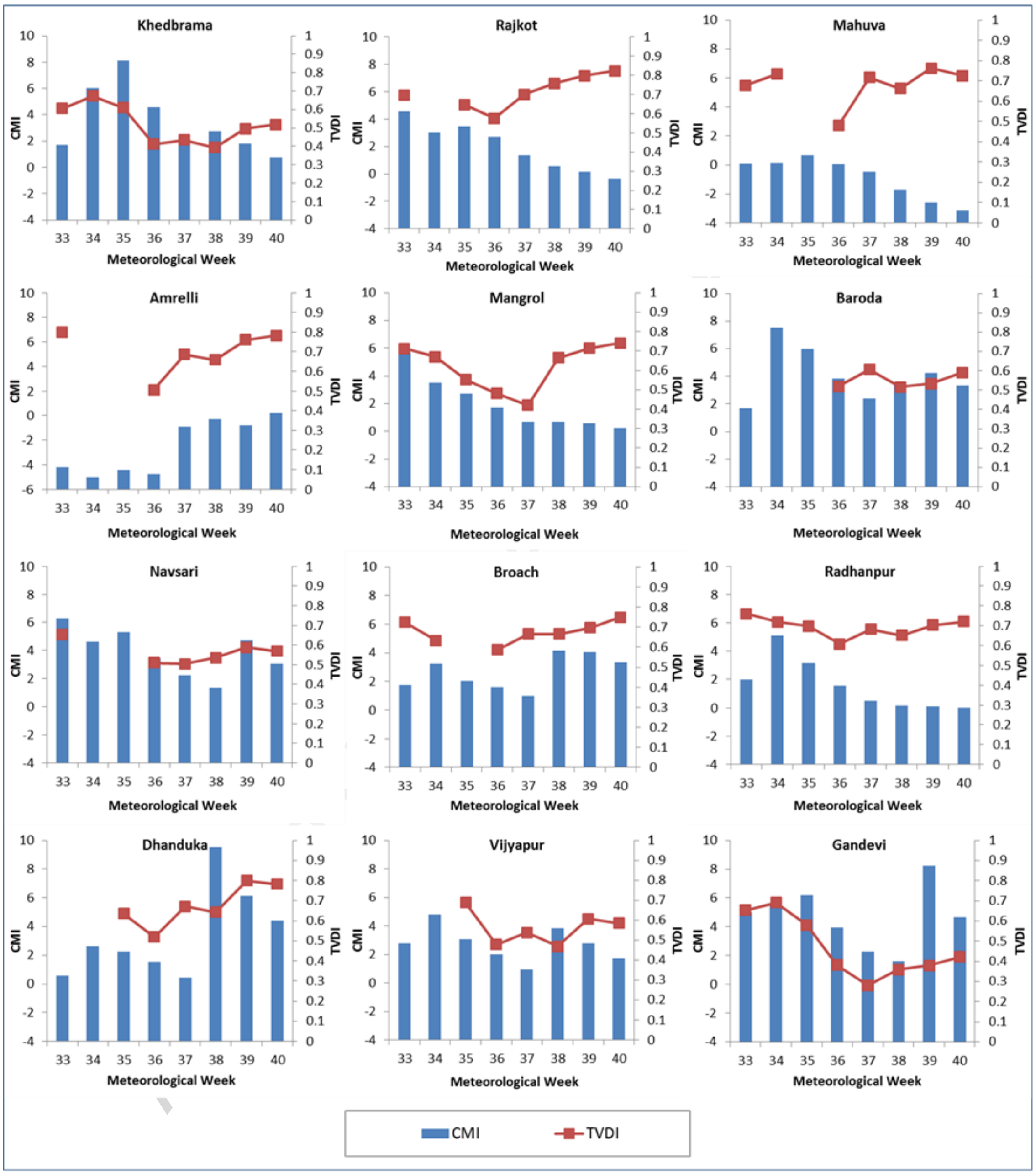

Figure 6: Weekly CMI and TVDI values at some selection locations in the year 2003

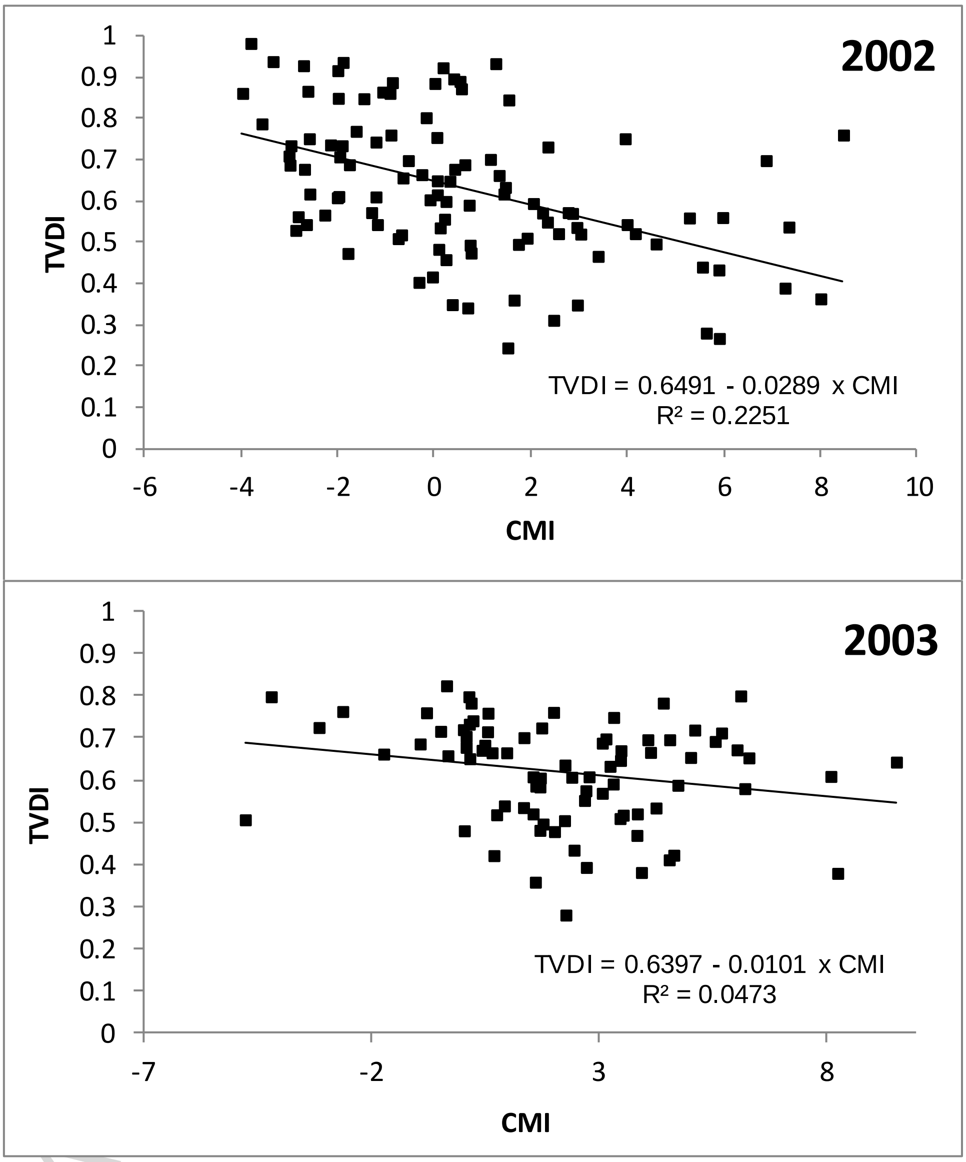

Figure 7: Relationship between TVDI and CMI during the years 2002 and 2003

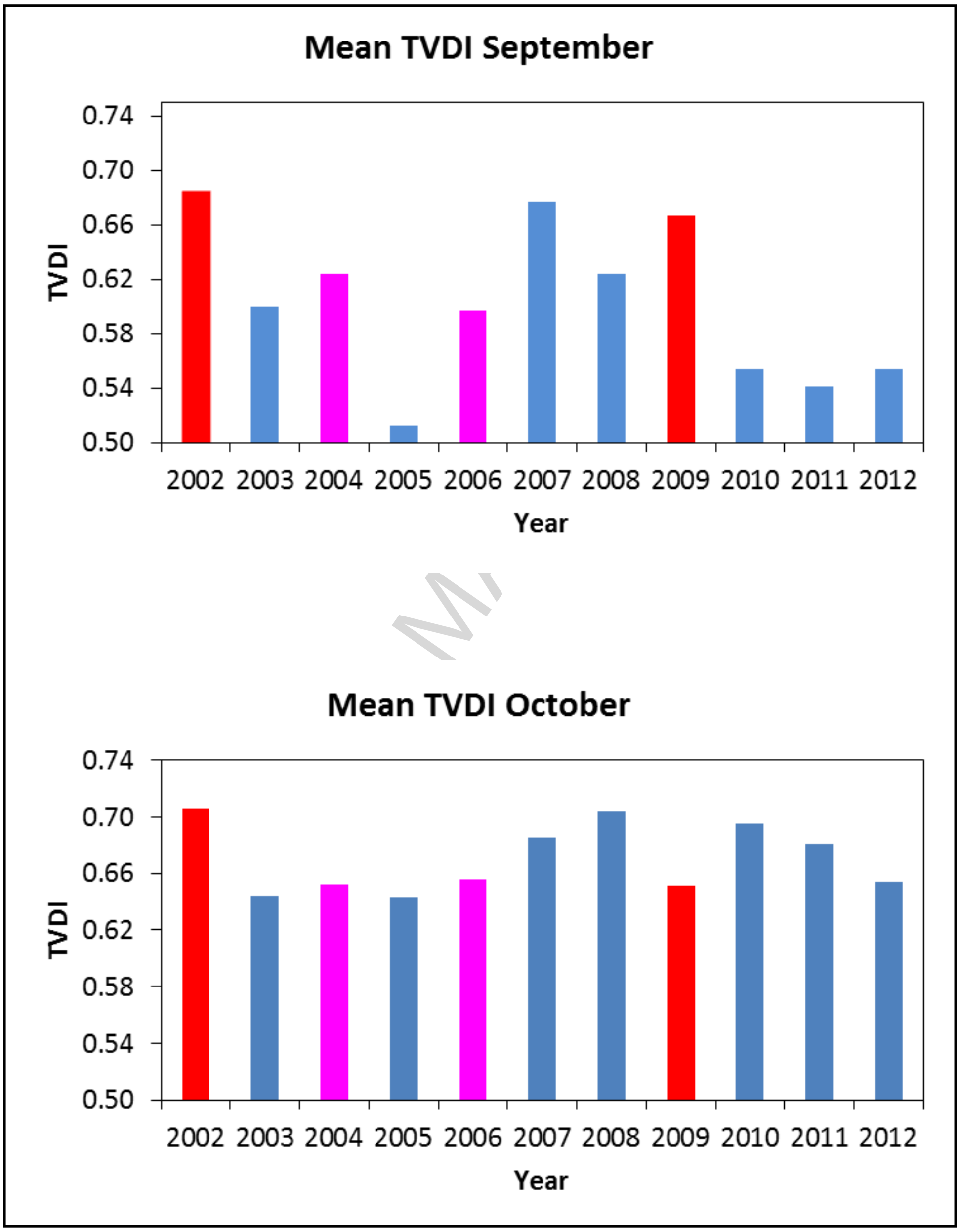

Figure 8: Yearly variation in TVDI mean over the study region. Red bars indicate moderate El Nino years and pink bars denote weak El Nino years.

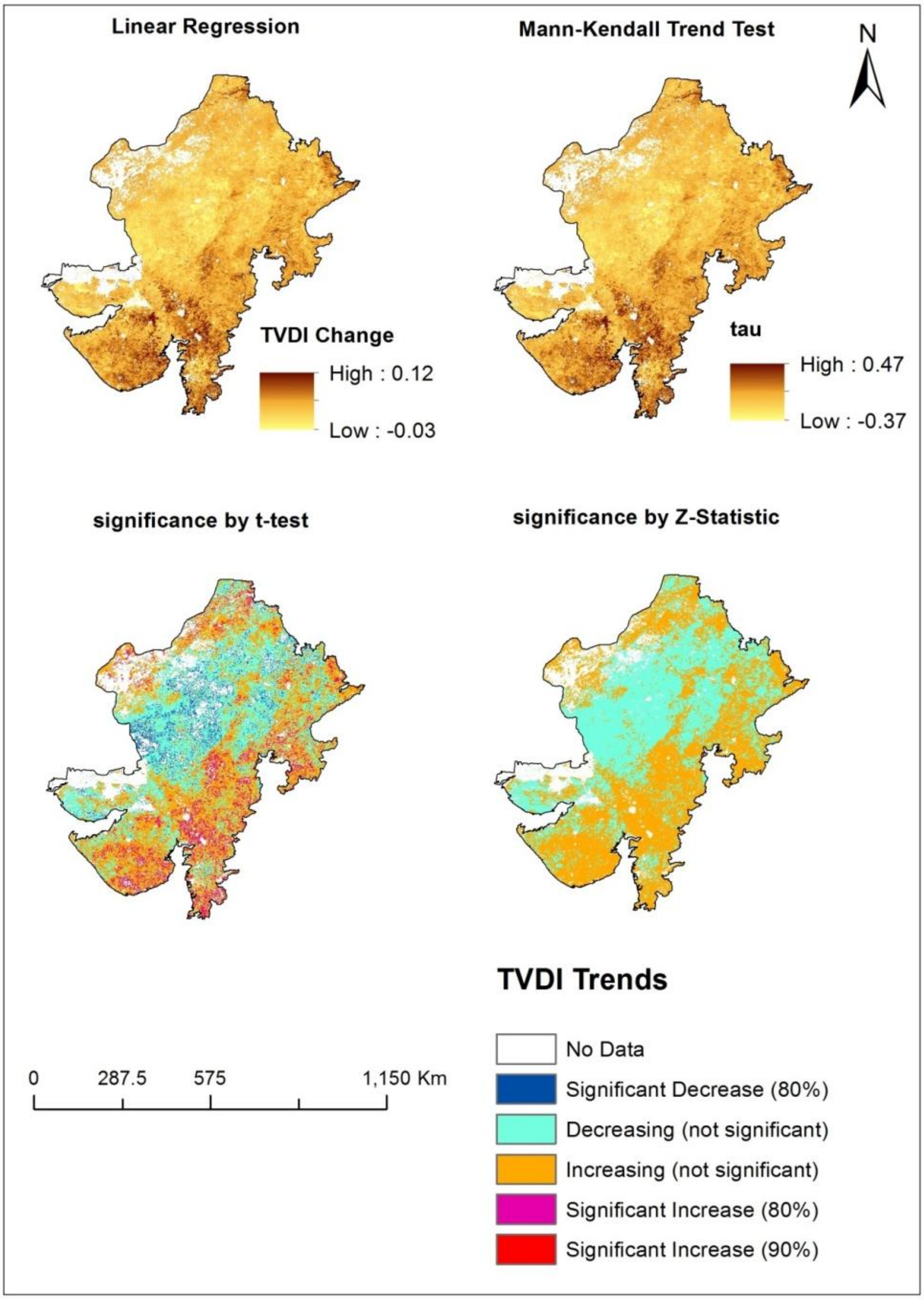

Figure 9: Spatial Trends in Terminal Drought Intensity during September

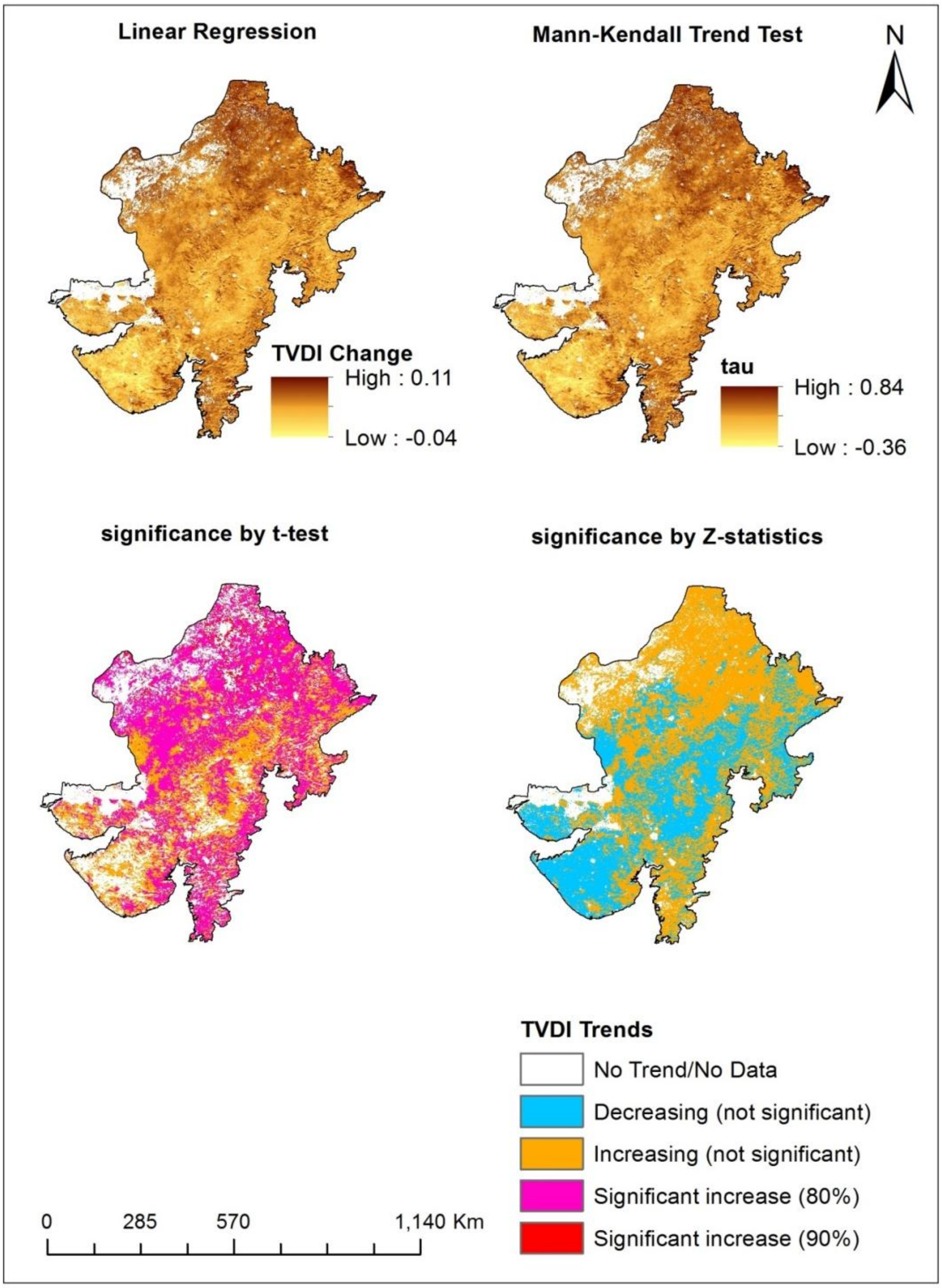

Figure 10: Spatial Trends in Terminal Drought Intensity during October

Highlights

Exploitation of LST-LAI space to linearly parameterized dry (LSTmax) and moist (LSTmin) edges

Derivation of long-term TVDI for September-October month as indicator of terminal drought

TVDI agrees to short-term moisture changes as evidenced from crop moisture index

Application of linear and Man Kendal l test for depicting long-term trends of TVDI