Agricultural Drought Assessment in Semi-Arid Region Using SPI and NDVI

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Abstract - *An Agricultural drought is a type of natural disaster that seriously impacts food security. It's difficult to accurately identify a drought scenario because the interactions between short-term rainfall, soil moisture, and crop growth are so complicated. To cope with drought in the current climate change scenario, it is vital to understand the features of agricultural droughts in water-scarce regions in order to design prudent plans for the use of water resources. Drought indices based on remote sensing, as well as Geographic Information Systems (GIS), are critical tools for mapping and monitoring agricultural droughts. The primary goal of the present study is to monitor agricultural drought dynamics over the semi-arid region of Buldhana District (Western Vidarbha) during the year 2011 to 2021 by using the Normalized Difference Vegetation Index derived (NDVI) and Standard Precipitation Index (SPI) from time-series remote sensing data products. The study clearly indicates NDVI and SPI's potential as reliable indices for assessing and monitoring agricultural droughts.*

Key Words: **Agricultural drought, Food security, climate change, GIS, Indices, NDVI, SPI**

1. INTRODUCTION

Food security has become a crucial issue for many developing countries as the world population continues to grow. Furthermore, global climate change increases the severity and frequency of extreme climate events, such as droughts, reducing water availability and posing a threat to livelihoods and global food security. Drought is a severe climatic hazard that occurs when the amount of water available falls below the predicted level for an extended period of time, which is a form of hydrological extreme. Drought is the most damaging of all natural hazards in terms of societal damage. Droughts occur in practically every region of the world however, their occurrence, duration, and intensity vary depending on climatic and hydrological regimes. During the drought period, water scarcity affects all human activities in general and agricultural activities in particular, leading to reductions in agricultural production and productivity in the arid and semi-arid regions. Drought is a natural occurrence caused by a lack of rainfall in a region that is less than its typical distribution. Drought is a non-permanent and repeating phenomenon, which occurs due to deficiency of precipitation over an extended period of time, as compared to long-term average conditions and it is prevalent and more frequent especially in semi-arid ecosystems. Drought in agriculture refers to a decrease in crop yield due to inconsistent rainfall and insufficient soil moisture in the crop root zones. Drought is a complicated phenomenon that is influenced by a variety of hydrological variables such as precipitation, evaporation, runoff, infiltration, surface, and groundwater storages. Droughts are frequently classified as meteorological, agricultural, hydrological, or socioeconomic. High temperatures and low precipitation cause a meteorological drought, resulting in water shortages. Crops suffer from water shortages as a result of meteorological drought, resulting in agricultural drought. Agriculture droughts are more difficult to comprehend than other droughts due to the complex relationship between vegetation and climate.

In India, about 15.8% (50.8Mha) of the geographical area is arid and nearly 37.6% (123.4Mha) is characterized by semiarid climatic conditions, around 68% of the country is vulnerable to drought in different degrees mainly in arid, semi-arid, and sub-humid regions of western and peninsular India. Since Maharashtra is a drought-prone state, identification and projection of drought are the main focus of hydrological studies. Although it is an example of an industrialized state, more than 50% of the population depend on the agriculture and allied activities for their livelihood, which increases the vulnerability of drought disaster. Therefore, drought is one of the major disasters, as it affects the agrarian economy of the state. That's why, drought monitoring is critical for providing scientific data for policy formulation and drought risk mitigation. Traditional methodologies and point-based datasets are insufficient for monitoring and assessing the agricultural drought on their own. The assessment of the relationship between environmental conditions and vegetation cover is required in arid and semi-arid regions to understand the spatiotemporal variations of agricultural droughts in order to plan and manage them.

Various drought indicators have recently been developed to assess drought characteristics, particularly its severity and spatial extent. Remote-sensing based drought indices are more trustworthy than site-based drought indices for monitoring the spatio-temporal pattern of drought conditions. The drought indices derived from time-series satellites are highly reliable to monitor and assess the drought severity by its spatio-temporal resolution especially where limited gauge stations are available In recent years, the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) dataset has been used as a substitute to ground-based precipitation data for the assessment of droughts Vegetation response depends on many factors, which include duration, severity and intensity of drought, vegetation phenology, and other environmental factors like soil type, agricultural practices, and elevation of the given location. Many vegetation indices have been developed to monitor vegetation conditions in time and space. NDVI is one of the most well-known vegetation indices, and it is used to monitor and analyse drought occurrence and vegetation health, particularly in semi-arid environments where vegetation covers <30% of the area. MODIS offers real-time land surface temperature (LST) data and the accessibility of such surface temperature data is helpful to monitor and quantify the association between seasonal and inter-seasonal vegetation dynamic with changes in surface temperature. LST retrieved from remote sensing data found to be an essential environmental variable in drought monitoring. Time-series remote sensing data play a vital role in the detection, assessment, and monitoring of agriculture drought with its real-time data availability and different range of spatial and temporal coverage.

2. STUDY AREA, DATA & METHODOLOGY

2.1Study Area

Buldhana district is a study area in the western Vidarbha region and at the northern end of Marathwada. This study area is spread in latitudes 19°51′ to 21°17′ in North, 75°57′ to 76°59′ longitudes towards East and it covers about 9670 km2 of India. In 2011, the population of Buldhana was 2,586,258 people. Normal rainfall in the district is around 713 mm. The net irrigated area of 1.55 lakh ha accounts for 21.95 percent of the net sown area of 7,06,300 ha, with 1,17,100 ha being cultivated multiple times. The cropping intensity is 116.58%. Ground water (well irrigation) provides irrigation facilities to about 63,689 ha which is 41.09 % of the net irrigated area. While canal network and other surface water sources including rivers provide irrigation facilities to about 91280 ha which is 58.91 % of the net irrigated area The district's main source of income is agriculture. 23% of land holdings are categorized as small that increases the vulnerability.

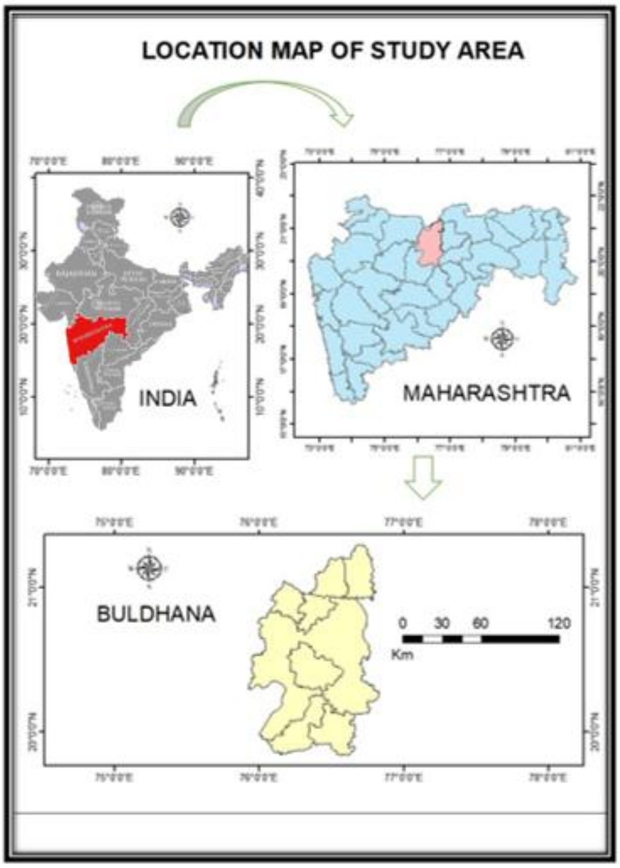

Fig -1: Study Area

2.2Data Used

CHIRPS data at 1-month temporal resolution and 5 km spatial resolution were obtained from the UCSB-Climate Hazards Group (CHG) website (https://www.chc.ucsb.edu/data/chirps) for January to December for a period of 10 years (2011 to 2021) and the same datasets were used to compute1-month SPI. MOD13Q1 data products of MODIS with 250 m 16 days composite and MOD11A2 8 days composite data products at 1 km resolution for 10 years (2011 to 2021) were downloaded (https://lpdaac.usgs.gov) to develop monthly NDVI

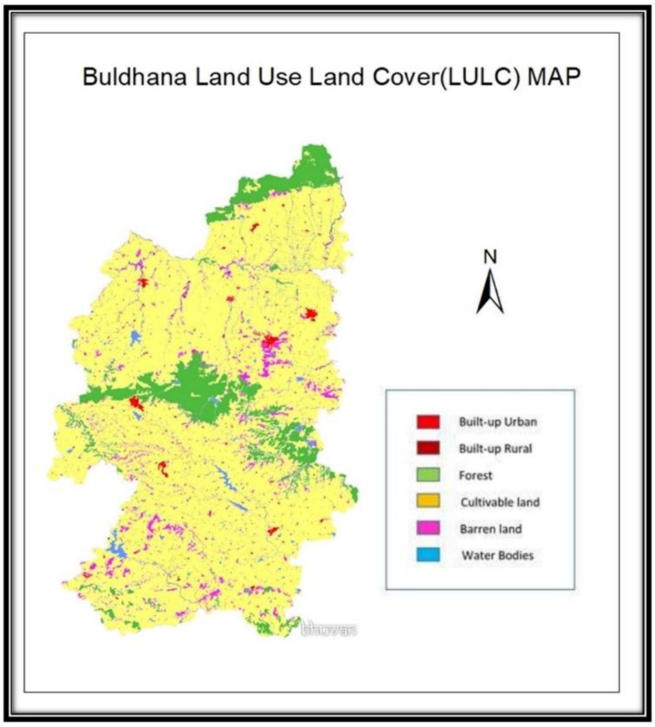

Fig -2: Map of the study area with general land use/land cover classes.

2.3 METHODOLOGY

2.3.1 Pre-processing of time-series CHIRPS data

In the study, the monthly CHIRPS rainfall data at 5 km resolution for the period of 10 years (2011 to 2021) were used. The raster was then transformed into a point in ArcGIS using the 'raster to point' tool. The values of each point were then derived from monthly rainfall rasters using the ArcGIS 'extract values to points' tool. Subsequently, the monthly rainfall data were interpolated by using the IDW interpolation technique in ArcGIS and generated monthly rainfall data products, then downscaled to 250 m by using the 'bilinear resampling technique' to achieve parity with the MODIS 250 m products utilised in the study.

2.3.2 Computation of SPI

As a drought indicator, the SPI is calculated using the probability of precipitation for each given time scale. A gamma probability density function is fitted to a given frequency distribution of precipitation totals for a certain station. Using the SPI tool, a 1-month SPI was computed for 10 years (2011 to 2011) from monthly rainfall data generated from CHIRPS data products to examine long-term monthly dry and wet conditions. Following that, using the IDW interpolation approach in Arc GIS, a seasonal SPI raster (June-September) was created for the period 2011-2021 based on 1-month SPI rasters for further study with vegetation indices produced from time-series satellite datasets for the same period. The SPI for one month was calculated using the following mathematical formula

SPI = Xij - Xim/σ

Where, "Xij" represents rainfall for the i^{th} station and the j^{th} observation, "Xim" represents the mean rainfall for the i^{th} station, and 'σ' represents the standard deviation for the i^{th} station.

2.3.3 Computation of NDVI

The MODIS Terra vegetation index 16-days NDVI composite with 250 m resolution (MOD13Q1) was obtained for the growing season from June to September, spanning the Julian dates for a 10-year period (2011 to 2021). Using the MRT tool downloaded from LPDAAC (https://lpdaac.usgs.gov/lpdaac/tools), the downloaded datasets were re-projected from the sinusoidal projection system to the Universal Transverse Mercator (UTM) projection system with WGS84 datum and then clipped with the study area boundary. Clouds and other atmospheric disturbances characterise the MODIS NDVI, lowering the quality of NDVI time-series datasets. The quality control flags were calculated using the MODIS LDOPE (Land Data Operational Products Evaluation) tool and ArcGIS software to create better filtered datasets. To get the quality grade file corresponding to NDVI, the CMD batch programme of the LDOPE tool was used to decode the quality information of the red and near-infrared bands in batches, and ArcGIS was utilized for batch grading synthesis. The atmospherically corrected NDVI products were eventually used to construct monthly NDVI composites for the growing season (June-September) and growing season mean NDVI composites for a 10-year period (2011-2021).

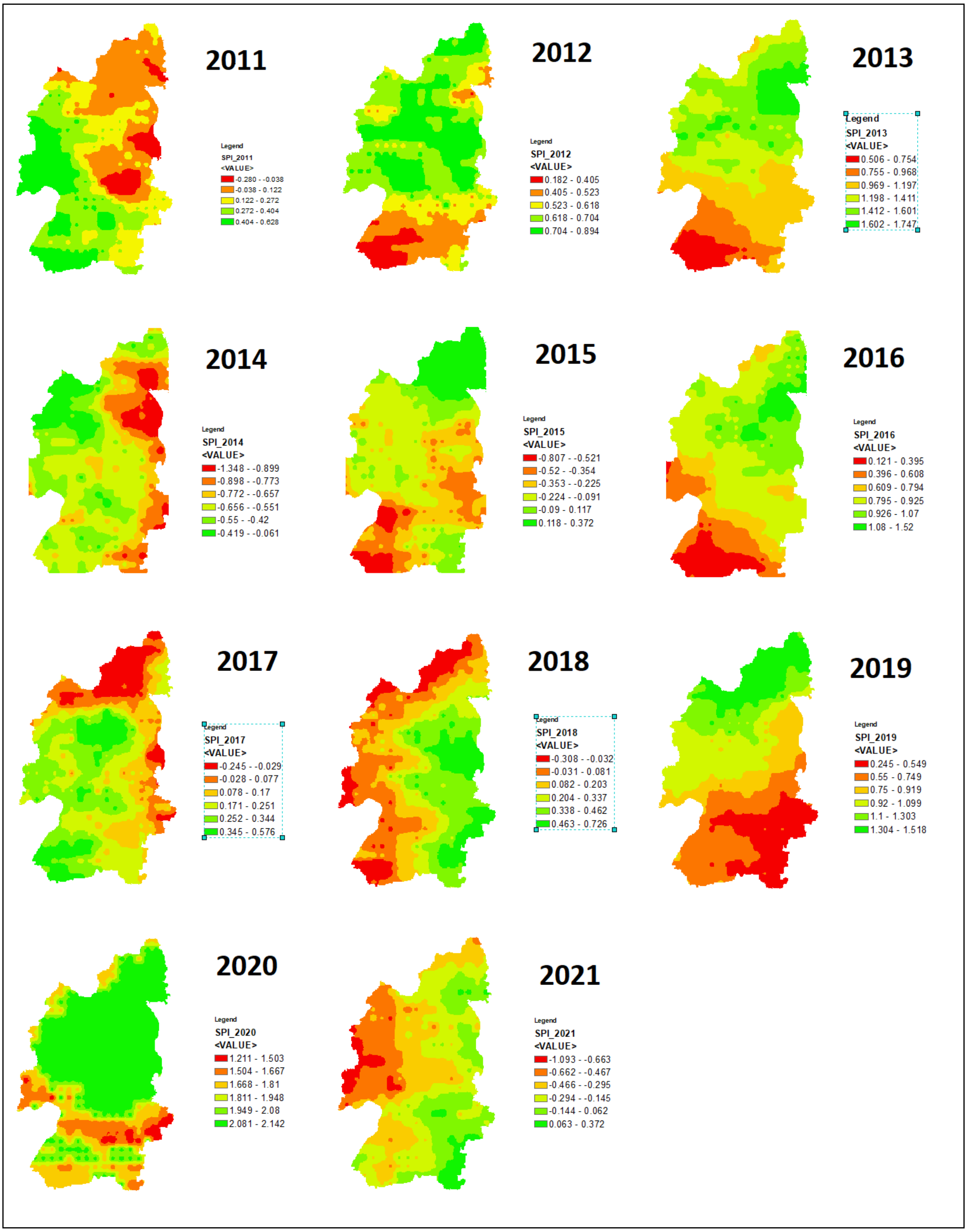

Fig. 3. Spatio-temporal patterns of 1-month SPI of the growing season over the study area during the period from 2011 to 2021.

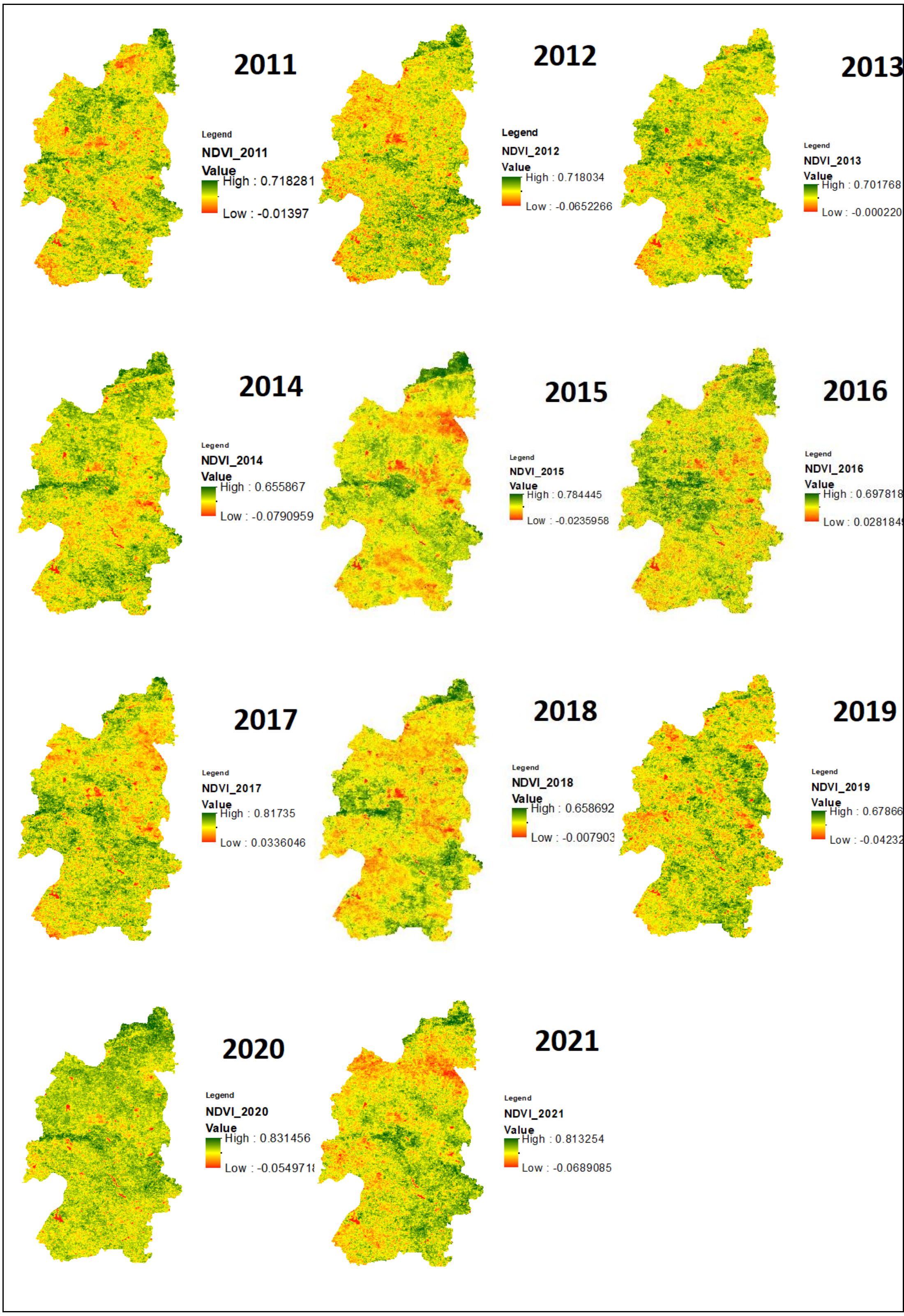

Fig. 4. Spatio-temporal patterns of mean LST of the growing season over the study area during the period from 2011 to 2021.

3. RESULTS & DISCUSSIONS

The temporal analysis of 1-month SPI and NDVI for the growing season indicates that drought is a frequent phenomenon in the majority of the years during the period from 2011 to 2021 in the Buldhana District. During the year of 2014 the district received the lowest rainfall of the decade and hence was affected by the most severe drought of the decade with the lowest SPI value of about -1.34 and corresponding years min NDVI was observed to be -0.07. The following year was also no good for the district, this year of 2015 was also dry because of the low monsoon rainfall with SPI -0.8, leading to a moderate to severe type of drought with a NDVI index of -0.07.

	SPI		NDVI		
Year	**Min**	**Max**	**Min**	**Max**	**Remark**
2011	-0.28	0.62	-0.01	0.71	Moderate Drought
2012	0.18	0.89	-0.06	0.71	-
2013	0.51	1.75	0.00	0.70	-
2014	-1.34	-0.06	-0.07	0.65	Severe Drought
2015	-0.8	0.37	-0.02	0.78	Moderate Drought
2016	0.12	1.52	0.02	0.69	-
2017	-0.24	0.57	0.03	0.81	Moderate Drought
2018	-0.30	0.72	0.00	0.65	Moderate Drought
2019	0.24	1.51	-0.04	0.67	-
2020	1.2	2.14	-0.05	0.83	-
2021	-1.09	0.37	-0.06	0.81	Severe Drought

Table1. Temporal analysis of drought using SPI and NDVI.

Once again recently in the year 2021 the due the deficit in rainfall during the monsoon with a minimum SPI of -1.09 and the effect of same was observed on the vegetation with the min NDVI of -0.06. The year of 2011,2017,2018 even though received lower rainfalls as compared to normal rainfall of the district but received better rainfall than the previous discussed years with the respective SPI indices as -0.28, -0.24, -0.30 and NDVIs as -0.01,0.03,0.00. In the years of 2012,2013,2019 the monsoon was good while in the year of 2020 the district received the best rainfall of the decade producing an SPI value of 1.20.

Year	**Affected Area**	**Affected Area**
2011	North-East	East
2012	South	North-West
2013	South	South-West
2014	East	East
2015	East/South-West	East/South
2016	South-West	East/South-West
2017	North/East	North/East
2018	West/North-West	North/North-East
2019	South/South-East	West
2020	-	-
2021	West	West

Table2. Spatial Analysis of drought.

Affected Area	**Frequency**
North	2
South	4
East	7
West	4
North-East	1
North-West	2
South-East	1
South-West	4

Table3. Spatial-Frequency Analysis of drought.

As can be seen from the above Spatial-Frequency analysis it can be observed that the most of the time when the district is affected by the drought, the eastern part of the district is seen to be affect by the agricultural drought. In the last decade itself it was affect the most that is 7 times. After that the southern, Western and South-Western part of the district were seen to be drought affected 4 times in the previous decade.

4. CONCLUSION

The spatio-temporal investigation of 1-month SPI derived from CHIRPS rainfall products for the growing season from the year 2011 to 2021 indicates that agricultural drought is a frequent phenomenon in the majority of the years in the Buldhana district. The analysis of mean NDVI of the growing season for the period from 2011 to 2021 clearly illustrates that the region witnessed consistent agricultural droughts, especially in eastern, southern, Western and South-Western parts. During the year 2015 the region experienced moderate to severe drought. However, in the year 2020the region was free from the agricultural droughts. The years 2012,2013,2016 and 2019 experienced mild droughts. While the years 2014 and 2021 were severely affected by the drought. The study clearly illustrates the utility of NDVI generated from time-series in mapping and monitoring agricultural drought in semi-arid regions, as it provides consistent and reliable spatio-temporal coverage for developing appropriate drought mitigation and adaptation measures. Though agricultural droughts are complicated and influenced by a variety of local to global climate variables, the study's wide framework for obtaining multiple vegetation indices from time-series was used. Satellite data could be used in the assessment and monitoring of agricultural drought, especially in arid and semi-arid zones, with minimal alterations to suit local conditions.

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