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Research Article

Evaluation of Remote Sensing-based Indices for Agricultural Drought Characterization

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ABSTRACT

The present study was carried out to characterize the agricultural drought in Marathwada region, one of the most frequent drought prone areas of Maharashtra, through remote sensing based indices namely Vegetation Condition Index derived from NDVI (VCI_N) and EVI (VCI_E) and Water Condition Index (WCI). The MODIS data (500 m resolution) from 2nd Jun to 16th Oct (at 16-day intervals) were used to compute the drought indices for 15 years (2000-2014). The area under drought observed by these remote sensing indices (VCI_N, VCI_E and WCI) was correlated with food grain production to identify the most suitable drought index for characterization of drought in the region. Correlation analysis indicated that all three indices had good correlation with food grain production during *kharif* season. The maximum correlation of food grain production was observed with VCI_N ($r = -0.811$) as compared to VCI_E ($r = -0.696$) and WCI ($r = -0.775$). This study showed that VCI_N is better index than VCI_E and WCI to characterize agricultural drought in the Marathwada region of Maharashtra.

Key words: Drought, Vegetation Condition Index (VCI), Water Condition Index (WCI), NDVI, EVI, NDWI, Marathwada, Maharashtra

Introduction

Drought is a complex natural phenomenon. It is very difficult to determine when a drought begins or ends. Developing countries like India and others particularly suffer significantly from frequent drought occurrence. Out of 3.29 million sq. km geographical area in India, about 1.07 million sq. km of land is subjected to different degrees of drought conditions leading to water stress (Mishra and Desai, 2005). An increased frequency of dry spells often triggers a drought situation to arise, which leads to adverse economic and social impacts especially the agriculture sector leads to decline in foodgrain production depending upon the intensity, duration, frequency and spatial coverage of drought stress.

The timely information of onset, progression and areal extent could be useful for proper planning and management of water resources. Approaches to characterize agricultural drought mainly evolve around monitoring soil water balance and the subsequent deficit in the event of a drought. Now as days, the use of remote sensing data for drought detection has been generalized due to development of the various satellite derived indices i.e. Vegetation Condition Index (VCI) (Kogan, 1995). Vegetation Indices are an effective measure for monitoring climate-related changes

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in vegetation conditions. The satellite-derived normalized difference vegetation index (NDVI) data has played an important role for vegetation drought monitoring (Kogan, 1995; Gu *et al.*, 2007; Brown *et al.*, 2008; Sahoo *et al.*, 2015). Normalized Difference Vegetation Index (NDVI) is a good indicator of green biomass, leaf area index and pattern of production (Thavorntam and Mongkolsawat, 2008). The principle behind this index is that the internal mesophyll structure of healthy green leaves strongly reflects NIR (near infrared) radiation and leaf chlorophyll and other pigments absorb a large proportion of the red VIS (visible red) radiation. This becomes reverse in case of unhealthy or water stressed vegetation. NDVI provides an estimate of vegetation health and a means of monitoring changes in vegetation over time. Satellite observations provide a valuable source of timely, spatially continuous information for monitoring vegetation dynamics (for example, physiological stages) and conditions across large areas (Brown *et al.*, 2008). Although, NDVI is a good indicator of the green biomass, leaf area index and pattern of production (Thenkabail *et al.*, 2004), however, a lagged response to drought was observed in some studies (Reed, 1993; Rundquist and Harrington, 2000).

The enhanced vegetation index (EVI) is an 'optimized' vegetation index designed to enhance the vegetation signal with improved sensitivity in high biomass regions and improved vegetation monitoring through a de-coupling of the canopy background signal and a reduction in atmospheric influences.

Another remote sensing measure, the normalized difference water index (NDWI) has also recently been used to monitor moisture conditions of vegetation canopies over large areas (Jackson *et al.*, 2004; Chen *et al.*, 2005). NDWI is to monitor moisture conditions of vegetation canopies as it can reflect changes in both water content and spongy mesophyll in vegetation canopies (Fensholt and Sandholt 2003; Gu *et al.*, 2007). Some studies found that NDWI exhibits a more rapid response to drought conditions than NDVI (Gu *et al.*, 2007; Gebrehiwot *et al.*, 2011). Similar to VCI, the water condition index (WCI) derived from NDWI was defined to separate short-term weather-related NDWI fluctuations from long-term ecosystem changes (Sun *et al.* 2012). Therefore, a study was carried out to assess the performance of remote sensing based drought indices namely VCI derived from NDVI (VCI_N), VCI derived from EVI (VCI_E) and WCI derived from NDWI for agricultural drought characterization in the Marathwada region of Maharashtra.

Material and methods

Study area

The study area comprised of nine districts of Maharashtra namely Ahmednagar, Aurangabad, Beed, Jalna, Latur, Osmanabad, Sangli, Satara and Solapur. Geographically, the region is located between 16°42′35.72′′N to 20°39′11.99′′N latitude and 73°32′39.10′′E to 77°17′43.49′′ E longitude and covering an area of 9.4 mha (Fig. 1). The Marathwada region of Maharashtra comes

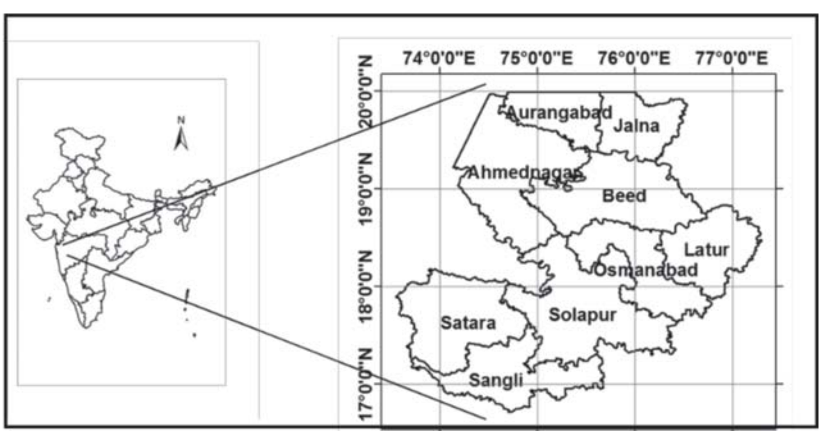

Fig. 1. Study area consisting of nine districts of Maharashtra, India

under drought prone areas and had many drought events of varying magnitude during its history. Topographically, it receives less rainfall compared to the rest of Maharashtra. Which leads to frequent dry spells and drought situation. It receives an average annual rainfall of about 500-600 mm, which mainly occurs during the monsoon period. The region is characterized as hot semiarid climate with dry summer and cool winter.

Data used

(i) *Satellite data:* The TERRA MODIS data (MOD09A1 and MOD13A1) from 2nd Jun to 16th Oct (16-day intervals) for *kharif* crop growing period of 500 m spatial resolution for 15 years (Year 2000 to 2014) were downloaded from *https://lpdaac.usgs.gov*.The tile considered for the study area was h25v07.005. The selected MODIS data product images were processed using the ENVI software.

(ii) *Crop data:* Production statistics of major crops grown in these districts were collected from Department of Agriculture, Government of Maharashtra for 15 years (year 2000-2014) to evaluate the drought indices.

Calculation of drought index

In the present study agricultural drought was characterized by using two remote sensing derived indices i.e., Vegetation Condition Index (VCI) and Water Condition Index (WCI).

Vegetation condition index (VCI)

VCI has been successfully used in recent years to detect drought and vegetation stress. It could be used for both localized/short-term and widespread/long-term droughts (Kogan 1987a,b, 1995). In this study two base indices NDVI (Normalized Difference Vegetation Index) and EVI (Enhanced Vegetation Index) were used to compute VCI. The NDVI and EVI data were taken from band 1 and band 2 respectively, of satellite (MODIS) data from 2nd Jun to 16th Oct (16 days' interval) for *kharif* crop growing period for 15 years (2000-2014) were used in this study.

VCI derived from NDVI (VCI_N)

VCI_N was derived from base index NDVI by using following equation.

$$VCI_N = (NDVI_i - NDVI_{min})/(NDVI_{max} - NDVI_{min}) \times 100 \quad \ldots(1)$$

VCI_N indicates how close the NDVI of the current period ($NDVI_i$) is to the minimum NDVI ($NDVI_{min}$). Here, the maximum NDVI ($NDVI_{max}$) and minimum NDVI ($NDVI_{min}$) were calculated from the long-term record for that particular period. The range of VCI_N is between 0 and 1.

VCI derived from EVI (VCI_E)

VCI_E was derived from base index EVI by using following equation.

$$VCI_E = (EVI_i - EVI_{min})/ (EVI_{max} - EVI_{min}) \times 100 \quad \ldots(2)$$

VCI_E indicates how close the EVI of the current period (EVI_i)is to the minimum EVI (EVI_{min}). Here, the maximum EVI (EVI_{max}) and minimum EVI (EVI_{min}) were calculated from the long-term record for that particular period. The range of VCI_E is between 0 and 1.

Water condition index (WCI)

Water Condition Index (WCI) was derived from base index NDWI (Normalized Difference Water Index). NDWI measures the moisture conditions of vegetation canopies. it was calculated by using satellite (MODIS) data from 2nd Jun to 16th Oct (16 days' interval) for *kharif* crop growing period for 15 years (2000-2014) with the help of following equation (Gu *et al.*, 2008).

$$NDWI = \frac{\rho\, NIR - \rho\, SWIR}{\rho\, NIR + \rho\, SWIR} \quad \ldots(3)$$

Where ρ *NIR* and ρ *SWIR* are the reflectances forbands 2 (841–876 nm) and 7 (2105–2155 nm) of surface reflectance (SR) product (MODIS), respectively. WCI was computed using following equation.

$$WCI = (NDWI_i - NDWI_{min})/(NDWI_{max} - NDWI_{min}) \times 100 \quad \ldots(4)$$

Table 1. Drought classification based on VCI

Agricultural conditions	VCI
Severe drought	< 0.35
Moderate drought	0.35-0.50
Normal (No drought)	> 0.50

Source: Kogan (1995)

WCI indicates how close the NDWI of the current period ($NDWI_i$) is to the minimum NDWI ($NDWI_{min}$). Here, the maximum NDWI ($NDWI_{max}$) and minimum NDWI ($NDWI_{min}$) were calculated from the long-term record for that particular period. The range of WCI is between 0 and 1.

The severity of drought expressed in term of severe and moderate drought adopted from Kogan (1995) classification scheme (Table 1).

The indices i.e. $VCI_{N,}$ VCI_E and WCI were calculated at every 16-day intervals from 2nd Jun to 16th Oct (*kharif* season) for 15 years (2000-2014) and average value for whole season (2nd Jun to 16th Oct) for each year was used for drought characterization.

Evaluation of drought indices

To identify the most suitable drought index for characterization of agricultural drought in the region, a correlation analysis was carried out between area under drought observed by $VCI_{N,}$ VCI_E and WCI and foodgrain production of region.

Results and Discussion

Agricultural drought was characterized by using remote sensing based indices i.e. $VCI_{N,}$ VCI_E and WCI. These indices were computed for *kharif* growing season from 2nd June- 16th November (16-day intervals) for 15 years (2000-2014). The average values of drought indices ($VCI_{N,}$ VCI_E and WCI) from 2nd June- 16th November were used to compute areal extent of drought affected area under different categories i.e. severe and moderate drought. According to India Meteorological Department (IMD) when the spatial coverage of drought is more than 40%, it could be considered as severe drought year (Attri and Tyagi, 2010). Severe drought year observed by $VCI_{N,}$ VCI_E and WCI are explained here.

VCI derived from NDVI (VCI_N)

Spatio-temporal conditions of drought for *kharif* crop growing period (June – October) for 15 years were studied through VCI_N (Fig. 2). The maximum area under severe and moderate drought was observed in year 2003 (52.15%) and year

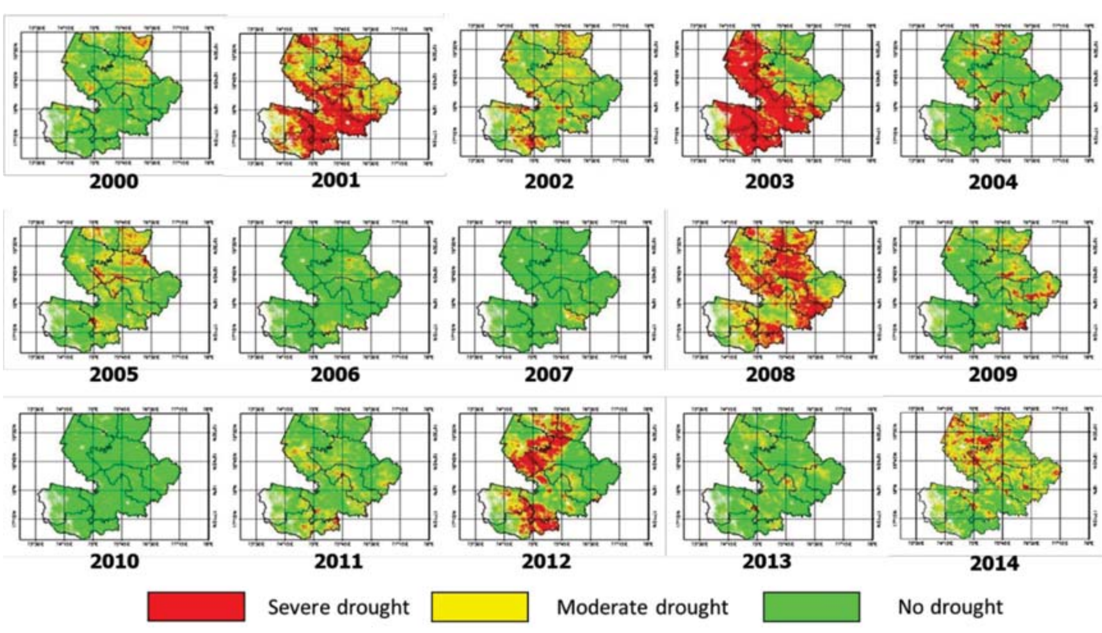

Fig. 2. Spatio-temporal conditions of agricultural drought observed by VCI_N during *kharif* season

2014 (49.27%), respectively, during *kharif* season. In the years 2001 and 2003 area under severe drought was observed more than 40%. Area under both severe and moderate drought was observed more than 40% in the years 2001, 2002, 2003, 2005, 2008, 2011, 2012 and 2014 (Table 2).

VCI derived from EVI (VCI_E)

Spatio-temporal conditions of drought for *kharif* crop growing period (June – October) for 15 years were studied through VCI_E (Fig. 3). The maximum area under severe and moderate drought was observed in year 2008 (61.08%) and year 2002 (48.89%), respectively, during kharif season. In the years 2001, 2003, 2008 and 2012 area under severe drought was observed more than 40%. Area under both severe and moderate drought was observed more than 40% in all the years except 2006, 2007 and 2010 (Table 2).

Water condition index (WCI)

Water Condition Index (WCI) derived from NDWI (Normalized Difference Water Index). Similar to VCI_N and $VCI_{E,}$ WCI was also computed for same period. Spatio-temporal conditions of drought for *kharif* crop growing season for 15 years studied through WCI is shown in Fig. 4. The maximum area under severe and moderate drought was observed in year 2003 (59.20%) and year 2008 (54.96%), respectively during *kharif* season. In the years 2002 and 2003 area under severe drought was observed more than 40%. Area under both severe and moderate drought was observed more than 40% in all the years except 2006, 2007, 2010 and 2013 (Table 2).

These indices are quite sensitive and capable to observe drought in the region however, sensitivity of the drought indicators were found different in term of severity both spatially and temporally.

VCI_N observed year 2001, 2002, 2003, 2005, 2008, 2011, 2012 and 2014 as severe drought years while VCI_E observed year 2000, 2004, 2009 and 2013 as severe drought years in addition to that of VCI_N. WCI observed 2000, 2004 and 2009 as severe drought years in addition to that of VCI_N. All the three remote sensing indices have different range of sensitivity for drought detection and this was why they have observed different extent and severity of drought. Total drought area (%) observed by these drought indices was

Table 2. Agricultural drought (area in %) observed by $VCI_{N,}$ VCI_E and WCI for 15 years during *kharif* season.

Years	VCI_N		VCI_E		WCI	
	Severe drought	Moderate drought	Severe drought	Moderate drought	Severe drought	Moderate drought
2000	3.24	31.83	10.24	44.72	14.43	49.27
2001	48.33	42.57	50.89	36.80	18.19	47.11
2002	9.98	48.63	31.73	48.89	46.33	42.85
2003	52.15	28.09	56.36	25.59	59.20	26.94
2004	5.94	28.01	14.01	30.12	8.86	39.77
2005	7.25	40.13	28.09	41.60	13.33	48.98
2006	1.41	14.84	2.26	12.64	4.24	31.06
2007	0.86	11.66	0.73	7.56	0.93	20.38
2008	36.64	46.24	61.08	29.78	16.05	54.96
2009	6.29	31.25	14.86	40.20	13.33	51.48
2010	0.23	5.19	0.43	6.42	1.80	17.25
2011	4.81	35.25	14.83	47.10	11.33	46.07
2012	24.65	34.02	44.39	30.76	38.14	36.38
2013	2.83	24.07	13.68	39.11	2.06	17.74
2014	11.17	49.27	29.71	39.21	27.58	40.12

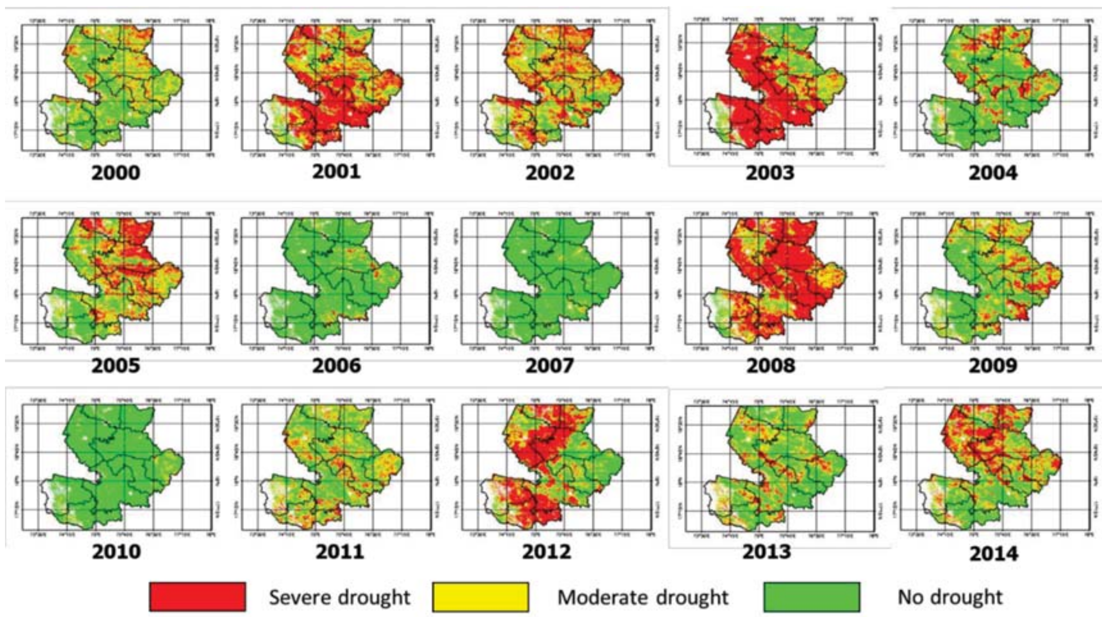

Fig. 3. Spatio-temporal conditions of agricultural drought observed by VCI_E during *kharif* season

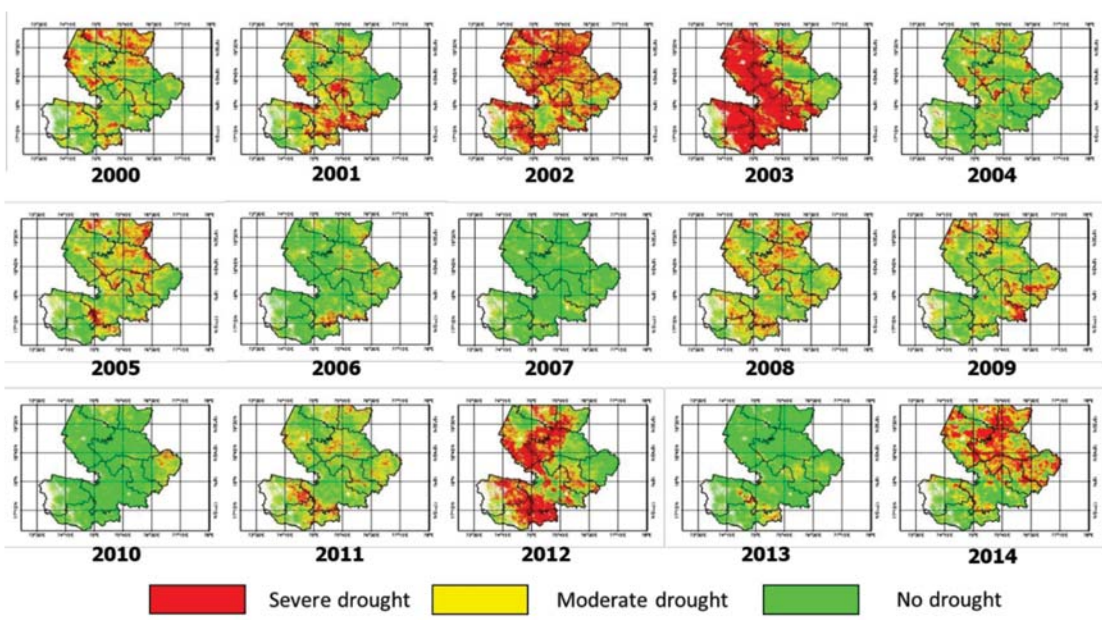

Fig. 4. Spatio-temporal conditions of agricultural drought observed by WCI during *kharif* season

correlated with foodgrain production of the region to identify the appropriate index for drought characterization.

Evaluation of remote sensing based indices (VCI_N, VCI_E and WCI) with foodgrain production

Agricultural drought characterized by remote-sensing based indices was evaluated using foodgrain production of the region. As drought has adverse impact on crop growth and development ultimately affect the foodgrain production. Correlation analysis among $VCI_{N,}$ $VCI_{E,}$ WCI and food grain productions, indicates significant correlation among them. $VCI_{N,}$ $VCI_{E,}$ and WCI were also strongly correlated to each-other. VCI_N strongly correlated with VCI_E and WCI as their correlation coefficient found to be

Table 3. Pearson correlation coefficients (r) among VCI_N, VCI_E and WCI

Drought index	Foodgrain production	VCI_N	VCI_E	WCI
VCI_N	-0.811**	1		
VCI_E	-0.696**	0.927**	1	
WCI	-0.775**	0.807**	0.846**	1

** Significant at the 0.01 level

0.927 and 0.807, respectively (Table 3). Gu *et al.* (2007) found strong relationships among NDVI, NDWI, and drought conditions in central USA. VCI_N had maximum correlation coefficient (r = -0.811) with foodgrain production (Table 3). Patel and Yadav, (2015) had also reported that VCI found to be significantly correlated to drought stress in terms crop yield anomaly of both food grains and pulses. Moreover, correlation coefficient of VCI_N with foodgrain production is slightly higher than that of WCI and $VCI_{E.}$ Zhang *et al.* (2017) found that standardized anomalies of NDVI were more sensitive to drought than that of EVI in southwestern China. Mu *et al.* (2006) also reported that NDWI is not as much sensitive to drought as VCI_N during the growing period.

Conclusion

Agricultural drought was characterized by using remote sensing based indices during *kharif* crop growing season. The strong correlation among the remote sensing indices ($VCI_{N,}$ $VCI_{E,}$ and WCI) indicated that either index can be used for agricultural drought characterization. However, the maximum correlation between VCI_N and foodgrain production implies that VCI_N is most suitable drought index to characterize agricultural drought in the region.

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