DROUGHT PATTERN ASSESSMENT OVER MARATHWADA, INDIA THROUGH THE DEVELOPMENT OF MULTIVARIATE ADVANCE DROUGHT RESPONSE INDEX

T.P. Singh[1], Mangesh Deshpande[1,*], Sandipan Das[1], Vidya Kumbhar[1]
[1] Symbiosis Institute of Geo-Informatics, Symbiosis International (Deemed University), Pune India ([*]mangeshd@hotmail.com)

KEY WORDS: Multivariate Drought Index, India, Remote Sensing, Aridity Drought Response Index, ADRI

ABSTRACT:

The intensity and frequency with which recent drought events are occurring has made management of food and water a challenge. The situation in Indian subcontinent is no difference. The presented study takes inspiration from such problems to propose a remote sensing based multivariate advance drought response index (ADRI). The proposed multivariate index takes into consideration long term conditions of precipitation, normalized difference vegetation index (NDVI), brightness temperature and soil moisture in a linear way for 8-day drought assessment over drought affected Marathwada region, Maharashtra, India. A value of 33 corresponding to ADRI was found to be normal condition over two decades which corresponds to normal vegetation condition index (VCI) value of 51.1 and 54.2. The last 7 years shows a consistent pattern in the change of regional ADRI values which suggests the years in which agricultural assistance is needed over the region. Drought over the region is found to shift from central to eastern and northern regions in the last 5 years. Temporal analysis for the duration suggests up to 5 percent of the area of Marathwada has been facing severe drought conditions over the last decade while up to 70 percent of the area is experience below normal conditions with varying intensities of water stress. The districts of Latur, Parbhani, Hingoli and Nanded which are downstream river Godavari have been affected the most due to large percentage of land being under agriculture.

1. INTRODUCTION

The intensity of drought is not going to holster its guns against any life form in near future. This is evident when we see the wrath over the years. Very little has been collectively achieved when we stand in front of such a natural crisis. Efforts are constantly made to understand the reasons and factors that cause such a catastrophe year after year and decade after decade. The notion that variations in precipitation drive the drought process has thus found substance in almost all the drought studies. This process differs from region to region as the onset and offset is not clearly understood (Fernandez et al., 2016). Extended drought spells have been studied throughout the globe (Xu et al. 2020, Mann et al. 2015, Um et al., 2018).
Drought as an event is pretty hard to understand as the implications are spread throughout different domains. Drought studies are often studied as aspects of environment, hydrology, meteorology and socio economic constraints (Wilhite, 2000; Mishra and Singh, 2010, Du et al., 2013, Heim, 2002). Researchers have tried to study the factors that trigger the drought and the widely documented ones include Z Index (Palmer, 1965), soil moisture index (Palmer, 1968), synthesized drought index (Du et.al, 2013), surface water supply index (Shafer and Dezman, 1982), multivariate drought index (Rajshekhar et al., 2015), vegetation health index (Kogan, 1995), Hybrid drought index (Karamouz et al., 2009), Vegetation drought response index (Brown et al., 2008), vegetation drought index (Sun et al., 2013), Drought severity index (Mu et al., 2013) and Synthesized drought index (Du et al., 2013). These indices mostly use precipitation and derivatives as the major factor to determine drought and are studied on monthly basis.
Precipitation based studies drought studies show that the uncertain patterns of extreme weather conditions are driven by environmental changes. In the last 2 decades India has witnessed frequent drought spells (De et al 2005; Mishra and Lui 2014, Pathak and Dodamani 2020). However lack of precipitation wasn't only the driving factor. Surface soil moisture has also seen similar variations driving the onset of agricultural drought. Reservoirs have seen less water accumulation causing imbalance in water supply and demand aiding socioeconomic inequality. Groundwater levels have also decreased assisting hydrological drought scenarios.
With satellites, earth observations studies saw new day as the means of collecting data was no longer governed by spatial and temporal constraints. Observations other than in-situ were providing valuable information to study weather events and their global patterns. Univariate indices based on remotely sensed data for various indicators (variables) include temperature condition index (TCI), vegetation condition index (VCI) (Kogan, 1995), water condition index (WCI) (Sun et al., 2013), normalized difference vegetation index (NDVI) (Rouse et al., 1974), normalized difference water index (NDWI) (Gao, 1996), enhanced vegetation index (EVI) (Huete et al., 1999), vegetation health index (VHI) are now popularly studied. These afore mentioned indices fall under the single index category as defined by (Hayes et al., 2011). These indices discuss the characteristics of only one variable and often come with limitations (Zargar et. al, 2011). Single index analysis may fall short of reliable results in the decision making process.
The present study considers remote sensing images to determine the drought pattern for the last 2 decades over the semi-arid region of Marathwada, India. Precipitation, soil moisture, vegetation greenness (NDVI) and land surface

temperature images were acquired to develop ADRI. Data for 17 years at a frequency of 46 reading per year helps in cautiously judging the spread of drought over the region. Assessment and monitoring of drought through such a linear multivariate method provides a reliable assessment window. This method helps in determining regions which suffer from unusual water scarcity leading to crop failure and economic losses as compared to the normal conditions observed.

2. STUDY AREA

The western state of Maharashtra, India was the study area chosen to demonstrate the capabilities of ADRI. Maharashtra is the third largest state by area, second most populous state and has the largest economy in India. The Marathwada region (64,590 sq. km) which comprises of 8 districts is a semi-arid and is badly affected by frequent droughts. Farmer suicide of which 17% is due to pure crop failure is recorded between 2009 and 2016 for a total number of 23000 suicides (Source: National Crime Records Bureau, Ministry of Home Affairs http://ncrb.gov.in/).

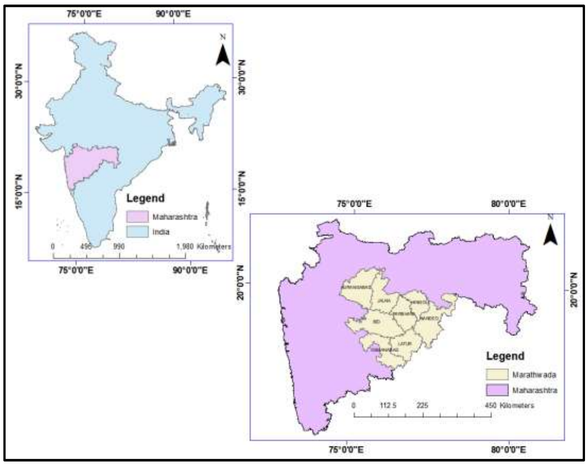

Figure 1: Study Area

3. MATERIALS AND METHOD

Data – The model uses satellite images as base data obtained for the parameters mentioned below along with the sensor details. Band 1 and 2 of surface reflectance obtained from MODIS (MOD09A1) was used to calculate NDVI and VCI for the years 2002 to 2017. The sensor has a temporal resolution of 8 days and spatial resolution of 500 meters. Band 12 (QA) was used to find cloud pixels in bands 1 and 2. Images with more than 25% of cloud pixels were not used to calculate NDVI using geo image processing. Pymodis, gdal, and numpy libraries of python were used for the processing as seen in equation (1).

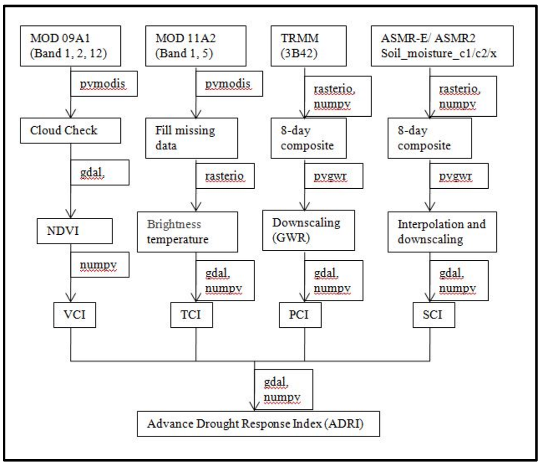

Figure 2: Methodology

Long term minimum and maximum images were created to calculate vegetation condition index (VCI) as seen in equation (2) (Liu and Kogan, 1996).

$$NDVI = \frac{NIR_{857} - R_{645}}{NIR_{857} + R_{645}} \quad (1)$$

$$VCI = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} * 100\% \quad (2)$$

Band 1 and 5 of MODIS land surface temperature product (MOD11A2) was used to calculate brightness temperature for the years 2002 to 2017. The temporal resolution of the satellite is 8 days and spatial resolution of 1000m. Rasterio and gdal libraries of python were used to replace no data pixels using one year composite data from previous year. The bands with filled data were resampled to 500m spatial resolution before calculating brightness temperature as seen in equation (3). Equation (4) (Kogan, 1995) is used to calculate TCI which considers long term minimum and maximum of temperature.

$$BT = \text{band } 5 - \text{band } 2 \quad (3)$$

$$TCI = \frac{BT_{max} - BT}{BT_{max} - BT_{min}} * 100 \quad (4)$$

The daily product of 3B42 from Tropical Rainfall Measuring Mission (TRMM) (2011) at spatial resolution of 0.25 X 0.25 degrees was used for precipitation estimation. The coarser resolution was processed to achieve 500m resolution by using pygwr library in python. The daily data was converted in to 8-day composites to maintain temporal consistency. Cartosat DEM at 30m resolution and above created NDVI at 500m resolution was used to down-sample the precipitation data. Numpy and gdal libraries were used to transform precipitation at 500m. Equation (5) below is used to perform downscaling. Equation (6) was used to calculate precipitation condition index (PCI) [Pani et al., 2016] after creating long term minimum and maximum images.

$$TRMM = \beta_0(u) + \beta_1(u)DEM_{0.25} + \beta_2(u)NDVI_{0.25} + \varepsilon(u) \quad (5)$$

$$PCI = \frac{TRMM - TRMM_{min}}{TRMM_{max} - TRMM_{min}} * 100 \quad (6)$$

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Soil moisture data was acquired from ASMR-E and ASMR2 sensors. The data captured in the descending mode i.e. night time data was used as it is consistent compared to ascending mode. The data in netCDF format has a daily temporal resolution and 0.25 X 0.25 degrees spatial resolution. This daily data was converted into 8-day composite and interpolated using inverse distance weighted (IDW) to fill missing values. Brightness temperature and NDVI at 500m resolution were used as input in the geographically weighted regression (GWR) model using pygwr library in python. Downscaling of the image was done as seen in equation (7) whereas equation (8) was used to calculate soil condition index.

$$\mathrm{Soil_{DS}} = \mathrm{intercept} + (\mathrm{NDVI\ parameter} * \mathrm{NDVI}) + (\mathrm{LST\ parameter} * \mathrm{LST}) + \mathrm{residual} \quad (7)$$

$$\mathrm{SCI} = \frac{\mathrm{AMSR} - \mathrm{AMSR_{min}}}{\mathrm{AMSR_{max}} - \mathrm{AMSR_{min}}} * 100 \quad (8)$$

The condition indices VCI, TCI, PCI and SCI are unit-less standardized values which fall in the range 0 and 100. The proposed ADRI is as given equation (9). ADRI like other condition indices have a standardized range of 0 and 100 and is linear in nature.

$$\mathrm{ADRI_{ijk}} = \left[\mathrm{L} * \mathrm{VCI} * \left\{\mathrm{c} + \frac{1}{\mathrm{L} * (\mathrm{VCI} + \mathrm{TCI} + \mathrm{PCI} + \mathrm{SCI}\ \ )} * (\mathrm{TCI} + \mathrm{PCI} + \mathrm{SCI})\right\}\right] \quad (9)$$

Where VCI, TCI, PCI and SCI are values of pixel i for composite j in year k, L is the normalization factor and c is constant to avoid a null denominator. The results discussed in this paper are calculated using L = 0.25 and c = 0.01.The unit less ADRI ranges from 0 to 100. Values close to 0 depict drought like conditions while values near 100 are healthy conditions.

4. RESULTS

Figure 3 shows the yearly mean ADRI over Marathwada for the years 2014 to 2020. Table 1 presents the annual mean ADRI over each district for the years (2004 to 2020). The values in italics correspond to the images in figure 3. The highs for these years for ADRI for the mentioned years oscillated between 50 and 58. The lows for the same were between 0 and 8.

The mean ADRI over Marathwada for 17 year duration was found to be around 33 (+/- 5%). The distribution of drought over the region of Marathwada is seen to be uneven. From figure 3 the shift in spatial distribution is evident. For the year 2014, Nanded, Parbhani and Hingoli districts were heavily affected followed by Latur, Osmanabad and Bid districts. Jalna and Aurangabad were the least affected districts in the year 2014.

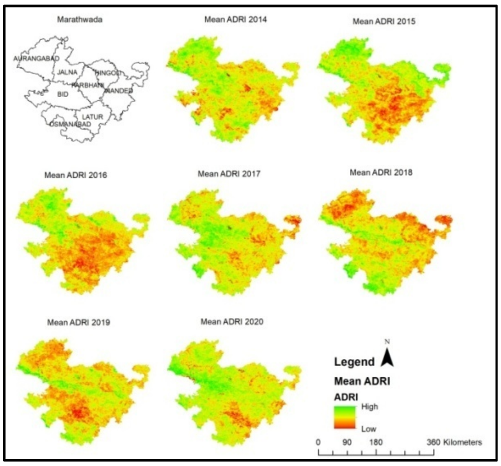

Figure 3: Annual mean ADRI over Marathwada for 2014-2020

The shift of pattern for 2015 clearly shows that the drought pattern has moved in the central and eastern regions of Marathwada in which Latur, Parbhani, Nanded and Bid were highly affected and needed support and relief from local governing bodies. 2016 saw the intensity reducing in the areas that were drought affected in 2015. This distribution of intensity in subsequent years has been seen to shift to the north and east of Marathwada region. The district of Aurangabad which was not affected significantly by drought in 2014 has seen increase in the intensity of drought in the last three years.

Figures 4 and 5 show the annual mean soil condition and vegetation condition over Marathwada from 2014 to 2020. The highs for SCI were in the range of 66 to 84. The lows for SCI over the years were very uneven. For 2015 it went as low as 14 while in 2020 it was 57. The highs and lows for VCI were found to have similar distribution. High values reached around 90 while lows were around 10.

The movement of Godavari River through the districts of Aurangabad, Bid, Parbhani and Nanded has created a fertile belt which helps in maintaining healthy soil and vegetation conditions in the vicinity. As the major river in southern India, the benefit the river provides to the livelihood of the farmers.

In order to verify the obvious facts, the correlation of annual ADRI and SCI along with that of ADRI and VCI were studied to find the consistency of the performance of ADRI. Table 2 and 3 below shows district wise annual mean of VCI and SCI over each district respectively.

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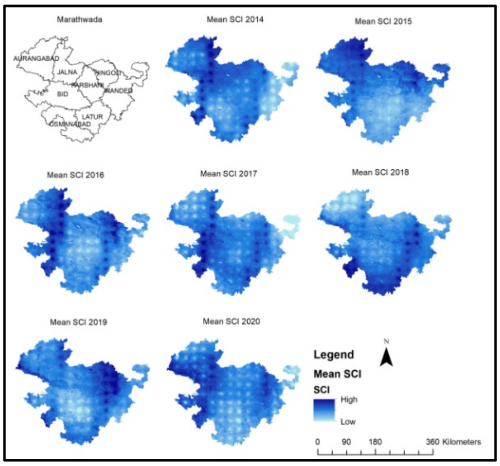

Figure 4: Annual mean SCI over Marathwada for 2014-2020

Districts of Parbhani, Latur and Nanded saw significant drop in annual average VCI for the years 2015 and 2016. The conditions improved in subsequent years. However new spots of low VCI starts to emerge in the districts of Beed and Latur in 2019 and 2020 showing the shift in pattern. The same pattern is observed to be true in case of annual average SCI values. The districts of Nanded, Parbhani, Hingoli and Latur follow similar trends for the duration 2011 to 2014.

This trend is different as seen over the districts of Aurangabad, Jalna, Beed and Osmanabad for the same time duration. This can be seen in figure 6. However, soil moisture data acquired from ASMR-E and ASMR2 saw a lack of data from early October 2011 to July 2012 due to unavailability of satellite. This lack of data forces ADRI to calculate the index without soil moisture data causing an abnormal trend in yearly observations. This shows how soil moisture affects drought conditions in the Marathwada region. Depletion of soil moisture often leads to agricultural drought (Zampieri et al., 2009)

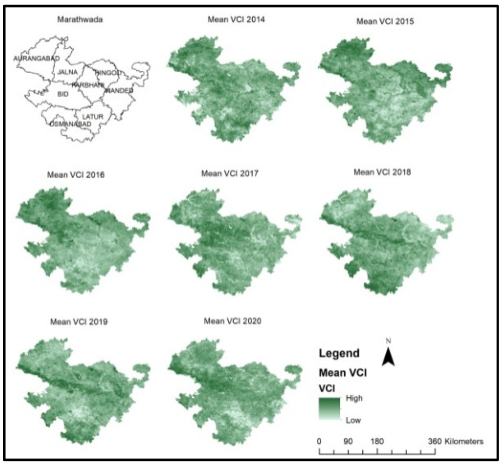

Figure 5: Annual mean VCI over Marathwada for 2014-2020

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Table 1: Annual mean ADRI over every district of Marathwada from 2004 to 2020

		Districts							
	Year	Aurangabad	Jalna	Beed	Latur	Parbhani	Nanded	Osmanabad	Hingoli
	2004	29.24124	25.68328	27.87744	27.84465	23.19855	28.51644	24.32709	20.81437
	2005	31.36114	28.56848	33.80396	33.34241	26.19729	31.25504	38.59073	19.99159
	2006	37.46471	39.44515	40.38691	40.6001	38.91479	33.85669	45.77959	34.73823
	2007	40.14311	35.57152	35.74702	30.84222	31.49611	25.49793	38.9573	31.93011
	2008	31.31761	27.75473	31.85063	28.17633	30.65654	22.91344	36.01073	30.84517
	2009	33.5827	30.63099	35.90114	28.09682	31.0928	22.29442	37.41836	26.89919
	2010	47.21653	42.72104	47.13559	31.99244	36.3301	29.25029	43.6391	31.47592
	2011	45.98525	44.03666	44.74545	39.56148	42.11983	39.68931	43.53785	39.80483
	2012	28.07285	27.66634	30.71517	37.73576	39.61353	38.50194	31.66225	40.61259
	2013	30.07454	28.35356	30.65483	37.11517	36.23706	37.535	28.8075	37.35792
	2014	*40.49128*	*39.93966*	*37.69257*	*37.99266*	*36.6879*	*35.44106*	*37.75389*	*36.73115*
	2015	*35.8083*	*32.75883*	*27.92374*	*22.10157*	*24.79982*	*29.9383*	*28.39666*	*33.67393*
	2016	*29.49176*	*28.97658*	*24.58595*	*20.17214*	*22.5438*	*23.72391*	*24.47416*	*26.22484*
	2017	*37.10947*	*39.1486*	*38.57214*	*34.97257*	*37.23781*	*33.19241*	*38.16466*	*33.76711*
	2018	*28.17687*	*31.1293*	*31.36137*	*32.34695*	*32.98208*	*27.0452*	*37.94846*	*26.43862*
Mean yearly ADRI Value over district	*2019*	*28.00423*	*28.05999*	*26.22814*	*26.14765*	*29.93949*	*28.52896*	*30.34293*	*27.89514*
	2020	*43.41262*	*44.25032*	*42.68313*	*37.69637*	*42.54454*	*40.61123*	*42.04662*	*40.33*
	mean	35.11495353	33.80559	34.5803047	32.1610171	33.0936494	31.0465629	35.75634588	31.7371006
	std	6.2699382	6.26120121	6.40180402	5.8885231	6.16274401	5.71932123	6.439120751	6.16394965

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Table 2: Annual mean VCI over every district of Marathwada from 2004 to 2020

		Districts							
	Year	Aurangabad	Jalna	Beed	Latur	Parbhani	Nanded	Osmanabad	Hingoli
	2004	44.90838	40.83982	43.2855	44.55522	38.89103	47.11255	36.7971	35.95979
	2005	50.12868	45.46531	50.61004	50.51736	40.58229	48.0966	57.25863	31.77686
	2006	57.78278	61.23872	61.71273	63.36223	60.90283	52.70706	70.23651	54.76704
	2007	61.39051	56.52742	55.19668	49.4967	49.65997	38.69733	60.59506	49.88732
	2008	49.53189	44.11281	49.36948	43.98941	47.86676	36.21336	55.02921	47.81165
	2009	54.52647	49.56748	56.14813	45.44132	50.87251	38.14868	57.5794	45.25978
	2010	69.43562	62.58667	68.53202	45.76338	52.92537	42.01864	62.92673	45.50834
	2011	65.91249	62.03404	61.82332	52.33437	57.3903	55.52103	62.24637	56.79556
	2012	48.68441	47.12632	49.1024	50.32492	53.96424	48.21811	49.91852	54.18604
	2013	45.60975	42.63516	47.6373	55.10009	54.0739	54.1162	44.65778	54.62662
	2014	*61.76509*	*59.60347*	*57.37689*	*58.83098*	*56.24345*	*56.0672*	*57.61494*	*55.95461*
	2015	*56.39908*	*50.93457*	*45.43653*	*36.94857*	*39.34787*	*47.95741*	*47.55743*	*52.99135*
	2016	*46.11249*	*43.97661*	*37.34031*	*29.90369*	*34.62526*	*36.87926*	*36.63391*	*40.12807*
	2017	*56.90016*	*60.23807*	*59.1864*	*52.95554*	*58.70961*	*51.53089*	*58.3297*	*52.96407*
	2018	*44.73975*	*49.45268*	*49.47215*	*49.26351*	*51.5627*	*40.60392*	*59.31271*	*40.12997*
Mean yearly VCI Value over district	*2019*	*41.86871*	*42.00501*	*39.05592*	*38.40806*	*44.68564*	*42.65243*	*45.56676*	*41.27037*
	2020	*65.62321*	*67.29919*	*64.74712*	*56.55322*	*65.38143*	*61.82061*	*63.59754*	*61.50543*
	mean	53.4810163	51.14651	51.9553625	47.9497094	49.5189831	46.0337919	53.8912975	47.50109
	std	8.02698324	7.71104216	8.35254391	8.07665858	7.59752782	6.60457649	9.19657143	7.53677163

Table 3: Annual mean SCI over every district of Marathwada from 2004 to 2020

		Districts							
	Year	Aurangabad	Jalna	Beed	Latur	Parbhani	Nanded	Osmanabad	Hingoli
	2004	52.72026	47.82023	53.42441	56.55749	49.45526	52.01717	56.56457	46.42466
	2005	52.52505	52.58978	67.55474	66.95116	59.25223	61.79727	72.06891	50.59844
	2006	57.88961	62.29191	63.26794	62.1223	64.27981	62.81288	64.51324	60.85224
	2007	55.9483	50.57064	53.00303	47.97377	49.80814	48.44204	53.68249	49.31658
	2008	51.01324	49.33796	54.97121	51.46558	53.14478	48.00229	58.18885	53.00802
	2009	47.68856	44.80243	53.32789	42.57498	43.02498	34.61187	55.39787	38.35737
	2010	69.96598	66.35052	68.39653	58.74125	59.44923	59.33498	66.57367	57.65931
	2011	59.62314	66.8728	66.29129	67.30334	71.93801	66.93944	67.31115	72.58331
	2012	29.61503	40.55042	37.21182	56.27125	56.98527	65.973	39.96165	72.0558
	2013	47.89094	49.93765	46.48069	59.33716	59.00063	67.48238	45.91963	67.89392
	2014	*54.0571*	*58.08483*	*52.79278*	*52.95523*	*53.79404*	*47.92592*	*53.2493*	*55.1224*
	2015	*46.80107*	*47.20684*	*38.16375*	*31.51341*	*37.37676*	*38.8942*	*36.27902*	*46.97737*
	2016	*46.45665*	*49.85843*	*46.55835*	*45.30204*	*43.54493*	*45.09228*	*46.76347*	*49.51515*
	2017	*56.80436*	*60.00903*	*60.85752*	*60.45889*	*58.2155*	*55.16887*	*60.14449*	*58.3527*
	2018	*41.39963*	*44.16133*	*45.44391*	*50.16408*	*45.7434*	*46.84917*	*52.5688*	*46.83022*
Mean yearly SCI Value over district	*2019*	*47.03579*	*47.25007*	*43.37409*	*45.39112*	*47.52892*	*47.2122*	*46.82809*	*52.98987*
	2020	*75.24502*	*76.0753*	*74.42832*	*70.78748*	*72.75827*	*72.67949*	*72.22455*	*74.48078*
	mean	51.08966938	52.3559294	53.1949969	53.4426906	53.2838681	53.0347475	54.75095	54.908585
	std	8.581653145	7.73736905	9.68071829	9.20117069	8.59995617	9.79244578	9.714757527	9.32120385

This lack of data forces ADRI to calculate the index without soil moisture data causing an abnormal trend in yearly observations. This shows how soil moisture affects drought conditions in the Marathwada region.

Depletion of soil moisture often leads to agricultural drought (Zampieri et al., 2009)

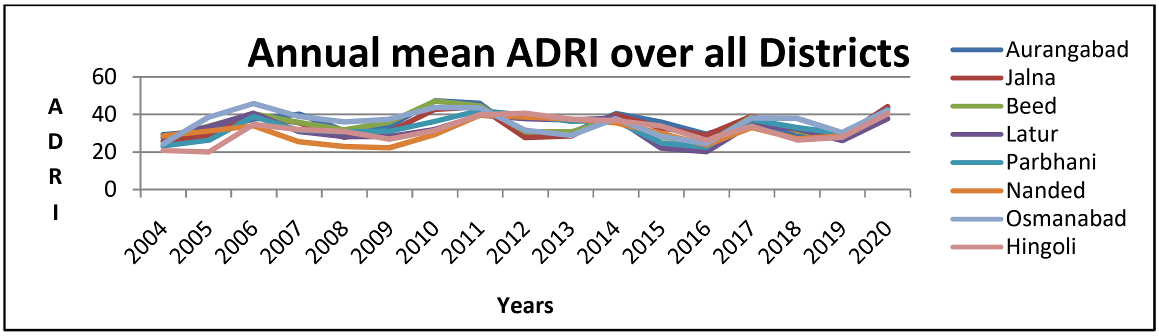

Figure 6: ADRI movement over Districts over Marathwada from 2004 to 2020

The correlation of yearly ADRI-VCI and ADRI-SCI values for 17 years is as seen in table 4.The districts of Latur, Hingoli, Nanded and Parbhani have relatively low values as compared to other districts (ADRI_VCI value). This clear indication supports the fact that the aforementioned districts have high percentage of land under agriculture. On the other hand districts of Latur, Parbhani and Osmanabad have low correlation values as compared to other districts (ADRI_SCI values). The overall correlation over Marathwada is strong for ADRI-VCI at 0.97 and that of ADRI-SCI at 0.79.

Table 4: Correlation of ADRI with VCI and SCI for 17 years

	Aurangabad	Jalna	Beed	Latur	Parbhani	Nanded	Osmanabad	Hingoli
correlation of yearly ADRI and VCI	0.980227682	0.97745106	0.981337	0.94177994	0.95683675	0.92488228	0.982746774	0.95954404
correlation of yearly ADRI and SCI	0.806359938	0.88606385	0.80137491	0.77408063	0.77972539	0.81955832	0.729994595	0.79901635

5. DISCUSSION

The districts of Latur, Parbhani, Nanded and Hingoli have over 75% of the land under agriculture. This results in rise in water demand for agricultural use. Tables 3 and 4 show a consistent pattern over the region. Better conditions are seen every third year as far as vegetation conditions and soil conditions are considered. Districts of Latur and Parbhani have been suffering from severe drought as compared to other districts. From the images it is also clear that Osmanabad is affected by soil moisture losses but even then manages to better the vegetation condition of the last two decades.

Table 5: Annual ADRI and SPI correlation for years with complete data

Year	ADRI-SPI correlation
2013	-0.011852
2014	0.03318275
2015	0.4462035
2016	0.15440775

The temporal analysis also shows that the drought severity is shifting down to the eastern region of Marathwada. The distribution of precipitation over the years show that the concentration of rainfall in the districts of Nanded, Hingoli, Latur and Parbhani experience majority of the rainfall in the August and September months which makes agriculture difficult as far as natural resources are concerned. The results further confirm that the onset of hydrological and agricultural droughts is triggered by meteorological drought. This information is also visible through the correlation of ADRI (agriculture focused drought index) and SPI (meteorological drought index) as seen in table 5. Whereas table 6 above shows the percentage difference of district-wise ADRI values when compared to the 17 year mean value.

	Aurangabad	Jalna	Beed	Latur	Parbhani	Nanded	Osmanabad	Hingoli
2004	164.8574302	184.265117	182.959464	193.160247	194.236088	202.318305	180.4245887	191.738498
2005	159.3289877	149.592538	153.275197	149.167453	150.506641	156.030283	150.1341613	155.390943
2006	145.2749751	145.946159	158.966818	160.024728	160.589058	154.613862	162.737127	167.022252
2007	135.8069859	132.52965	154.214633	132.380702	130.009778	111.483742	154.9315755	120.859717
2008	199.2483913	196.270853	197.79042	182.647364	179.63939	191.116099	186.1870064	181.677938
2009	169.7941589	197.815805	191.702446	209.269937	217.377084	215.609825	188.2495214	228.701768
2010	84.33737489	119.951819	107.609867	174.967259	172.193974	212.496952	111.7610008	227.039643
2011	136.3833216	147.720096	134.413766	184.50026	178.283843	217.358618	128.4237213	213.926032
2012	153.943248	171.820193	152.667191	164.656578	162.550945	154.367877	148.9226561	173.684423
2013	133.2796011	139.642112	110.362677	97.9863601	112.942394	125.276991	101.461766	148.020358
2014	132.2987654	147.485756	134.638345	140.860098	131.580925	145.240812	130.783694	156.016615
2015	161.7668665	177.512151	175.988964	187.988116	175.911394	177.69719	168.2064778	183.862731
2016	117.8974364	130.633218	131.415586	155.977903	138.224103	150.899699	147.0194974	147.556705
2017	133.9480343	139.769991	125.43004	141.137079	143.619458	152.069007	130.9644172	166.965063
2018	214.2819866	225.037634	215.233268	220.103363	219.855686	234.098345	201.9908585	234.68048
2019	145.4926299	154.873586	153.83033	166.172265	161.009345	170.823249	153.1223302	173.010716
2020	24.43874271	22.8878391	27.9948901	28.6097006	25.9867265	31.541159	27.16932418	29.3700548

Table 6: Percentage of drought as compared to 17 year means of respective districts

6. CONCLUSION

Decadal studies often help us in finding patterns of extreme weather events helping us update the knowledge of global scenarios on a frequent basis to make necessary adjustments and show human resilience in tough conditions. The development of ADRI as a means to study and assess the local drought condition of Marathwada has yielded significant results specially in identifying the propagation of drought. The drought patterns as seen through the images above shows a consistent pattern where 2 year events of unfavorable agricultural conditions is padded by events of less intensity. This helps to establish that the region of Marathwada is affected by varying drought intensities for nearly two decades.

The objective of developing a reliable, consistent and extensive drought monitor index for assessment of drought has been achieved to a certain degree. Images obtained from the index will help provide timely update of drought propagation.

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