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Responses of NDVI anomaly to SPI for vegetation over the years 2000-2019: A case Study of Raichur district

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Abstract

Precipitation is the most important parameter which helps the growth of vegetative cover, without it all the land on the planet would be desert. So, understanding precipitation-vegetation interaction is of great importance for understanding how it affects the vegetation especially agricultural crops. Here, comprehensive investigation of spatiotemporal pattern of vegetation response to precipitation for Raichur district is done, using remotely sensed vegetation index NDVI and meteorological based SPI for the years 2000-2019. Raichur District, of Karnataka (India) falls in a plateau region and located between 16°9’17.804” N to 16°15’2.521” N in latitude and 77°18’23.912” E to 77°24’43.895” E in longitude. It is a drought prone region and falls within the most semi-arid part of the country. The purpose of the study is to analyze NDVI anomaly response to SPI in Raichur district. The MODIS/terra 16_day Global_250m is used for the calculation of NDVI anomaly and IMD annual precipitation data is used for the calculation of SPI. The result shows Maximum and Minimum NDVI anomaly for cropland is 0.047293 and -0.018942, for mixed-forest 0.0486 and -0.0376 and for Shrub-land 0.0479 and -0.0242 respectively. Also, for SPI year 2009 has the highest value with +3.675 indicating extreme wet condition while the lowest value of SPI over 2 decades is -0.781 which indicates near normal condition of precipitation in Raichur district. The results also shows that the variation graph between NDVI anomaly and SPI for Cropland, mixed-forest and shrub-land NDVI anomaly responses was not strongly positive to SPI values for the years 2002-2007 however, strong positive responses has been observed between NDVI anomaly to SPI in middle and final stage for these three vegetative cover. It has been concluded that the anomalous behaviour of NDVI anomaly and SPI graph could be the reason of precipitation lag time.

Introduction

The Normalized Difference Vegetation Index (NDVI) is an index of plant “greenness” or photosynthetic activity, and is one of the most commonly used vegetation indices. Vegetation indices are based on the observation that different surfaces reflect different types of light differently. Photosynthetically active vegetation, in particular, absorbs most of the red light that hits it while reflecting much of the near infrared light. Vegetation that is dead or stressed reflects more red light and less near infrared light. Likewise, non-vegetated surfaces have a much more even reflectance across the light spectrum.

NDVI is calculated on a per-pixel basis as the normalized difference between the red and near infrared bands from an image: [13]

$$NDVI = (NIR – RED/NIR + RED)$$

NIR - reflection in the near-infrared spectrum.
RED - reflection in the red range of the Spectrum.

The index values range from -1.0 to 1.0, where negative values are mainly formed from clouds, water and snow, and values close to zero are primarily formed from rocks and bare soil. Very small values (0.1 or less) of the NDVI function correspond to empty areas of rocks, sand or snow. Moderate values (from 0.2 to 0.3) represent shrubs and meadows, while large values (from 0.6 to 0.8) indicate temperate and tropical forests.

Chlorophyll (a health indicator) strongly absorbs visible light, and the cellular structure of the leaves strongly reflect near-infrared light. When the plant becomes dehydrated, sick, afflicted with disease, etc., the spongy layer deteriorates, and the plant absorbs more of the near-infrared light, rather than reflecting it. Thus, observing how NIR changes compared to red light provides an accurate indication of the presence of chlorophyll, which correlates with plant health [14].

Many factors affect NDVI values like plant photosynthetic activity, total plant cover, biomass, plant and soil moisture, and plant stress. Because of this, NDVI is correlated with many ecosystem attributes that are of interest to researchers and managers (e.g., net primary productivity, canopy cover, bare ground cover). Also, because it is a ratio of two bands, NDVI helps compensate for differences both in illumination within an image due to slope and aspect, and differences between images due things like time of day or season when the images were acquired. Thus, vegetation indices like NDVI make it possible to compare images over time to look for ecologically significant changes. [13]

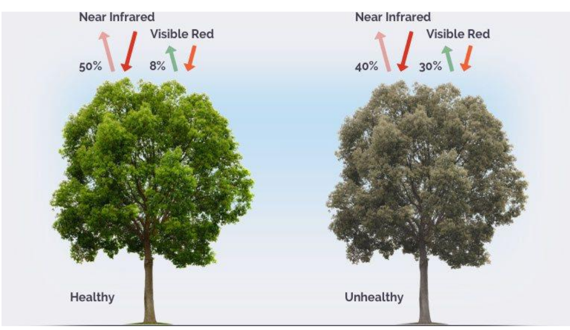


Fig 1. Absorption and reflection of NIR and Visible red for healthy and Unhealthy plants [14].

Over the years, many drought indices were developed and used by meteorologists and climatologists around the world. Those ranged from simple indices such as percentage of normal precipitation and precipitation percentiles to more complicated indices such as the Palmer Drought Severity Index. However, scientists in the United States realized that an index needed to be simple, easy to calculate and statistically relevant and meaningful. Moreover, the understanding that a deficit of precipitation has different impacts on groundwater, reservoir storage, soil moisture, snowpack and streamflow led American scientists McKee, Doesken and Kleist to develop the Standardized Precipitation Index (SPI) in 1993.

The SPI (McKee and others, 1993, 1995) is a powerful, flexible index that is simple to calculate. In fact, precipitation is the only required input parameter. In addition, it is just as effective in analysing wet periods/cycles as it is in analysing dry periods/cycles.

The SPI was designed to quantify the precipitation deficit for multiple timescales. These timescales reflect the impact of drought on the availability of the different water resources. Soil moisture conditions respond to precipitation anomalies on a relatively short scale. Groundwater, streamflow and reservoir storage reflect the longer-term precipitation anomalies. For these reasons, McKee and others (1993) originally calculated the SPI for 3, 6,12, 24and 48month timescales.

McKee and others (1993) used the classification system shown in the SPI value table below (Table 1) to define drought intensities resulting from the SPI. They also defined the criteria for a drought event for any of the timescales. A drought event occurs any time the SPI is continuously negative and reaches an intensity of -1.0 or less. The event ends when the SPI becomes positive. Each drought event, therefore, has a duration defined by its beginning and end, and an intensity for each month that the event continues. The positive sum of the SPI for all the months within a drought event can be termed the drought’s “magnitude” [15][16].

VALUES	CONDITIONS
+2.0	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
-2 and less	Extremely dry

Table 1: SPI values

Materials and methods

Data has been acquired mainly from two sources, firstly NDVI was derived from satellite sources and secondly rainfall data obtained from ground stations.

Satellite data: MODIS/Terra MOD13Q1.006 Vegetation Indices 16_day Global_250m sinusoidal data has been downloaded from USGS earth explorer https://earthexplorer.usgs.gov/ [17] in HDF format. Global MOD13Q1 provides temporal resolution of 16 days with 250m spatial resolution as a gridded level-3 processing level in the sinusoidal projection. MOD13Q1 consists of 12 parameters and they are NDVI, EVI, VI quality, red reflectance, NIR reflectance, blue reflectance, MIR reflectance, view zenith angle, sun zenith angle, relative azimuth angle, composite day of the year and pixel reliability.

Global MODIS vegetation indices are designed to provide consistent spatial and temporal comparisons of vegetation conditions. Blue, red, and near-infrared reflectances, centered at 469-nanometers, 645-nanometers, and 858-nanometers, respectively, are used to determine the MODIS daily vegetation indices.

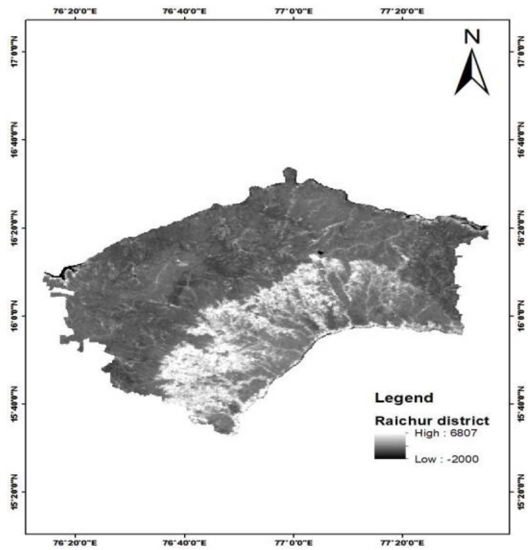


Fig 2. MODIS raw data for Raichur district.

Meteorological data: Annual rainfall gridded data published by IMD a resolution of (0.25*0.25 degree) for the period of 2000- 2019 were used. The unit of rainfall is in millimeter (mm). Data is arranged in 135x129 grid points. Fig 3 shows the location of weather stations in raichur district.

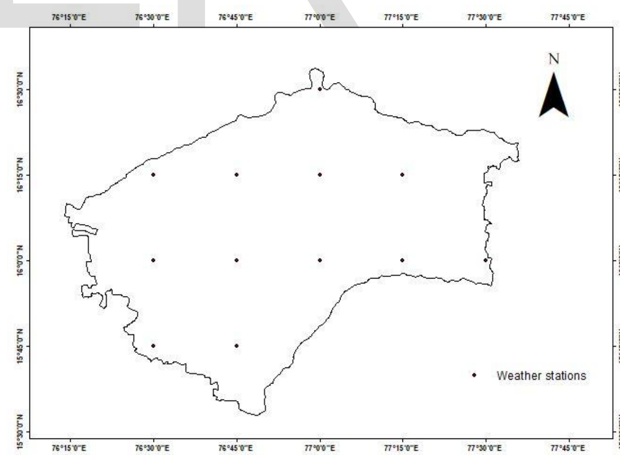


Fig 3. Location of weather stations in Raichur district.

Software used

1. Arc GIS 10.6.
2. MRT tool.
3. IMD data extraction program.
4. Microsoft Excel for arrangement of data and

preparing of graphs.

Calculation of NDVI Anomaly: Normalized Difference Vegetation Index (NDVI) is an important vegetation index as the seasonal and inter-annual changes in vegetation growth and activity can be monitored (Jensen, 2016). [10]

Firstly, MODIS/ terra acquired data was imported into MRT tool were projection, pixel size, lat-long were given to extract NDVI directly for each year for the period of 2000-2019 into TIFF format from HDF file.

Secondly, these data were imported into Arc GIS and all images for the period of 2000-2019 were rescaled by multiplying with the scale factor of 0.0001 using raster calculator. After that raichur district has been extracted from the given tile using Extract by mask tool. Average NDVI was calculated in raster calculator for every year. These average NDVI data was then joint with the 2005 classified image of raichur provided by ORNL DAAC for each year using Zonal statistics as a table tool and only mean NDVI was calculated for each classes.

Lastly, all NDVI mean values were then imported in Microsoft Excel for arranging datasets. For each class again average was taken for the period of 2000-2019 and the closest value was considered as the normal value. Deviation of each year NDVI value was then calculated with this normal mean value as NDVI anomaly and finally graph was plotted between NDVI anomaly and respective years for a particular class.

SPI calculation: Annual rainfall data from 2000-2019 was used as input to calculate SPI.

Rainfall gridded data was extracted from IMD Converter tool for whole India. Raichur district was then extracted as shapefile using clip tool in Arc GIS. Attribute table was then exported into CSV format for every year. Average rainfall was calculated in mm for every station for monthly wise .Then, SPI was calculate by the formula ;

$$SPI = (Xi - Mean\ (all\ year))/\ St.dev(all\ year)$$

Where,

Xi = rainfall value in mm for the given month.

Mean (all year) = mean rainfall for the period of 2000-2019.

St.dev (all year) = Standard deviation for the period of 2000-2019.

Results and discussion

NDVI anomaly for raichur district was calculated from mean NDVI datasets on yearly basis for 2005 classified image with eight classes. Average of NDVI mean was calculated for particular class and the closest value to this average was considered as the normal and deviation from this normal value was calculated as NDVI anomaly. The anomaly graphs for the following classes can be seen in fig.4 and the maximum and minimum NDVI anomaly values for different classes like Cropland, built-up, mixed forest, shrub land, barren land , fallow land, waste land and water bodies has been shown in table 2.

Figure 4.A illustrates NDVI anomaly for Cropland throughout the year in raichur district, In 2009 NDVI anomaly was zero while there were sharp negative anomaly between 2016 to 2019 with the year 2018 having the most negative anomaly with value -0.0189 which means that the cropland was less healthier than the normal in this year and the strongest greenness in the year 2010 with the maximum value +0.0472 tells that cropland was more healthier than the normal in this year.

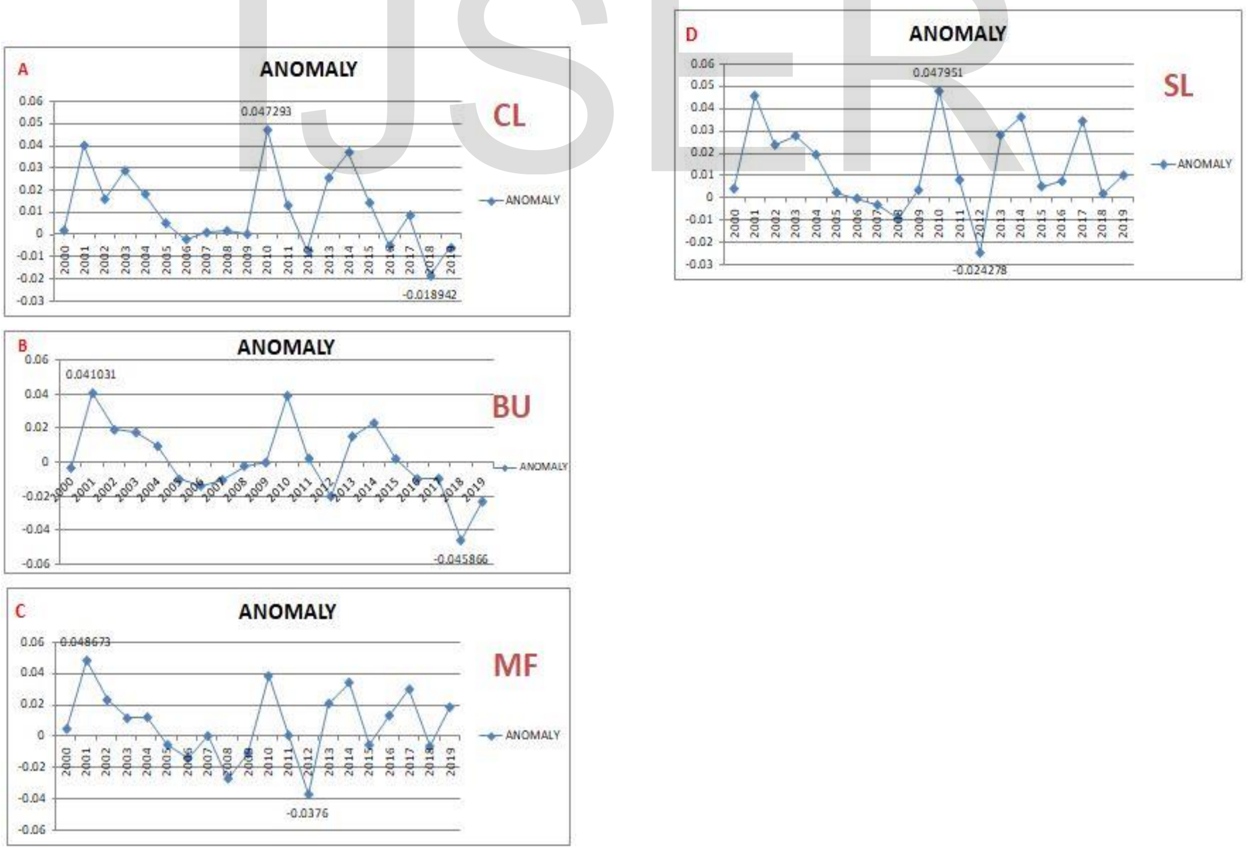
Figure 4.C illustrates NDVI anomaly for Mixed-forest throughout the year in raichur district, in 2007 anomaly for this class is showing zero while there is a sharp negative anomaly for the year 2012 with value -0.0376 depicts that health has been decline rapidly while 2001 shows strong positive anomaly with value +0.0486 which depicts that the health of the forest was good at this time.

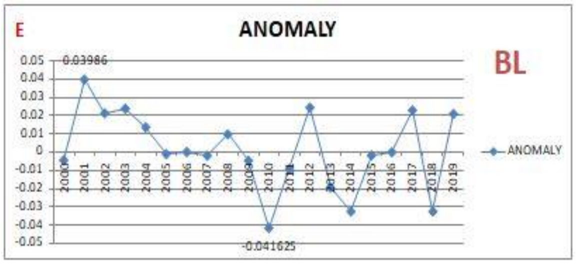
Figure 4.D illustrates NDVI anomaly for shrub land over the period of 2000-2019 for raichur district, shrub land shows zero anomaly for the year 2006 while 2012 shows the greatest negative anomaly with value -0.0242 which

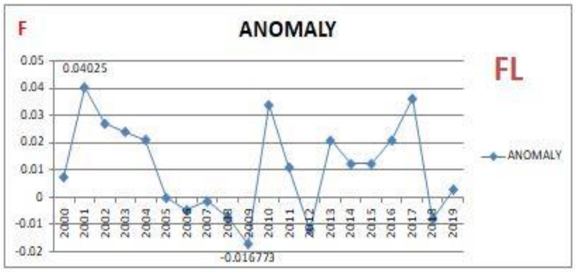
depicts the unhealthy condition of shrubs while the year 2010 shows the most positive NDVI anomaly with value 0.0479 over entire period and depicts that shrub land was healthier than any other year.

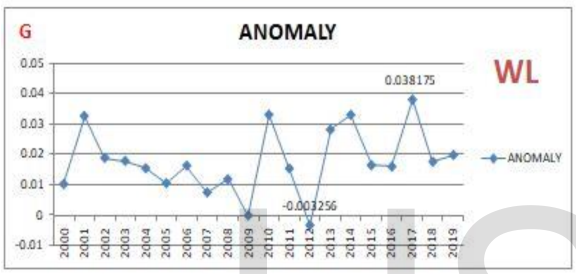
	CLASSES							
ANOMALY	**CL**	**BU**	**MF**	**SL**	**BL**	**FL**	**WL**	**WB**
MAXIMUM	0.047293	0.041031	0.048673	0.047951	0.03986	0.04025	0.038175	0.028199
MINIMUM	-0.018942	-0.045866	-0.0376	-0.024278	-0.041625	-0.016773	-0.003256	-0.020042

Table 2. NDVI anomaly Maximum and Minimum values for different classes of Raichur district.









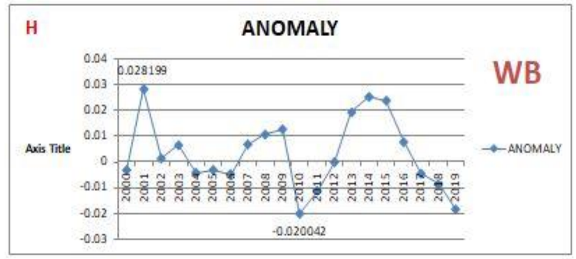


Fig 4. NDVI Anomaly for different classes.

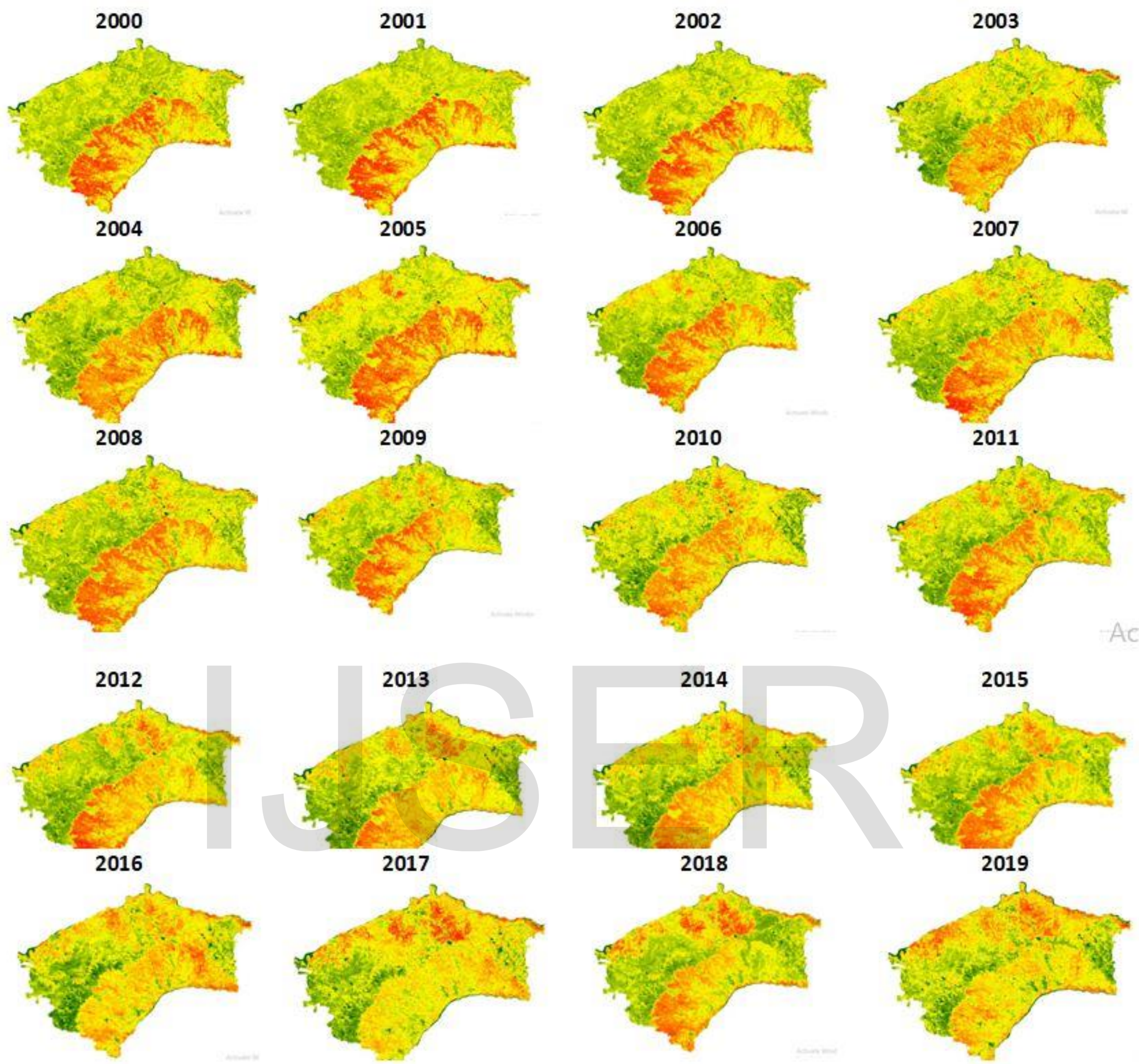


Fig 5. NDVI image for Raichur district over the period of 2000-2019.

SPI is also calculated in excel for the year range from 2000 to 2019 on monthly basis for Raichur district.

In the year 2009 , the value of SPI is the highest among any of the year which is 3.675 that indicates extremely wet condition while the lowest value of SPI in raichur district over past 20 years is -0.781 which comes in the category of near normal condition.

Maximum and minimum SPI values for different years can be seen in table 3.

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YEAR	**MAX SPI**	**MIN SPI**
2000	2.069	-0.781
2001	3.455	-0.781
2002	1.062	-0.781
2003	0.730	-0.781
2004	1.487	-0.781
2005	1.859	-0.781
2006	0.582	-0.781
2007	3.571	-0.781
2008	1.153	-0.781
2009	3.675	-0.781
2010	2.673	-0.781
2011	0.913	-0.781
2012	1.157	-0.781
2013	3.331	-0.781
2014	3.202	-0.781
2015	3.171	-0.781
2016	2.264	-0.781
2017	2.794	-0.781
2018	0.646	-0.781
2019	2.783	-0.781

Table 3. Maximum and minimum SPI values for raichur district from 2000 to 2019.

After computing NDVI and SPI, variation graphs were prepared to see the relationships between these two indices and how this responses to each other over the period of 2000-2019. Relationships between NDVI anomaly and SPI was analysed for Cropland and Mixed-forest because changes in the values of NDVI with respect to SPI can only be analysed.

Figure 6.A illustrates variation graph between NDVI anomaly and SPI for cropland, this graph depicts the moderate linear relationships between them, for year 2003 to 2005 variation is not linear which could be due to the precipitation time lag. Although the value of SPI decreases rapidly between 2003-2005 but NDVI anomaly doesn’t respond to it positively this could be due to the previous water storage and ground water availability was enough to compensate SPI effect.

Figure 6.C illustrates variation graph between NDVI anomaly and SPI for Mixed-forest, it depicts moderate linear relationship between them, here in year 2005 it can be clearly seen that SPI value has been increased compared to 2004 but NDVI anomaly shows a sharp decline in value which could be due to precipitation time lag because in previous years SPI value was continuously low for 3 years from 2002-2004.

Figure 6.D illustrates variation graph between NDVI anomaly and SPI for Shrub-land, it depicts moderate linear relationship between them but more uncertainty in variation than the cropland and Mixed-forest, from 2003-2007 NDVI anomaly response was not linearly with respect to SPI.

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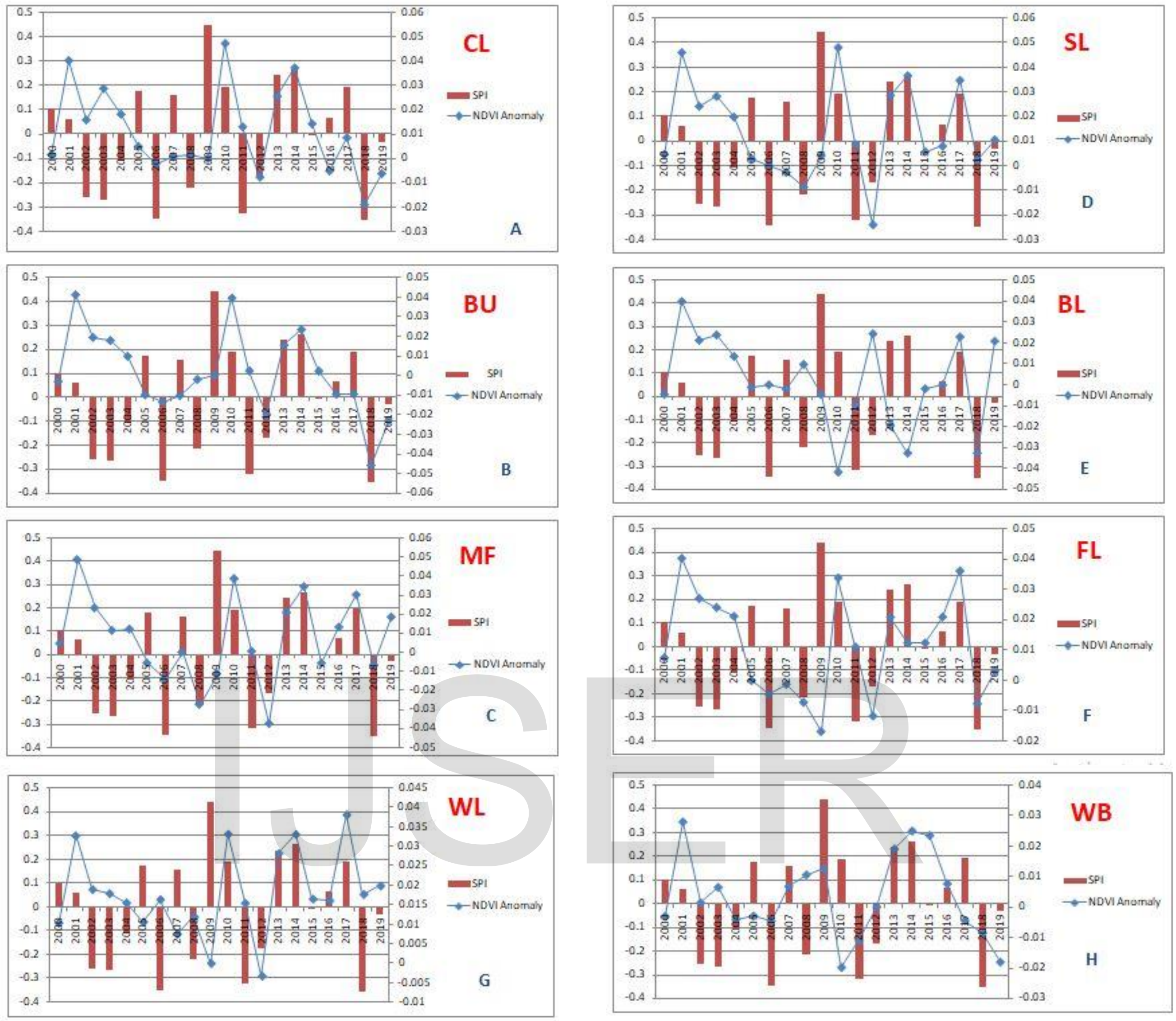

Figure 6. Variation graph between NDVI anomaly and SPI.

Conclusion

In this study impacts of rainfall on vegetation using meteorological based SPI a climatic parameter and vegetation index NDVI were examined for Raichur district, Karnataka over 2 decades.

After assessing NDVI anomaly using MODIS/terra 16_day Global_250m Sinusoidal projection data and then examined the NDVI anomaly responses with precipitation data over the period of 2000-2019. The results indicate that the precipitation data SPI and remotely-sensed based NDVI exhibited anomalous responses in the beginning of the years. In the beginning of the years between 2002-2007 NDVI anomaly for shrub-land, Mixed-forest and cropland does not responded positively with SPI values which could be the reason due to precipitation time lag. For cropland 2003-2005 NDVI anomaly response to SPI was not effectively positive, for Mixed-forest 2002-2004

NDVI anomaly to SPI exhibited anomalous response and for Shrub-land 2002-2007 NDVI anomaly response to SPI was not positive. However in middle and final stage of the year NDVI anomaly for all these vegetation types responded positively with SPI values and shows strong linear relationship between them. The observational evidences revealed that the responses of NDVI to the SPI varied significantly in the different stages, which should receive more attention in future studies.

Results depicts the initial years 2002-2007 NDVI anomaly exhibited anomalous responses to SPI for cropland, mixed-forest and shrub-land, however in middle and final stages after 2008 NDVI anomaly and SPI has a strong linear relationship between them for these vegetation classes. This finding may be attributed to the coupling effects of precipitation and vegetation conditions.

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