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 different. 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 be 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 (Rajsekhar 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.
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/).

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).

\[
NDVI = \frac{R_{band 1} - R_{band 2}}{R_{band 1} + R_{band 2}}
\] (1)

\[
VCI = \frac{NDVI_{max} - NDVI_{min} + 100\%}{NDVI_{max} - NDVI_{min} + NDVI_{max} - NDVI_{min} + 100\%}
\] (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).

\[
BT = band 5 - band 2
\] (3)

\[
TCI = \frac{BT_{max} - BT_{min}}{BT_{max} - BT_{min} + 100\%}
\] (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.

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

\[
PCI = \frac{TRMM_{max} - TRMM_{min}}{TRMM_{max} - TRMM_{min} + 100\%}
\] (6)
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.

\[
\text{Soil}_{\text{DS}} = \text{intercept} + (\text{NDVI parameter} \times \text{NDVI}) + (\text{LST parameter} \times \text{LST}) + \text{residual} \tag{7}
\]

\[
\text{SCI} = \frac{\text{AMSR}_{\text{max}} - \text{AMSR}_{\text{min}}} {\text{AMSR}_{\text{max}} - \text{AMSR}_{\text{min}}} \times 100 \tag{8}
\]

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.

\[
\text{ADRI}_{\text{IPK}} = \left[ L \times \text{VCI} \times \left\{ \frac{1} {\frac{1} {L} (\text{VCI} + \text{TCI} + \text{PCI} + \text{SCI})} \times (\text{TCI} + \text{PCI} + \text{SCI}) \right\} \right] \tag{9}
\]

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.

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.

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.

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.
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).

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

| Year | Aurangabad | Jalna | Beed | Latur | Parbhani | Nanded | Osmanabad | Hingoli |
|------|------------|-------|------|-------|----------|--------|-----------|--------|
| 2004 | 29.24124   | 25.68328 | 27.87744 | 27.84656 | 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 | 37.46791   | 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 | 31.37161   | 27.75473 | 31.85063 | 28.76359 | 30.65558 | 22.91344 | 36.01073 | 30.84517 |
| 2009 | 33.58207   | 30.63699 | 35.90114 | 28.09662 | 31.89229 | 22.29442 | 37.41826 | 26.89919 |
| 2010 | 47.21653   | 42.72104 | 47.13559 | 31.99244 | 36.33091 | 29.25029 | 43.6394  | 31.47592 |
| 2011 | 45.98525   | 44.03666 | 44.74545 | 39.56148 | 42.11983 | 39.68531 | 43.53785 | 39.80683 |
| 2012 | 28.07285   | 27.66634 | 30.71517 | 37.73576 | 39.61535 | 38.50194 | 31.66225 | 40.61259 |
| 2013 | 30.07454   | 28.35556 | 30.65483 | 37.11517 | 36.23706 | 37.5355  | 28.8075  | 37.35792 |
| 2014 | 40.49128   | 39.93966 | 37.69257 | 37.99266 | 36.68791 | 35.44186 | 37.55889 | 37.73115 |
| 2015 | 33.8081    | 32.75883 | 27.92174 | 22.10157 | 24.79882 | 29.9383  | 28.3666  | 33.67393 |
| 2016 | 29.49176   | 28.97658 | 27.92174 | 22.10157 | 24.79882 | 29.9383  | 28.3666  | 33.67393 |
| 2017 | 37.19047   | 39.1498  | 38.57121 | 34.97257 | 37.23781 | 31.19241 | 38.16466 | 33.76713 |
| 2018 | 28.17057   | 31.1293  | 31.16237 | 32.34905 | 32.82608 | 27.0452  | 37.94546 | 26.43682 |
| 2019 | 28.04232   | 28.05999 | 26.22814 | 26.14765 | 29.93849 | 26.52967 | 30.34239 | 27.89514 |
| 2020 | 34.41262   | 44.25020 | 42.68313 | 37.69367 | 42.54552 | 40.61235 | 42.04862 | 40.53 |

| Mean yearly ADRI Value over district |
|--------------------------------------|
| Mean 35.1149535 | 33.80591 | 34.5803047 | 32.1610171 | 33.9936498 | 31.8466529 | 35.7565458 | 31.7371006 |
| std 6.2099362 | 6.26120121 | 6.40188042 | 5.8885231 | 8.1627440 | 5.71932123 | 6.43912072 | 8.16394965 |

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https://doi.org/10.5194/isprs-archives-XLIII-B3-2022-1173-2022 | © Author(s) 2022. CC BY 4.0 License.
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.
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

| Year | Aurangabad | Jalna | Beed | Latur | Parbhani | Nanded | Osmanabad | Hingoli |
|------|------------|-------|------|-------|----------|--------|-----------|---------|
| 2004 | 0.987368   | 0.9745106 | 0.981337 | 0.94177994 | 0.95683675 | 0.92488228 | 0.982746774 | 0.95954404 |
| 2005 | 0.986359358 | 0.88605365 | 0.80137491 | 0.77408063 | 0.77972359 | 0.81955832 | 0.729945954 | 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 it 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.
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.

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

| Year | Aurangabad | Jalna | Beed | Parbhani | Latur | Nanded | Osmanabad | Hingoli |
|------|------------|-------|------|----------|-------|--------|-----------|--------|
| 2004 | 164.8574302| 184.265117 | 182.959464 | 193.160124 | 194.236388 | 202.318305 | 180.424588 | 191.738498 |
| 2005 | 159.3289877| 149.592538 | 153.275197 | 149.167455 | 150.506641 | 150.030283 | 150.134163 | 155.390943 |
| 2006 | 145.2749751| 145.946159 | 158.966818 | 160.024728 | 160.589058 | 154.613862 | 162.737127 | 167.022525 |
| 2007 | 135.8088859| 132.529365 | 154.214633 | 132.380702 | 130.099778 | 111.483742 | 154.931575 | 120.859771 |
| 2008 | 199.2483913| 196.270853 | 197.79042 | 182.647364 | 179.63939 | 191.116099 | 186.187006 | 181.677938 |
| 2009 | 198.415892 | 197.813807 | 191.702446 | 209.269937 | 217.377084 | 215.609825 | 188.249521 | 228.701768 |
| 2010 | 84.3373489 | 119.951189 | 107.609867 | 174.962594 | 172.193974 | 212.496952 | 111.761000 | 227.039643 |
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