KEYNOTE SPEAKER – SESSION 5

Assessment of Meteorological Drought in Bundelkhand Region of MP (India) Using Standardized Precipitation Index (SPI) and Remote Sensing Derived Vegetation Condition Index (VCI)

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ABSTRACT

Drought is a natural, unpredictable, temporary, and regional climatic phenomenon that occurs when there is a lack of precipitation, resulting in a water shortage. Many drought indices are being used worldwide to assess drought duration, magnitude and severity which are helpful in the formulation of drought mitigation strategies. The satellite-based data, information and indices have been found very efficient and useful for quick assessment of drought situations and can be proved more effective if tested using suitable similar physically observed climatic data-based indicators. In this study, the MODIS NDVI data has been used for vegetation health and drought monitoring through NDVI based Vegetation Condition Index (VCI) and results were compared with the Standardized Precipitation Index (SPI) in the Bundelkhand region in Central India covering five districts of Madhya Pradesh namely, Sagar, Damoh, Tikamgarh, Chhatarpur and Panna. The VCI is a pixel-wise normalisation of the NDVI whose values can be averaged spatially and temporally to make comparisons with meteorological drought indicators.

The Bundelkhand region of India has been experiencing recurrent droughts and causing adverse impacts on water resources, agriculture, rural livelihood and economy. The monthly rainfall data of five stations for 38 years from 1980-2017 was used to analyse the extent of meteorological drought and identifying the driest years using rainfall departure analysis and 3 Month time scale SPI. The VCI was analysed for the NDVI data from 2000 to 2020. From the Annual rainfall Departure and SPI analysis, the years 2007, 2015 and 2017 were observed as the severe drought years with the larger spatial extent in the study area. The spatial variabilities of droughts in 2007, 2015 and 2017 were also assessed based on the satellite-based indices. The VCI shows that about 49, 87 and 40% area of the Bundelkhand region was under drought in October while 18, 7 and 10% area was under drought in August in the years 2007, 2015 and 2017 respectively. The drought severity was observed very high during October 2015 however in the years 2007 and 2017, the whole monsoon seasons have experienced drought. Both SPI and VCI indicated very high drought severity during October 2015. The satellite-based indicator VCI has been found interpreting results in agreement with the SPI results.

INTRODUCTION

Droughts are one of the most dangerous environmental disasters, causing adverse impacts on the natural ecosystem, hydrological and agricultural systems (Bond et al., 2008). Drought arises due to lack of precipitation and availability of variation in rainfall patterns. Generally, it occurs in almost all climatic regions. Droughts seem like a situation of below-normal rainfall and evolve into a dangerous climatic event with significant consequences for the environment. Drought has affected about half of the world's population (Kogan et al., 2019). It is one of the serious phenomena and always ranks on top among all the natural hazards concerning the number of people gets affected globally (Dunn et al., 2018). Drought risks build up gradually, which often accumulate over a long period, and might last for years after the drought is over (Mishra and Singh, 2010). The drought severity, their onset as well as withdrawal, are not only difficult to identify but quantify also. According to a recent Intergovernmental Panel on Climate Change (IPCC) report, maize, wheat, and rice output has decreased in various regions of Asia during the last several decades owing to rising temperatures, water stress, a decrease in the number of rainy days, and the frequency of El Nino occurrences (Change, 2014). In the last five decades, India has been one of the most vulnerable and drought-prone countries, with drought occurring at least once every three years (Miyan, 2015).

Drought is a common natural hazard in India and was seen prominently in the years 1877, 1899, 1918, 1972, 1987 and 2002 (Yadav, 2009). The total geographical area of India is 3.38 million km^2, out of that about 1.08 million km^2 of land is subjected to various degrees of drought and water stress (Jain et al., 2009). Drought areas are mainly confined to the peninsular western and central parts of the country. The recurrent droughts in the Bundelkhand region of Madhya Pradesh state in Central India are causing adverse impacts on water resources, agriculture, rural livelihood and economy (Pandey et al. 2010 and Kundu et al. 2015). Due to uncertainty in the monsoon season, high temperatures and unfavourable meteorological conditions, the incidence of drought are frequent in these regions. The National Commission on Agriculture in India classify droughts into three types i.e. meteorological, hydrological and agricultural (Mirdha, 1973). A meteorological drought is an event that occurs when an area receives precipitation less than 25% of its normal. Hydrological drought is the outcome of long-term meteorological droughts resulting in the drying up of rivers, streams, lakes, reservoirs, and a decrease in groundwater level. Agricultural drought occurs when soil moisture is insufficient due to continuous meteorological drought to support healthy crop growth during the growing season, resulting in crop stress and wilting.

Drought must be assessed and monitored using scientific techniques to reduce future risk and potential dangers. Traditional drought monitoring relies on ground-based observations of meteorological and hydrological data including precipitation, temperature, evapotranspiration, soil moisture, surface runoff, and groundwater levels. Several drought indicators have been developed in recent years based on this single location data such as the Standardized Precipitation Index (SPI) (Guttman, 1999), Crop Moisture Index (Palmer, 1968), Palmer Drought Severity Index (Palmer, 1965), Soil Moisture Drought Index and Streamflow Drought Severity Index, Groundwater Drought Index and many more. Many studies have successfully applied the SPI, which is related to the probability of occurrence of wet and dry events, by many researchers efficiently for monitoring the spatial extension and intensity of droughts, at different time scales of 3, 6, 12, and 24 months (Khan et al., 2008; Belayneh and Adamowski, 2012; Thomas et al., 2015). It takes longer for deficiency precipitation to affect the streamflow, soil moisture, reservoir and groundwater levels. SPI on 1 and 3-month time scales are associated with soil moisture and precipitation deficit however the hydrological drought is associated with the SPI-6 which indicates precipitation deficit for more than 6 months (Van Loon, 2015). Although meteorological data from ground-based stations have a high level of accuracy and is widely utilised across the world, the density and distribution of meteorological stations are insufficient for spatial data extraction. Without an optimal network of meteorological stations throughout the study region, the geographical extent of drought cannot be accurately assessed (Vicente-Serrano and López-Moreno, 2005). Even yet, the time and cost of data preparation, as well as the risk of errors, may cause a delay in drought mitigation operations. In this context, drought monitoring using satellite-based data has gained widespread acceptance in recent decades because of its low cost, ease of data acquisition, synoptic perspective and reliability.

Remote sensing is a state of the art and useful technique for monitoring drought. Many drought indices are developed based on remote sensing data such as the normalized difference vegetation index (NDVI) (Tucker, 1979), Land Surface Temperature (LST), Temperature Vegetation Drought Index (TVDI), Vegetation Condition Index (VCI) (Kogan, 1990) and many others. VCI is more significant in drought monitoring when compared to NDVI and TVDI. VCI distinguishes between climatic and long-term biological signals, making it more diagnostic of moisture deficit. As a result, when compared to other remote sensing-based indices, VCI can provide more exact findings for monitoring and quantifying droughts in non-homogeneous areas. Therefore, VCI is widely utilised in drought monitoring and analysis, with several studies confirming its accuracy (Unganai and Kogan, 1998; Jain et al., 2009; Du et al., 2013; Liu et al., 2020). Thus, the present study focuses on evaluating drought indicators based on the integration of meteorological and satellite-based indices in the Bundelkhand region of Madhya Pradesh, which experiences very frequent droughts of higher intensities in India. Rainfall based departure analyses were used to identify the dry periods using long term rainfall data of five stations. The monthly rainfall based index, 3 Month SPI is estimated for the monsoon season of the identified severe drought years. Furthermore, satellite-based data index VCI is calculated over the area using long-term MODIS based NDVI for the monsoon season of the same classified drought years.

STUDY AREA

Madhya Pradesh is a centrally located state in India. The present study has been carried out in the Bundelkhand region located in the northern part of Madhya Pradesh state comprising 5 districts Sagar, Damoh, Chhatarpur, Tikamgarh and Panna as shown in Figure 1. The Bundelkhand region is located between 23.14 and 25.55 latitude and 78.05 and 80.67 longitude covering an area of 37 479 km^2. The Bundelkhand region of Madhya Pradesh state faces the problems of recurrent droughts that are unpredictable both in their occurrence and duration; hence predictions and preparedness against droughts would be key elements for minimizing their impacts (Galkate et al., 2015). The Bundelkhand region has long been regarded as a drought-prone region of the country, but drought frequency and severity have increased in recent decades. (Gupta et al., 2014). The region receives an annual rainfall of more than 1 100 mm. Around 80% of the population are directly dependent on agriculture which is mostly rainfed and susceptible to drought. The major rivers flowing through the study area includes Betwa, Sindh, Tons and Chambal and all are tributaries to the Ganga river. The topography of the region is undulating, with boulder-strewn plains and rocky outcrops and in a rocky landscape. Wheat and Soybeans are the major crops grown in the rabi and Kharif season, respectively. The major soils in this region include alluvial, black soils and mixed red soil.

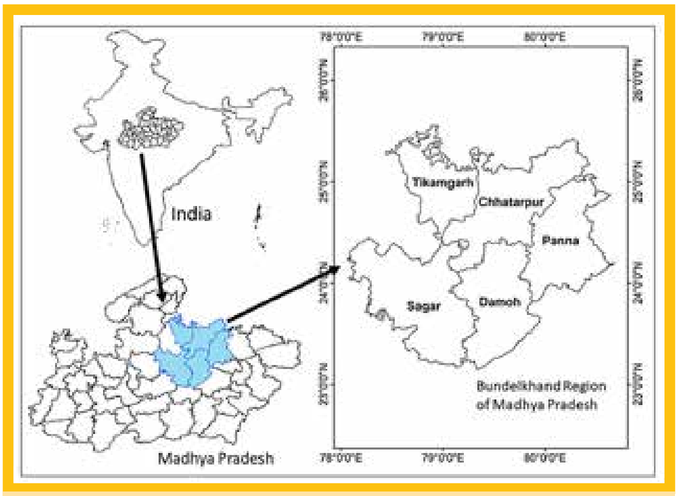

FIGURE 1: Location of Study Area (Bundelkhand region of Madhya Pradesh)

MATERIALS AND METHODOLOGY

Statistical analysis

The rainfall statistics of five rain gauge stations Sagar, Damoh, Panna, Tikamgarh and Chhatarpur of Bundelkhand region has been worked out using 38 years of rainfall data from the year 1980 to 2017. The rainfall data has been collected from India Meteorological Department and State Data Centre, Madhya Pradesh Water Resources Department, Bhopal. The statistical analysis of annual, monsoon, non-monsoon and monthly rainfall have been carried out to estimate average rainfall, standard deviation and coefficient of variation of five stations and Bundelkhand region to understand rainfall pattern and its variability.

Rainfall Departure Analysis

The annual rainfall departure analysis was performed for the determination of drought years, frequency Return period and severity in the study area. As suggested by India Meteorological Department, a year can be considered as a drought year when the annual rainfall deficit is more than 25% of its long term normal rainfall (Appa Rao, 1986). Further, the meteorological drought can be classified according to its severity level. It is considered as a Moderate drought when the annual rainfall deficit is between 25% to 50%, Severe drought when the annual rainfall deficit is between 50% to

75% and Extreme drought when the annual rainfall deficit is more than 75%. The percentage departure of the annual rainfall time series has been calculated using equation 1.

$$\text{Percentage of Departure} = \frac{Annual\ Rainfall - Average\ Annual\ Rainfall}{Average\ Annual\ Rainfall} \times 100 \qquad \textit{Equation 1}$$

Standardized Precipitation Index (SPI)

The Standardized Precipitation Index (SPI) assigns a numeric value to the precipitation based on the deficit severity and it can be associated across regions with a different environment. In brief, SPI is the number that represents the standard deviation of precipitation data from its long-term average for a normally distributed series. As the precipitation data is not normally distributed, a transformation technique is used in the first stage of SPI to convert the data series to a normal distribution. The SPI determines the probability of occurrence of wet and dry events at different time scales i.e. 1 month to 24 months which are associated with different droughts such as soil moisture drought, agricultural drought, meteorological drought and hydrological drought. The 3 Month SPI values are indicative of soil moisture condition as well as meteorological drought, hence in this study, analysis has been carried out to assess drought severity in the study area using 3-month SPI values and its comparison with satellite-derived index. For this analysis monthly rainfall time series of 38 years from the year, 1980 to 2017 was used for five stations of the Bundelkhand region.

Drought characteristics based on their severity can be assessed using an analytic method to determine the cumulative probability (McKee et al., 1993). The cumulative probability, H(x), is then converted into the standard normal random variable 'Z,' which has a mean of zero and a variance of one and is the SPI value. The Z or SPI values are more easily estimated using an approximation that converts cumulative probability to the standard normal random variable Z (Abramowitz and Stegun, 1965). The SPI computation for each place is based on the long-term precipitation data of the selected period. This long-term data fitted to a probability distribution, which is then converted into a normal distribution, resulting in a mean SPI of zero for the chosen place and duration (Edwards, 1997). The SPI values and their classification indicating severity range are shown in Table-1.

TABLE 1: SPI classification and their values

2.0 +	Extremely Wet
1.5 to 1.99	Very Wet
1.0 to 1.49	Moderately Wet
-.99 to .99	Near Normal
-1.0 to -1.49	Moderately Dry
-1.5 to -1.99	Severely Dry
-2 and less	Extremely Dry

In the derived SPI series, when continuous negative values of SPI reach an intensity of -1.0 or less and then SPI remains constantly negative, a drought event has begun, which will terminate when the SPI becomes positive. As a result, each drought event has a duration that is determined by its start and end dates, as well as its intensity and severity.

Satellite Data

Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data provides a new generation of land resources products to support natural resource management and global change research (Didan, Kamel, 2015). Drought monitoring is one of the many environmental concerns for which these products are used. (Gu et al., 2008; Bajgain et al., 2015, 2017). In this study, the MODIS data were accessed using Google Earth Engine (GEE), which is a cloud-based remote sensing platform. The 16-Day composite (MOD13Q1) MODIS Terra Vegetation Indices product was used to estimate NDVI based VCI. The datasets are available for global coverage at a 250 m spatial resolution from the year 2000 onwards.

Vegetation Condition Index (VCI)

Normalized Difference Vegetation Index (NDVI) is a widely used remote sensing index that gives quantification of quantitative estimation of vegetation growth based on surface reflectance. NDVI is calculated as the ratio between the reflectance of a red band (0.6-0.7 µm) and a near-infrared (NIR) band (>0.7 µm). The NDVI values range from -1 to 1, the responses of healthy vegetation in this range are towards one while water and the built-up area will be represented as negative and near-zero values. The NDVI can be estimated using equation 2.

$$NDVI = \frac{NIR - Red}{NIR + Red} \qquad \textit{Equation 2}$$

To normalised current NDVI w.r.t maximum and minimum NDVI over a single pixel, Kogan proposed Vegetation Condition Index (VCI). VCI compares the current vegetation index to the values observed in a similar period over a specific pixel. VCI can be estimated with equation 3

$$VCI_{ijk} = \frac{NDVI_{ijk} - NDVI_{ij\,min}}{NDVI_{ij\,max} + NDVI_{ij\,min}} \qquad \textit{Equation 3}$$

Whereas VCIijk is the VCI value for the pixel i during the month j for year k, NDVIijk is the VCI value for the pixel i during the month j for year k, NDVIijk min is the multiyear minimum NDVI for i pixel during the month i and NDVIijk max is the multiyear maximum NDVI for i pixel during the month j. The VCI values less than 0.4 indicates mild to extreme drought conditions while VCI above 0.4 shows normal conditions as shown in Table 2. When compared to NDVI, this VCI normalises NDVI responses and removes the long-term ecological indication from the short-term climatic signal, proving to be a better index for monitoring water stress conditions.

TABLE 2: VCI Classification

VCI Values	Category
0.0 - 0.1	Extreme Drought
0.1 - 0.2	Severe Drought
0.2 - 0.3	Moderate Drought
0.3 - 0.4	Mild Drought
0.4 - 1.0	No Drought

RESULTS AND DISCUSSION

The long term rainfall data of 38 years from 1980 to 2017 were analyzed to assess the average rainfall pattern and variability for five stations Sagar, Damoh, Panna, Tikamgarh and Chhatarpur of the Bundelkhand region of Madhya Pradesh. Rainfall statistics of these stations is summarized in Table 3. The Distribution of monthly rainfall of all five stations is shown in Figure 2.

From Table 3, the average annual rainfall in the Bundelkhand region was observed varying between 1 202 (Sagar) to 960 (Chhatarpur) with an average of 1 105 mm. The average annual monsoon and non-monsoon rainfall in the region were observed as 1 008 mm and 97 mm respectively. The region receives a major portion of rainfall during the monsoon season as shown in Figure 2. The rainfall pattern in Bundelkhand has a very high temporal variation, the average standard deviation annual, monsoon and non-monsoon rainfall has been estimated as 336, 320 and 97 mm. The high values of coefficient of variation for annual and monsoon rainfall 0.31 and 0.32 indicate high rainfall variation and non-monsoon rainfall seems to be

TABLE 3: Rainfall statistics of five stations of Bundelkhand region (data used 1980-2017)

No	Station Name	Annual			Monsoon			Non-Monsoon		
		Avg.(mm)	Std Dev	CV	Avg. (mm)	Std Dev	CV	Avg. (mm)	Std Dev	CV
1	Sagar	1 202	390	0.32	1 092	365	0.33	110	76	0.69
2	Damoh	1 207	333	0.28	1 114	325	0.29	92	75	0.81
3	Panna	1 174	331	0.28	1 074	333	0.31	100	72	0.72
4	Tikamgarh	960	309	0.32	876	295	0.34	84	84	1.00
5	Chhatarpur	984	318	0.32	884	282	0.32	100	140	1.40
	Average	**1 105**	**336**	**0.31**	**1 008**	**320**	**0.32**	**97**	**89**	**0.92**

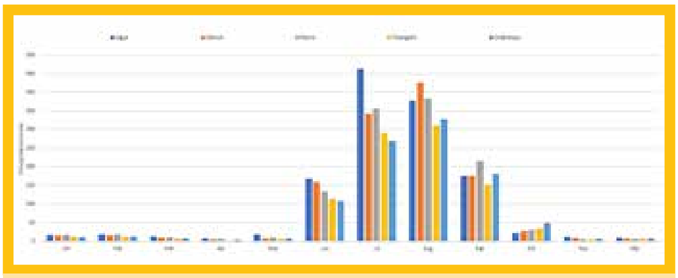

FIGURE 2: Distribution of Monthly Rainfall of all stations

very erratic with a very high coefficient of variation value of 0.92. Very high temporal variation has been seen in the non-monsoon rainfall time series at Chhatarpur and Tikamgarh stations. High variation in rainfall is one of the causes of frequent and severe droughts in the Bundelkhand region.

Rainfall Departure Analysis

Departure analyses were performed using 38 years of annual rainfall data from the year 1981 to 2017. Drought years were identified based on annual rainfall deficit and drought years were classified based on their severity. Drought years of rainfall deficit between 25 to 50% were grouped as moderate drought years and deficit more than 50% were considered as severe drought years as shown in Table 4.

TABLE 4: Rainfall Departure Analysis using annual rainfall time series (data used 1980-2017)

Sr No	Station Name	Frequency (%)	Return Period	Drought Years (Deficit less than 25 to 50%)	Severe Drought Years (Deficit greater than 50%)
1	Sagar	28.94	1 in 3-4 years	1986, 1988, 1989, 2002, **2007**, 2010, 2012, **2015**, **2017**	1981, 2004
2	Damoh	21.05	1 in 4-5 years	1989, 1998, 2002, 2006, **2007**, 2014, **2015**, **2017**	--
3	Panna	18.42	1 in 5-6 years	1981, 1985, 2000, 2006, 2010, **2015**	**2007**
4	Tikamgarh	23.68	1 in 4-5 years	1986, 1991, 2000, 2006, **2007**, 2010, **2015**, **2017**	1989
5	Chhatarpur	23.68	1 in 4-5 years	1995, 1998, 2000, 2006, **2007**, 2012, 2014, **2015**	**2017**

From Table 4, it has been observed that the drought frequency is very high at all five stations however drought frequency was observed highest at Sagar (29.34%), Tikamgarh (23.68%) and Chhatarpur (23.68%). Thus the drought return period is very low at these three stations. Most of the stations in Bundelkhand experience a very low drought return period i.e. one drought after every 4 to 5 years. Sagar station has a chance of occurring drought year after every 3 to 4 years. From the analysis, it can predominantly be seen that the years 2007, 2015 and 2017 were the most common and severe drought years at almost all stations in the Bundelkhand region. Thus the dry event probability was typically examined for these widespread and severe drought years 2007, 2015 and 2017 for comparison of SPI and VCI.

Standardized Precipitation Index (SPI)

As 3 month time step SPI i.e. SPI-3 is indicative of meteorological drought situation, it has been used as a seasonal drought index to characterize the short-term drought and its impact on vegetation. The probability of occurrence of dry events of SPI-3 indicates the severity of drought as shown in Table 5.

TABLE 5: Probability of occurrence of 3 Month SPI in Bundelkhand

Sr No	Severity	Probability of occurrence of 3 Month SPI (%)				
		Chhatarpur	Damoh	Panna	Sagar	Tikamgarh
1	Extremely Wet	1.77	2.65	3.03	4.00	2.56
2	Severely Wet	5.96	4.87	4.55	3.06	5.12
3	Moderately Wet	9.05	11.50	8.44	8.71	7.68
4	Near Normal	74.61	71.46	70.35	70.12	78.25
5	Moderate Dry	5.74	7.52	10.17	8.94	2.77
6	Severely Dry	1.99	1.33	2.60	4.00	2.13
7	Extremely Dry	0.88	0.66	0.87	1.18	1.49

The analysis of Table 5 shows the probability of occurrence of dry events of SPI-3 at all five stations of the Bundelkhand region. It is broadly seen that the probability of occurrence of moderate dry situation is very high at Panna, Sagar and Damoh with the probability of occurrence 10.17, 8.94 and 7.52% respectively. The probability of occurrence of severe drought events has been observed high at Sagar, Panna and Tikamgarh. The probability of extremely dry events was also seen high at Tikamgarh and Sagar with the probability of occurrence 1.49 and 1.18% respectively. From the overall analysis, it can be seen that the probability of occurrence of severely and extremely dry events is very high at Sagar and Tikamgarh stations. Though the Sagar station receives a good amount of rainfall as compared to other stations, the probability of severely and extremely dry events has been observed very high at this station. Tikamgarh station has also shown a high probability of severe and extreme events. In the Bundelkhand region, the rainfall season comprises four to five rainy months i.e. June, July, August, September and October, and rainfall deficit during these months will have cumulative impacts during later monsoon months i.e. August, September and October. Thus for the 3-month SPI, analysis was especially focused on the drought severity during the August, September and October months. From the rainfall departure analysis, years 2007, 2015 and 2017 were identified as severe dry years for which further analysis of SPI and VCI has been performed. The SPI-3 severity values of the monsoon months for severe and widespread drought years 2007, 2015 and 2017 in the Bundelkhand region are given in Table 6.

TABLE 6: SPI-3 values for monsoon months of drought years 2007, 2015 and 2017

Months	Sagar	Damoh	Panna	Tikamgarh	Chhatarpur
Aug-07	-1.26	-0.79	-2.05	**-2.18**	-2.01
Sep-07	-2.22	-0.87	-2.04	**-2.28**	-1.77
Oct-07	-1.31	-0.65	-1.61	-1.44	**-1.15**
Aug-15	-0.64	-0.78	-1.29	**-0.73**	-0.58
Sep-15	-0.89	-1.34	-1.69	**-1.12**	**-1.46**
Oct-15		-1.12	-1.45	**-0.79**	**-1.79**
Aug-17	-0.80	-1.41	0.15	**-0.69**	**-1.45**
Sep-17	-0.57	-1.47	-0.05	**-1.43**	**-1.64**
Oct-17	-0.78	-2.09	-0.93	**-1.87**	**-1.80**

To monitor drought from a long-term space-based observation, the VCI index derived from NDVI is used in the study, The spatial extent and temporal change of VCI in the study area in August, September and October for the years 2007, 2015 and 2017 are shown in Figure 3. First of all the VCI is classified into five classes from extreme drought to no drought and then the percentage of the area falling in each class in the Bundelkhand region is calculated and is given in Table 7.

From the analysis of Figure 3 and Table 7, the extent and onset of drought events can be detected from the VCI maps of successive fortnights of the three driest years 2007, 2015 and 2017. Severe vegetation stress is evident all over the area during the last fortnight of October 2015. The situation was seen normal in August 2015 in Bundelkhand, where the majority of the area was under no-drought condition. The drought situation started worsening after the first fortnight of August 2015. By the end of October 2015 around 27.5, 24.7 and 13.5% area of the region were found under extreme, severe and moderate stress conditions respectively. A similar progression of drought situation from August to October has been seen in the years 2007 and 2017 in the whole region. Some exception was seen in the middle of September 2007, when more area was under drought as compared to October 2007 especially in the southern part of the Bundelkhand region. From the overlaying of VCI maps, it is observed that the Sagar and Tikamgarh district of the study area is prone to water stress and severe drought. In a comparison of the dry periods identified using SPI and water stress conditions identified using VCI, it is observed that both indices are showing droughts almost at the same period and with the same severity. VCI analysis of all the three severe drought years indicated the increase of spatial extent of drought from August to September especially in the Sagar and Tikamgarh districts which are quite relatable and in agreement with the results derived from the SPI-3. The present study justifies the advantage of satellite-based data for identifying the spatial and temporal extent of vegetation stress and prevailing drought situation in the larger area with ease.

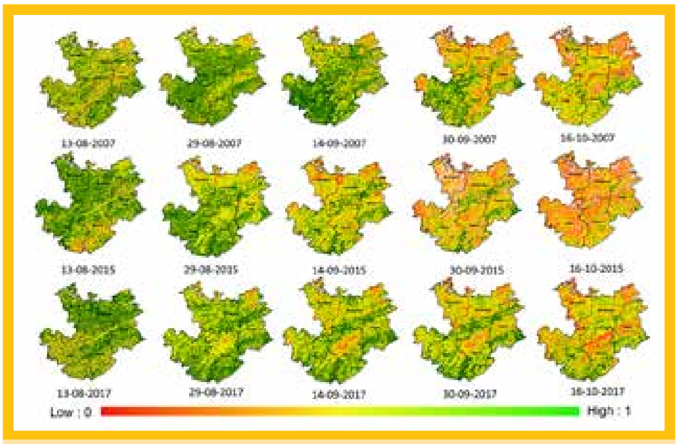

FIGURE 3: Fortnightly spatio-temporal variation of Vegetation Condition Index (VCI) for the years 2007, 2015 and 2017 (low VCI value indicates drought severity)

TABLE 7: Area in percentage under different VCI classes in Bundelkhand

Dates	Extreme Drought	Severe Drought	Moderate Drought	Mild Drought	No Drought
8/13/2007	3.63	3.41	4.92	6.72	81.32
8/29/2007	0.20	0.36	0.72	1.46	97.26
9/14/2007	0.72	0.51	1.39	2.84	94.55
9/30/2007	7.01	9.13	11.52	11.98	60.37
10/16/2007	10.16	10.12	13.44	15.34	50.95
8/13/2015	0.91	1.32	2.14	3.20	92.43
8/29/2015	0.03	0.12	0.41	1.29	98.14
9/14/2015	0.59	2.95	6.98	11.39	78.09
9/30/2015	18.66	11.92	13.85	14.63	40.95
10/16/2015	27.52	24.86	21.74	13.55	12.33
8/13/2017	1.57	1.87	2.73	3.75	90.08
8/29/2017	0.07	0.14	0.34	0.84	98.61
9/14/2017	0.20	0.70	2.18	5.19	91.74
9/30/2017	1.16	2.97	6.32	10.64	78.91
10/16/2017	5.77	8.81	11.58	13.51	60.32

CONCLUSIONS

The present study examined the spatial and temporal extent of drought over five districts, Sagar, Damoh, Panna, Tikamgarh and Chhatarpur of the Bundelkhand region in the Madhya Pradesh state of India using the annual rainfall departure analysis and combination of station-based rainfall drought severity index (SPI) and remote sensing-based index (VCI). The annual rainfall departure analysis indicated a very high drought frequency at most of the stations with an overall drought return period of 4 to 5 years in the region. Years 2007, 2015 and 2017 were identified as the severe drought years which had a wide coverage over the region and were common in all the five districts and further analysis for comparison between SPI and VCI was carried out for those years. SPI-3 values were estimated for all five stations using the long-term monthly rainfall data. Analysis of SPI-3 shown that, though the Sagar station receives a good amount of annual rainfall as compared to other stations, the probability of severely and extremely dry events is very high at this station. Tikamgarh station has also shown a high probability of severe and extreme events. The results of SPI-3 were further analyzed for the August, September and October months of dry years 2007, 2015 and 2017. VCI is estimated for August to October of dry years using the MODIS long term fortnightly NDVI data. The VCI analysis during all the three severe drought years indicated an increase in the spatial extent of drought from August to October at all stations of the region and August to September especially at Sagar and Tikamgarh. Similar temporal and spatial pattern of drought severity has also been interpreted through SPI-3. The present study justifies the advantage of satellite-based data for identifying the spatial and temporal extent of vegetation stress related drought. The study can be extended further by linking data of crop production with SPI and VCI for drought and wet years, it can be helpful to quantify the economic impact of droughts. The VCI findings may be influenced by inaccuracies in optical satellite data caused by cloud cover, which causes a shift in the real reflectance from ground objects. Conclusively, it can be said that the onset and progression of drought can be monitored with the application of station-based and satellite-based data, which will certainly help the various stakeholders to take necessary disaster management decisions.

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