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Improving remote sensing based agricultural drought characterization in Saurashtra, Gujarat : A region-specific threshold approach

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सार – सुदूर संवेदन तकनीक ने वैश्विक स्तर पर कृषि सूखे की निगरानी और मानचित्रण में अपनी महत्वपूर्ण उपयोगिता प्रदर्शित की है। यह अध्ययन भारत में गुजरात के सौराष्ट्र क्षेत्र में कृषि सूखे के आकलन पर केंद्रित है, जिसमें लैंड्स और सेंटिनल उपग्रहों से 33 वर्षों के व्यापक डेटासेट का उपयोग किया गया। इसने सूखे की स्थिति का आकलन करने के लिए NDVI (सामान्यीकृत अंतर वनस्पति सूचकांक), असंगति सूचकांक (NAI), वनस्पति स्थिति सूचकांक (VCI), और NDWI असंगति सूचकांक (NDWIA) सहित विभिन्न वनस्पति सूचकांकों को नियोजित किया। इन सूचकांकों के प्रदर्शन का मूल्यांकन सूखे की प्रचंडता मानचित्रों के निर्माण और क्षेत्र की प्रमुख खरीफ फसलों, विशेष रूप से कपास और मूंगफली के साथ उनके सहसंबंध विश्लेषण के माध्यम से किया गया। विश्लेषण में 1986, 1987, 1991, 2000, 2002 और 2012 जैसे प्रमुख कृषि सूखे वर्षों को इंगित किया गया, जो कपास के लिए 37% से 76% और मूंगफली के लिए 66% से 95% तक की फसल उपज हानि के अनुरूप थे जो जिले के अनुसार अलग-अलग थे। विभिन्न जिलों में NAI की तुलना में VCI द्वारा फसल की पैदावार (कपास के लिए 0.32 से 0.73 और मूंगफली के लिए 0.33 से 0.75 तक) के साथ समतुल्य या बेहतर सहसंबंध प्रदर्शित करने के बावजूद, यह सूखे की प्रचंडता को कम आंकने की प्रवृत्ति रखता है, विभिन्न जिलों के लिए केवल 2 से 9 सूखे वर्ष निर्दिष्ट करता है। नतीजतन, यह अध्ययन संशोधित VCI सूखा प्रचंडता सीमा की सिफारिश करता है, जो प्रचंडता के स्तर और गुजरात के सौराष्ट्र क्षेत्र में कपास और मूंगफली के लिए उपज के नुकसान के संदर्भ में कृषि सूखे के वर्गीकरण को बढ़ाता है। इसके अलावा, यह कृषि सूखे की प्रभावी मात्रा के निर्धारण के लिए सबसे उपयुक्त वनस्पति सूचकांक की पहचान करके क्षेत्र-विशिष्ट सूखा प्रचंडता सीमा स्थापित करने की आवश्यकता को रेखांकित करता है, जिससे सूखा शमन उपायों की सुविधा मिलती है।

ABSTRACT. Remote sensing technology has demonstrated its significant utility in the monitoring and mapping of agricultural drought on a global scale. This study focused on the assessment of agricultural drought in the Saurashtra region of Gujarat, India, utilizing a comprehensive dataset spanning 33 years from Landsat and Sentinel satellites. It employed various vegetation indices, including NDVI (Normalized Difference Vegetation Index), Anomaly Index (NAI), Vegetation Condition Index (VCI) and NDWI Anomaly index (NDWIA), to gauge drought conditions. The performance of these indices was evaluated through the generation of drought severity maps and their correlation analysis with major *Kharif* crops in the region, specifically cotton and groundnut. The analysis pinpointed major agricultural drought years, such as 1986, 1987, 1991, 2000, 2002 and 2012, which corresponded to substantial crop yield losses ranging from 37% to 76% for cotton and 66% to 95% for groundnut, varying by district. Despite VCI demonstrating equivalent or superior correlations with crop yields (ranging from 0.32 to 0.73 for cotton and 0.33 to 0.75 for groundnut) compared to NAI in various districts, it tended to underestimate drought severities, designating only 2 to 9 drought years for different districts. Consequently, this study recommends revised VCI drought severity thresholds, which enhance the categorization of agricultural drought in terms of severity levels and corresponding yield losses for cotton and groundnut in the Saurashtra region of Gujarat. Furthermore, it underscores the need to establish region-specific drought severity thresholds by identifying the most suitable vegetation index for effective quantification of agricultural drought, thereby facilitating informed drought mitigation measures.

Key words – Agricultural drought, NDVI, Vegetation condition index, Landsat, Cotton, Groundnut.

1. Introduction

Drought is a recurrent feature of the arid and semi-arid regions, which may lead to depletion of surface and sub-surface water resources, crop failure and reduced food & fodder availability affecting humans, livestock, and wildlife. Drought can be categorized into four types *i.e.*, Meteorological, Hydrological, Agricultural and Socioeconomic drought (Wilhite and Glantz, 1985). Agricultural drought is characterized by poor crop health and a reduction in crop production as a result of soil moisture deficiency due to inadequate rainfall coupled with higher evapotranspiration rates.

The meteorological drought indices assemble information from point data on parameters like rainfall, temperature, soil moisture, evapotranspiration, *etc*. and found capable to be linked with agricultural droughts up to a certain extent. The traditional practices of quantifying agricultural droughts in India involve decisions based on meteorological indices as well as judging the crop conditions based on eye estimations and crop-cutting surveys (Anonymous, 2016). However, meteorological drought indices do not reflect spatial patterns of agricultural drought more clearly, while eye estimations and crop-cutting experiments require several resources, and estimates across larger geographical regions are available very late. One of the potential solutions to the above-mentioned difficulties is to use remote sensing-based vegetation drought indices for quantifying agricultural droughts. The improvement in capabilities of remote sensing satellites in terms of spatial, spectral, and temporal resolutions as well as availability as open-source products have inspired researchers to incorporate several vegetation indices in agricultural drought characterization (Dong *et al*., 2019; He *et al*., 2019; Tuvdendorj *et al*., 2019; Pandya *et al*., 2022). Out of several possible options for satellite data, AVHRR, MODIS, Landsat, and Sentinel-derived products are most widely used for agricultural drought analysis (Kundu *et al*., 2016; Tran *et al*., 2017; Faridatul and Ahmed, 2020; Marusig *et al*., 2020; Mohammed *et al*., 2020; Sur and Lunagaria, 2020). The agricultural drought was quantified efficiently using remote-sensing based indices like the NDVI anomaly Index, Vegetation Condition Index (VCI), Temperature Condition Index (TCI), Vegetation Health Index (VHI), Temperature Vegetation Index (TVX), Temperature Vegetation Index (TVI), Normalized Difference Water Index (NDWI), *etc*. (Osman *et al*., 2014; Dong *et al*., 2019; He *et al*., 2019; Tuvdendorj *et al*., 2019; Lim *et al*., 2019; Lunagaria and Sur, 2019). Each index and satellite product has its strength and limitations and their choice depends on several factors, including crop, climate, geographical extent, length of data required, the purpose of analysis, *etc*. Hence, it is necessary to evaluate and validate the suitability of vegetation indices and satellite data products for specific regions and crops. The universal thresholds defined by various indices to classify droughts in various categories such as no drought or mild, moderate, severe, and extreme drought may have a possibility to overestimate or underestimate drought severity category due to the complex interactions soil, water, plant and climate across different regions of the globe. Hence, it is also necessary to validate the drought severity categories classification by vegetation indices by studying historic droughts using long-term records.

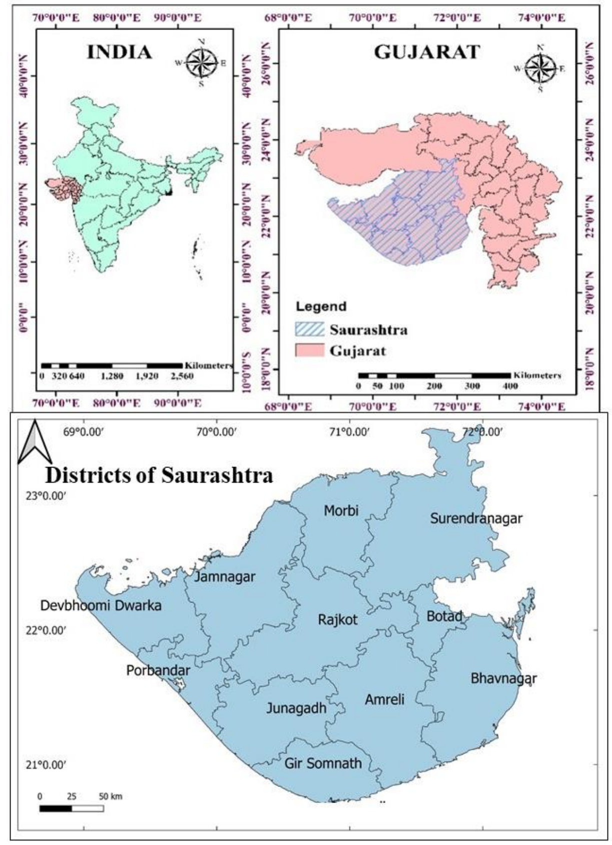

Fig. 1. Location of the study area

Indian agriculture is heavily dependent on the southwest monsoon season (June-September) and has experienced an increase in intensity and percentage of areas affected by droughts along with frequent occurrence of multi-year droughts during recent decades (Niranjan *et al.*, 2013; Mallya *et al.*, 2016; Pandya *et al.*, 2023). Gujarat is a chronic drought-prone state in India with substantial portions of the state being arid and semiarid. The Saurashtra region of Gujarat state is vulnerable to drought conditions due to rainfed crop production systems with less irrigation facilitates (Pathak *et al.*, 2016; Pandya *et al*., 2020; Sur and Lunagaria, 2020).

TABLE 1

Details of data used in the study

Type of data	Duration	Temporal Resolution	Spatial Resolution	Source
Crop yield data	1980-2019	Yearly	District average	Directorate of Agriculture, Govt. of Gujarat
Satellite data	1986-2016 (except 1988)	Yearly Late Sep. / early Oct.	30 m × 30 m	Landsat 5, Landsat 7 & Landsat 8 Thematic Mapper (TM). https://earthexplorer.usgs.gov/
	2017-2019	Yearly Late Sep. / early Oct.	10 m × 10 m and 20 m × 20 m	Sentinel-2 https://scihub.copernicus.eu/

The effectiveness of agricultural drought assessment, support for the farming community, and mitigation planning hinges upon the precise quantification of drought categories, ranging from no drought to mild, moderate, severe, and extreme drought. In this study, we utilized three widely recognized vegetation indices derived from long-term remote sensing data to investigate their efficacy in quantifying historical agricultural drought events within the Saurashtra region of Gujarat. Our research revealed the need to recalibrate the Vegetation Condition Index (VCI) drought severity thresholds specifically for this region. As a result, region-specific VCI drought severity thresholds were proposed, enabling more accurate quantification of agricultural drought severity levels and corresponding crop yield losses.

2. Data and methodology

2.1. *Description of the study area and data used for the study*

The present study was conducted in the semi-arid Saurashtra region of Gujarat State (India) located in the extreme west of India (Fig. 1). The region is spread over a 6.49 Mha area covering 11 districts. Seasonal rainfall plays a significant role in crop production in the region. The *Kharif* crops are sown in the middle of June depending on the commencement of rainfall. Groundnut and cotton are the major *Kharif* crops of the Saurashtra region. The satellite-derived indices were estimated for 33 years (1986 to 2019, except 1988). Details of remote sensing data used in the study are given in Table 1. The satellite images of Landsat 5, Landsat 7, and Landsat 8 Thematic Mapper (TM) with a spatial resolution of 30 meters were used for analysis. The surface reflectance from the Landsat program is already preprocessed and it is a Level-2 product, thus, it eliminates the need for any further atmospheric correction (Osman *et al.*, 2014; Ghaleb *et al.*, 2015). For the year 1986, Landsat MSS (Multi-spectral scanner) was utilized while for the year, 2017 to 2019, Sentinel-2 data having a spatial resolution of 10/20 meters were utilized. Due to the data deficit of Landsat products in 1988 across the Indian subcontinent, especially in western India, no data sources were found available, so the year 1988 was excluded from the study to estimate vegetation indices.

2.2. *Estimation of satellite-based indices*

The estimation of vegetation indices and preparation of drought severity maps were performed using QGIS open source environment. The crop masking was also performed using ESRI land cover to remove the influence of non-cropped areas in the estimation of vegetation indices. The vegetation indices were estimated for the duration of late September/early October when cotton and groundnut crops are at the maximum vegetation growth stage during this period. The computation of indices was performed to judge the anomalies in crop development for each year under the study. The study used three vegetation-based indices, NDVI Anomaly Index (NAI), Vegetation Condition Index (VCI), and NDWI Anomaly Index (NDWIA) which were computed using equations given below.

(*i*) NDVI Anomaly Index (NAI)

It may be defined as the deviation of NDVI values from the long-term mean of NDVI values. The NDVI Anomaly Index (NAI) (Anyamba *et al.*, 2001) is estimated as:

$$NAI = \frac{NDVI_i - NDVI_{mean}}{NDVI_{mean}} X100 \tag{1}$$

$NDVI_i$ is NDVI for a particular month, $NDVI_{mean}$ is the long-term mean NDVI.

TABLE 2

Drought severity categories of various vegetation drought indices

Category	NAI	VCI	NDWI Anomaly
No Drought	>0	>40	>0
Mild drought	0 to -10	30 to 40	0 to -1
Moderately drought	-10 to -25	20 to 30	-1 to -2
Severe drought	-25 to -50	10 to 20	-2 to -3
Extremely drought	Below -50	<10	-3 to -4

(*ii*) Vegetation Condition Index (VCI)

It shows how close the NDVI of the current year is to the minimum NDVI calculated from the long-term record, and thus, separates the short-term weather-related fluctuations from long-term ecosystem changes. The VCI values range between 0 and 100, which reflect relative changes in the vegetation conditions from bad to optimal. The drought categories based on VCI are as given in Table 2.

It is calculated with the following formula (Kogan, 1995 and Kogan, 1997)

$$\text{VCIj} = \frac{(\text{NDVIj} - \text{NDVI}_{\text{min}})}{(\text{NDVI}_{\text{max}} - \text{NDVI}_{\text{min}})} \text{X} 100 \tag{2}$$

NDVIj is NDVI for a particular month/year, NDVI_{max} and NDVI_{min} are maximum NDVI and minimum NDVI, calculated by the corresponding pixels in the same period from the long-term NDVI values.

(*iii*) NDWI Anomaly Index (NDWIA)

NDWI is computed using near infrared NIR and short wave infrared (SWIR) reflectance. The Shortwave Infrared (SWIR) band is sensitive to moisture available in the soil as well as in the crop canopy. NDWI using SWIR can complement NDVI for drought assessment. Higher values of NDWI signify more surface wetness (Gao, 1996).

The NDWI can be calculated as follows (Gao, 1996).

$$\text{NDWI}_{t} = \frac{\text{NIR}_{t} - \text{SWIR}_{t}}{\text{NIR}_{t} + \text{SWIR}_{t}} \tag{3}$$

NIR and SWIR are the reflected radiation in Near Infrared and Shortwave Infrared channels.

$$\text{NDWI Anomaly} = \frac{\text{X}_{t} - \overline{\text{X}}}{\delta} \tag{4}$$

X_t = NDWI of the particular period of the particular month/year

$\bar{X}$ = long-term average NDWI

δ = standard deviation calculated for the same period using the available time series.

The drought severity categories by various drought indices are given in Table 2.

The indices were compared based on their behaviors to classify the historic years under various drought categories and also with Pearson's correlation coefficient (r) between vegetation indices and *Kharif* crop yields. The drought severities thresholds categories were also validated and necessary revision was suggested for better quantification of agricultural drought in terms of crop yield losses.

3. Results and discussion

3.1. *Temporal and spatial agricultural drought characterization based on vegetation drought indices*

The comparison of vegetation drought indices NAI, VCI, and NDWIA over a long period at the same location provides information about the relative health of the vegetation in a given year. As crop yields were available at the district scale, values of NAI, VCI, and NDWIA were averaged over at the district scale using zonal statistics in QGIS. Based on the district-wise average values NAI, VCI, and NDWIA, the number of drought years with categories as mild, moderate, severe and extreme by vegetation indices are presented in Table 3. It can be observed from Table 3 that for various districts,

TABLE 3

Number of drought years under various severity categories by vegetation indices out of 33 years

District	Vegetation Index	No Drought	Mild	Moderate	Severe	Extreme
Amreli	NAI	16	7	6	2	2
	VCI	29	2	0	1	1
	NDWIA	14	16	2	1	0
Bhavnagar	NAI	18	5	6	2	2
	VCI	29	2	1	0	1
	NDWIA	16	14	2	1	0
Botad	NAI	15	5	8	3	2
	VCI	28	3	0	1	1
	NDWIA	14	16	2	1	0
Dev. Dwarka	NAI	17	1	8	4	3
	VCI	26	4	1	1	1
	NDWIA	16	14	3	0	0
Girsomnath	NAI	16	9	6	0	2
	VCI	31	0	0	1	1
	NDWIA	15	15	2	1	0
Jamnagar	NAI	18	1	7	5	2
	VCI	27	4	1	0	1
	NDWIA	17	12	3	1	0
Junagadh	NAI	13	9	8	1	2
	VCI	31	0	0	1	1
	NDWIA	14	16	3	0	0
Morbi	NAI	15	3	8	5	2
	VCI	24	7	0	1	1
	NDWIA	15	15	2	1	0
Porbandar	NAI	17	5	8	1	2
	VCI	29	2	1	0	1
	NDWIA	14	16	2	1	0
Rajkot	NAI	15	7	6	3	2
	VCI	30	1	0	1	1
	NDWIA	15	15	2	1	0
Surendranagar	NAI	15	5	9	2	2
	VCI	29	2	0	1	1
	NDWIA	15	15	2	1	0

NAI indicated 15 to 20 years under drought out of 33 years among which 1 to 9 years were under mild, 6 to 9 years under moderate, 0 to 5 years under severe and 2 to 3 years were under extreme drought categories. Districts Junagadh, Gir Somnath, and Rajkot suffered from high drought frequency but the severity was low with more years under mild and moderate drought categories. The more severe droughts were dominant in the districts

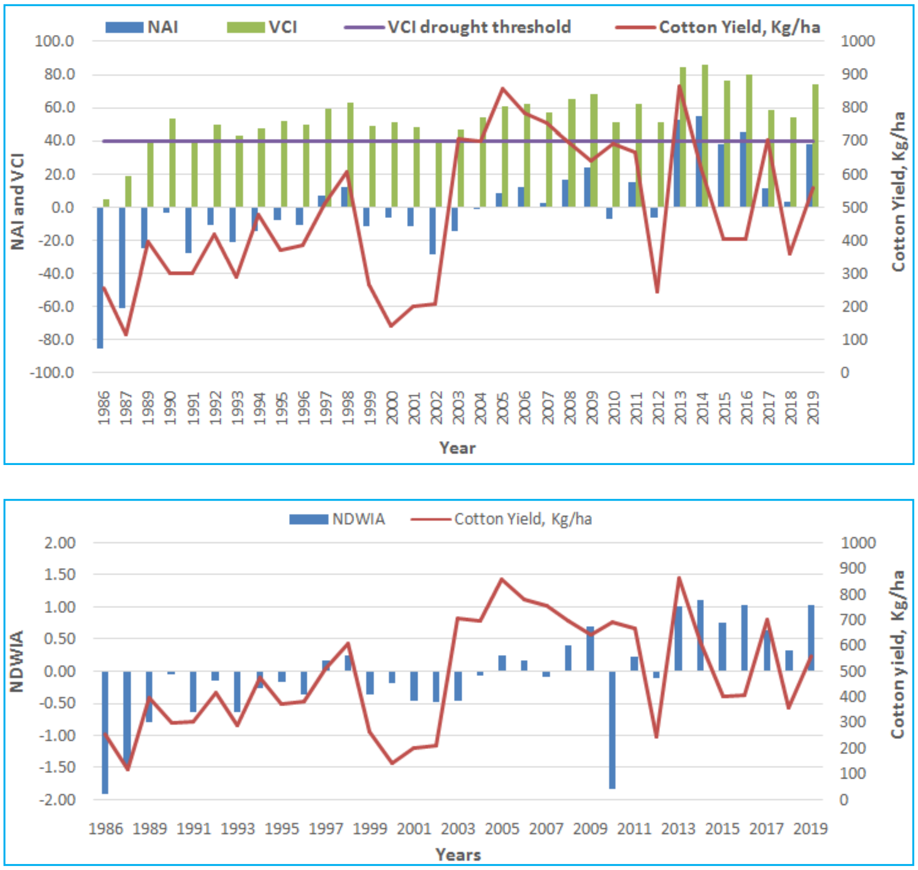

Fig. 2. Average historic NAI, VCI and NDWIA and productivity of cotton in various districts of Saurashtra (1986-2019)

Devbhumi Dwarka, Jamnagar and Morbi with 7 years under severe or extreme drought categories as per NAI. The VCI showed less drought frequency as compared to NAI with a total number of drought years ranging between 2 to 9 for various districts. The VCI designated most of the mild and many moderate drought years under NAI as non-drought years. The districts Junagadh, Girsomanth, and Rajkot showed a high number of weak droughts by NAI which were fallen under the no drought category by VCI. VCI showed only 2 to 3 drought years out of 30 years in these three districts. Bayissa *et al.* (2019) also mentioned this fact during the study in Ethiopia, where VCI registered a smaller magnitude of drought severity in some cases as compared to other drought indices. It is clear from the historic drought analysis results that VCI has underestimated the drought severities as compared to NAI even though both indices are based on NDVI.

The NDWIA showed 16 to 19 years of droughts which included no extreme drought events, 0 to 1 severe drought, 2 to 3 moderate droughts, and 12 to 16 mild drought events for various districts. NDWIA showed less spatial variation in terms of average NDWIA in various districts as compared to NAI and VCI. The drought frequency by NDWIA was analogous to NAI but showed weaker severities.

The historic average values of NAI, VCI, and NDWIA and the corresponding crop yield of cotton and groundnut for Saurashtra were plotted in Figs. 2&3 respectively to analyze historic agricultural droughts in the region. It can be observed that the years 1986 and 1987 were the most detrimental drought years in the region with an average crop yield loss of 47% and 45% in the year 1986 and as high as 76% and 95% in the year 1987 for cotton and groundnut respectively. The disastrous effects of the 1987 droughts due to consecutively high rainfall deficiencies in the years 1986 and 1987 were documented in several studies in terms of huge loss to agriculture, livestock, water resources, and the economy (Gupta *et al.*, 2011; Kaushalya *et al.*, 2015; Bandyopadhyay and Saha, 2016). These observations are also reflected in the severities of NAI, VCI and NDWIA in the present study. In addition to this, the years 1991, 1999 to 2000 and 2012

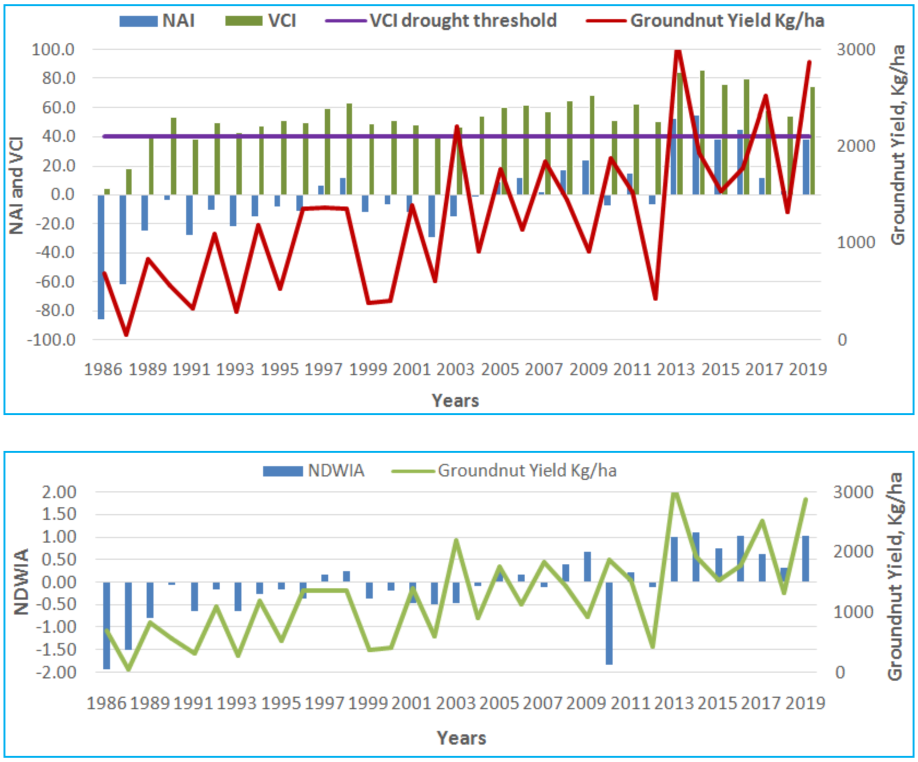

Fig. 3. Average historic NAI, VCI and NDWIA and productivity of groundnut in various districts of Saurashtra (1986-2019)

were other significant drought years showing low values of NAI, VCI and NDWIA. The average crop yield loss of cotton and groundnut for these drought years ranged between 37 to 71% for cotton and 66% to 75% for groundnut. The indices also revealed that no major agricultural drought was observed in Saurashtra after 2012 except mild/moderate drought in the year 2018. For comparing the drought characterization behavior of NAI, VCI and NDWIA to detect spatial patterns in drought years 1987, 1991, 1991 2000 and 2012 covering various drought severity ranges and each decade under study are generated as displayed in Fig. 4.

The spatial variability of the 1987 year drought suggests that the entire region suffered from agricultural droughts, with NAI showing almost the entire region under severe droughts, VCI showing part of the eastern side of the region under extreme or severe droughts and the western side of the region under severe or moderate droughts. The NDWIA underestimated the 1987 year drought in a few parts of Amreli, Girsomanth, Junagadh, Rajkot, and Bhavnagar districts under severe drought and the rest of the region under moderate drought. The average NAI, VCI and NDWIA ranged between -55.3 to -67.9, 14.1 to 22.6, and -1.1 to -2.0 respectively for various districts in 1987. Gupta *et al*. (2011) also confirmed the fact, stating that the NAI for Gujarat ranged between -30 to -100 due to heavy scarcity of rainfall in the year 1987. The results also match well with a study by Kaushalya *et al*. (2015) and Bandyopadhyay and Saha (2016). The drought severity maps of the year 1991 indicate that the extreme northwest part of the region suffered from extreme and severe droughts, and the eastern part of the region covering districts Botad, Bhavnagar, and Amreli faced severe drought as per NAI. While the districts of south Saurashtra and Rajkot were observed with moderate/mild droughts in the year 1991. The VCI showed a majority of the portion of south Saurashtra as drought-free, and the rest of the region under mild or moderate drought. Only a few pockets in the northern part of Devbhumi Dwarka were observed under extreme drought as per VCI in the year 1991. While NDWIA showed almost the entire region under mild drought except for a few pockets in South Saurashtra. The average NAI, VCI and NDWIA ranged between -9.7 to -42.2, 30.5 to 50.1, and -0.3 to -0.9 respectively for various districts in 1991.

The spatial drought patterns based on NAI for the year 2000 suggest moderate to severe drought was observed in the eastern part of the region while mild or no drought was observed in the extreme west of the region. The same pattern was observed for NDWIA but with a low drought severity range. While VCI showed the entire

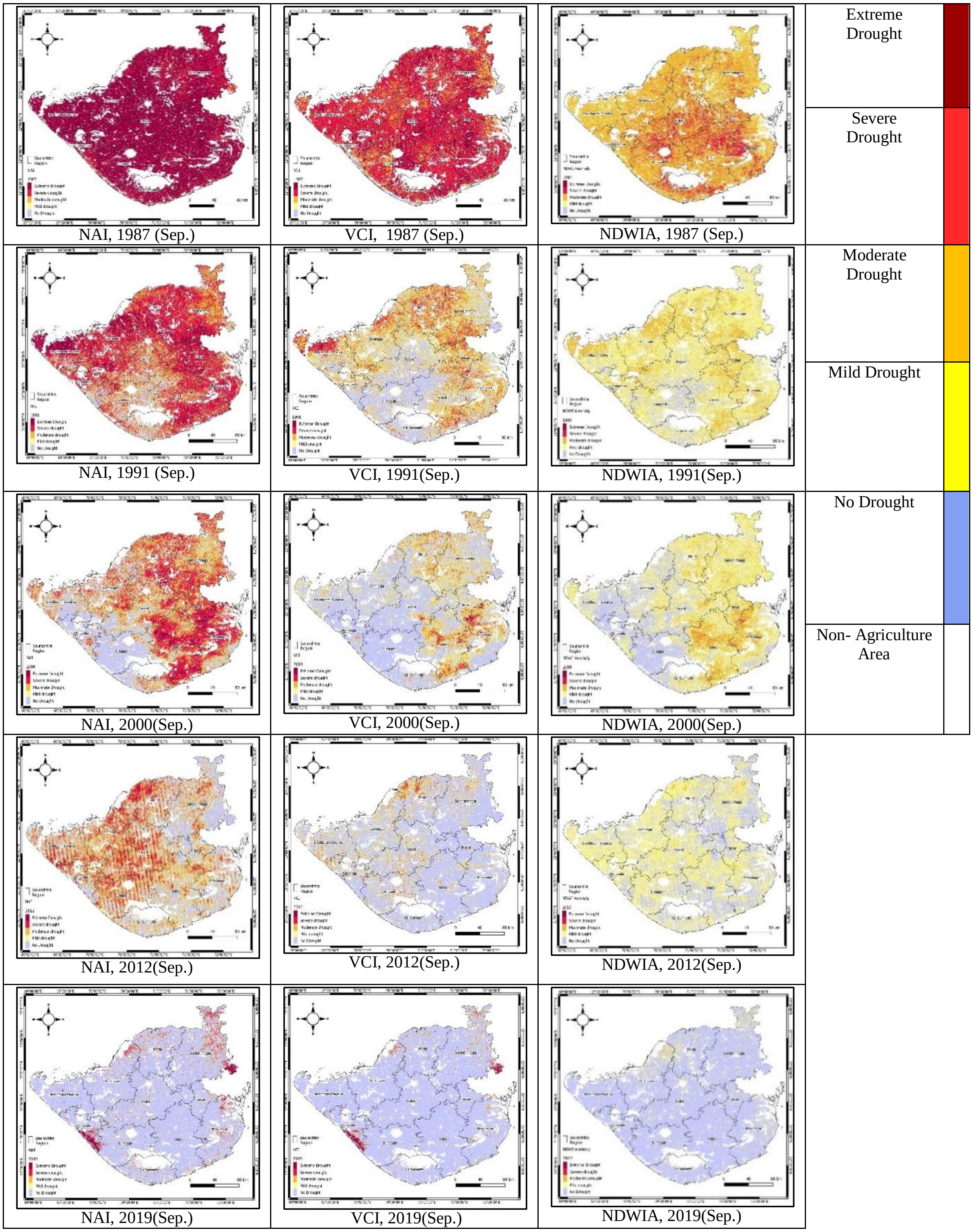

Fig. 4. Spatial patterns of selected years by NAI, VCI and NDWIA vegetation indices

TABLE 4

Correlations between vegetation indices and crop yields

District	Cotton			Groundnut		
	NAI	VCI	NDWIA	NAI	VCI	NDWIA
Amreli	0.50	0.50	0.31 NS	0.48	0.47	0.36
Bhavnagar	0.35	0.43	0.28 NS	0.61	0.61	0.50
Botad	0.52	0.52	0.38	0.73	0.72	0.61
Dev. Dwarka	0.52	0.53	0.40	0.62	0.62	0.49
Gir Somnath	0.44	0.45	0.42	0.55	0.51	0.52
Jamnagar	0.54	0.53	0.65	0.70	0.68	0.67
Junagadh	0.28 NS	0.32 NS	0.24 NS	0.31 NS	0.33 NS	0.20
Morbi	0.65	0.65	0.51	0.57	0.54	0.40
Porbandar	0.30 NS	0.34 NS	0.32 NS	0.45	0.42	0.51
Rajkot	0.43	0.42	0.31 NS	0.46	0.44	0.33 NS
Surendranagar	0.74	0.73	0.51	0.77	0.75	0.66

NS = Non Significant, Except NS, all are significant with P<0.05

region drought-free, expect a few pockets on the eastern side. Overall, severity values of all three indices suggested that for the year 2000, high drought severities were observed in the eastern half of the region as compared to the western half, the same was also reflected in crop yields of cotton and groundnut in the year 2000.

The average crop yield anomalies of cotton and groundnut in 2000 for districts laid in the western part, *i.e*., Devbhumi Dwarka, Jamnagar, Junagadh, Porbandar, and Girsomnath was -59% and -57% respectively, while for the rest of the districts representing the eastern part, the crop yield anomalies of cotton and groundnut were -78% and -81% respectively. This conformation shows the effectiveness of vegetation-based indices to quantify spatial variations of agricultural droughts. The average NAI, VCI and NDWIA for various districts ranged between 19.4 to -28.4, 98.5 to 69.1 and -0.43 to 0.82 respectively for the year 2000.

The year 2012 also observed drought. However, the spatial variability in terms of drought severities was reversed from that of the year 2000 as depicted by all indices. The major areas of the region in extreme eastern and extreme southern parts observed no drought or mild droughts as per NAI, while the drought severity of the northwestern parts experienced moderate to severe droughts. The average yield anomalies of the northwestern parts the districts were very high (-63% for cotton and -92% for groundnut) as compared to the rest of the districts, (-33% for cotton and -58%). The average NAI, VCI and NDWIA for various districts ranged between 7.2 to -16.5, 44.6 to 61.6, and 0.05 to -0.25 respectively for the year 2012. In addition to drought years, the severity maps of the non-drought year 2019 were also prepared to illustrate the capability of vegetation indices to examine the non-drought conditions. The year 2019 was observed with adequate rainfall sufficiently meeting the crop water requirement of cotton and groundnut across Saurashtra as shown in Fig. 4. The maps of NAI and VCI for the year 2019 revealed that the entire Saurashtra was drought-free except for Porbandar district and a few areas of Surendranagar, while NDWIA showed the entire region as drought-free. The average yield of cotton and groundnut were observed to be 557 kg/ha (25% higher than average) and 2875 kg/ha (145% higher than average) respectively, which confirms the effectiveness of various vegetation drought indices considered for the study to describe good crop health conditions. Moreover, the remote sensing-based vegetation drought indices have shown the capability to serve as a useful tool for analyzing the spatial variations in drought severities in a region, which is crucial prioritization for efficient drought mitigation measures and resource allocation.

3.2. *Correlations between drought indices and crop yields*

The performance vegetation indices were tested to explain the yield variability of cotton and groundnut crops in terms of correlations of the indices with crop yields. The correlations of vegetation indices with cotton and groundnut yield are shown in Table 4. The correlation coefficient *r* for groundnut was ranged between 0.28 to

TABLE 5

Existing and revised (RVCI) drought severity thresholds and corresponding average crop yield anomalies

Drought Categories	VCI	RVCI	Cotton Yield Anomalies, %		Groundnut Yield Anomalies, %	
			VCI	RVCI	VCI	RVCI
No Drought	>40	>55	09	34	11.5	28
Mild Drought	30 to 40	45-55	-52	-12	-70	-16
Moderate Drought	20 to 30	35-45	-56	-25	-89	-25
Severe Drought	10 to 20	20-35	-79.6	-53	-96.2	-85
Extreme Drought	<10	<20	-48.6	-61	-47.5	-67

0.74 for NAI, 0.32 to 0.73 for VCI, and 0.24 to 0.65 for NDWIA. The correlations of VCI and NAI were almost identical for all districts except Bhavnagar, Junagadh, and Porbandar, where VCI performed better. The correlation coefficients with groundnut yield ranged between 0.37 to 0.77 for NAI, 0.33 to 0.75 for VCI and 0.20 to 0.67 for NDWIA. Only Jamnagar in the case of cotton and no district in the case of groundnut were observed with better correlations with crop yields by NDWIA as compared to NAI/VCI. NDWI is more useful in crop health monitoring at the beginning of the cropping season (Kavitha *et al.*, 2018). In the present study, the vegetation indices were estimated at 90 to 100 days after sowing, hence NDVI based NDVIA and VCI showed a greater association with crop yields as compared to NDWIA. The spatial variability of correlations between vegetation indices and crop yields for various districts was observed due to variability in the homogeneity of crop cover, irrigation, and soil type. Yingxin *et al*. (2008) during a study in the USA viewed that areas with relatively homogeneous vegetation cover and with silt loam soils showed better correlations as compared to an area with heterogeneous vegetation cover and loam soils.

The ranges of correlation coefficients between vegetation indices and cotton and groundnut yields obtained in the current study are better than several studies in the region using coarse resolution data like MODIS and AVHRR and relatively shorter durations (Chopra, 2006; Bhandhopadhyay and Shah, 2016; Lunagaria and Sur 2019) as compared to this study. Not only this but a better performance of fine resolution satellite data like Landsat Tran *et al*. (2017); Sreekesh *et al*. (2019) with longer duration. Landsat data showed many advantages in monitoring drought in remote and small areas compared to MODIS. (Kundu *et al*., 2016). Especially in a country like India, with a very high share of small and marginal farmers with fragmented land holdings, a single crop evenly grown across a large area is rare. Hence, the use of long-term fine-resolution data is essential for agricultural drought analysis as well as crop health monitoring using remote sensing. However, in the current study, we observed non-significant correlations between vegetation indices and crop yields, particularly in Junagadh and Porbandar districts. To eliminate non-cropped pixels, we conducted crop masking; nevertheless, the significant variability in crop cultivation practices and cropping patterns within these regions may have limited the ability of remote sensing-based indices to capture the nuanced aspects of crop growth and drought conditions. NDVI/VCI, which assesses plant health based on reflectance and greenness, represents only one facet of crop performance, and crop yield is subject to multifaceted influences extending beyond vegetation health. To enhance the correlation between remote sensing data and crop yield, it is imperative to account for additional factors such as irrigation status, crop development stage during data acquisition, soil characteristics, and other variables that contribute to the intricate dynamics of agricultural systems and their impact on crop performance.

3.3. *Revision of drought severity thresholds of VCI*

It is worth noting that almost equal and in many cases, a higher correlation for VCI than NAI for cotton and groundnut crop yields was observed for various districts of Saurashtra. The significance of VCI is strongly related to the relationship between the vegetation index and the vitality of the vegetation cover under investigation. However, the temporal and spatial drought analysis of Saurashtra in the present study observed a very high number of non-drought years and less severity by VCI as compared to NAI. These facts indicate that the underestimation of drought severity by VCI is not due to the inefficiency of VCI itself but due to inconsistencies in ranges of VCI severity for classifying droughts into mild/moderate/severe/extreme and no drought categories. Therefore, the drought category thresholds used in the study need revision. In the present study, no drought

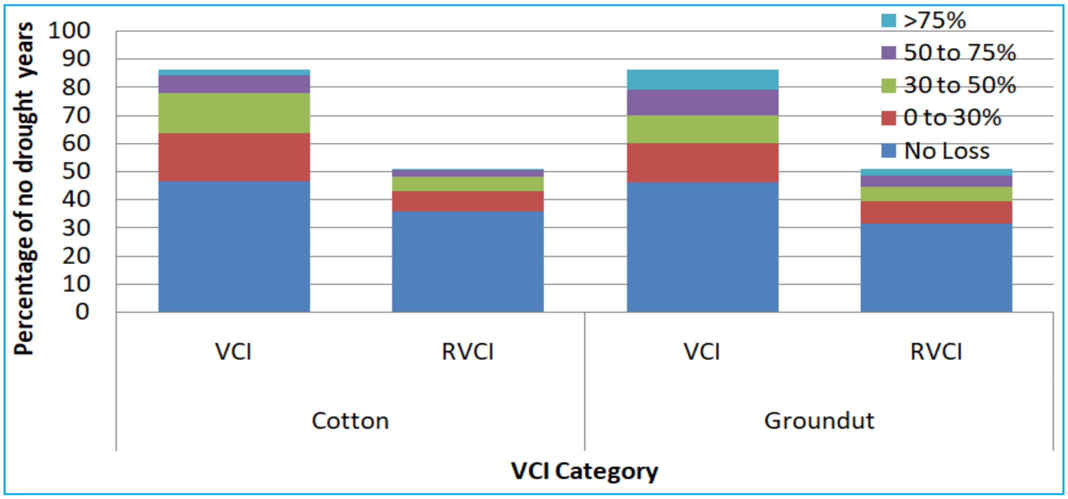

Fig. 5. Percentage of no drought years and corresponding yield loss by VCI and RVCI

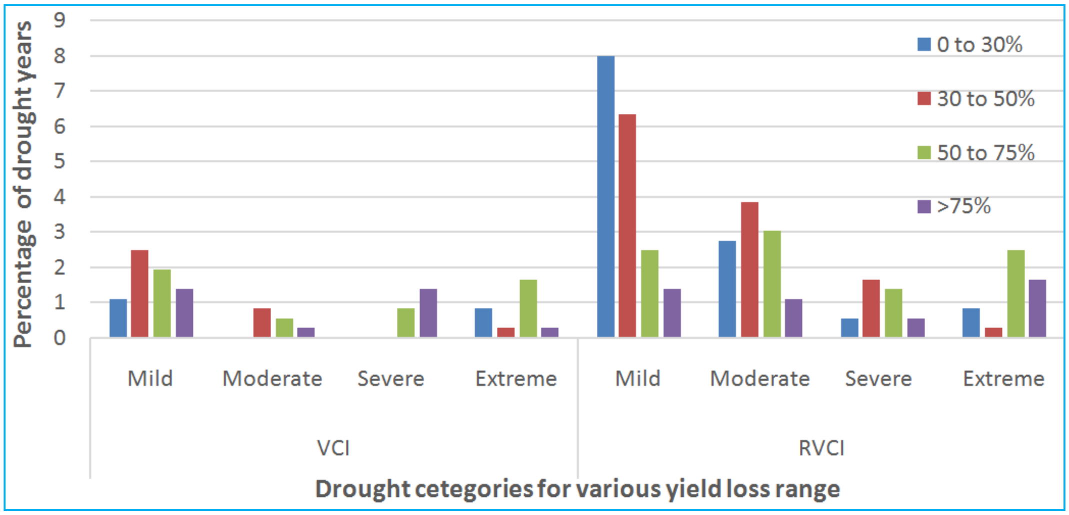

Fig. 6. Percentage of drought years and corresponding yield loss by VCI and RVCI for cotton

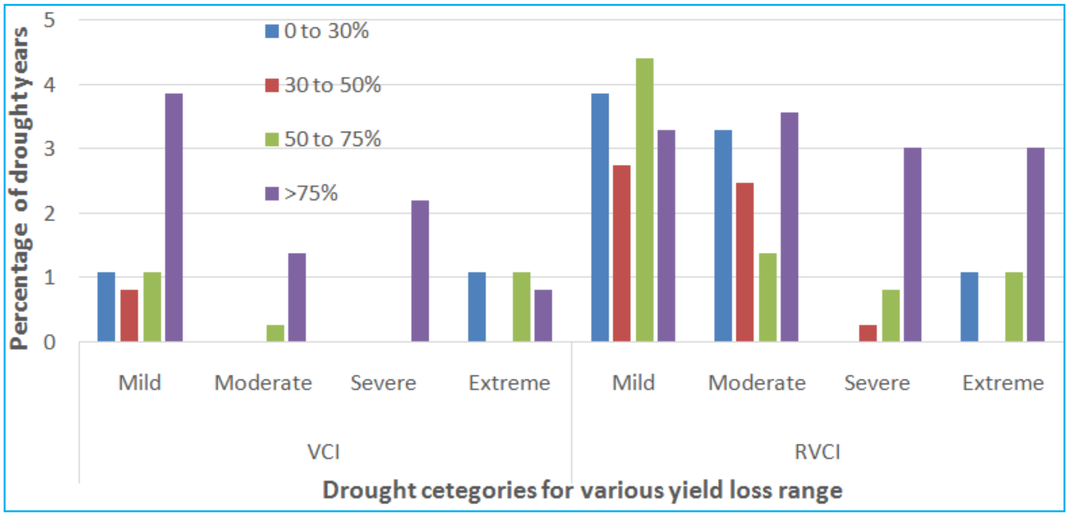

Fig. 7. Percentage of drought years and corresponding yield loss by VCI and RVCI for groundnut

conditions were categorized for VCI value of less than 40, in line with the Indian Drought Manual, 2016 (Anonymous, 2016) and adopted by many researchers (Ghaleb *et al.*, 2015; Bandyopadhyay and Saha, 2016; Amalo *et al.*, 2017). The revised drought categories by VCI for the region under study to enhance its performance to classify various drought severity categories are mentioned in the subsequent section. In the present study, the correlation coefficient between NAI and VCI was 0.97; hence, the severity categories of VCI were revised by comparing it with categories of NAI using 330 data points (11 × 3). We propose the revised drought severity thresholds for VCI to be utilized for the Saurashtra region Table 5. The average crop yield anomalies of cotton and groundnut yield for the original and revised drought severity categories of VCI are also given in Table 5. The clearer link of the drought severity thresholds with crop yield anomalies by revised VCI thresholds as compared to existing ones is evident from Table 5. The existing drought severity thresholds do not reveal a clear demarcation of yield anomalies from mild to extreme droughts, while revised categories show incremental negative yield anomalies from mild to extreme droughts.

In addition to this, the revised VCI severity thresholds were validated by generating the pairs of drought severity categories and crop yield loss % into five categories as no loss, 0 to 30%, 30 to 50%, 50 to 70% and more than 70% loss. The hypothesis of judging the performance of existing and revised thresholds is based on the fact that no yield loss years should be categorized under no drought, lower yield loss years should be designated as mild/moderate drought years and high yield loss years should fall under the severe/extreme drought category. The classification of drought severity classes showed that by existing VCI thresholds, 86% of years were under no drought and 7%, 2%, 2% and 3% years were under mild, moderate, severe, and extreme drought respectively. While in the case of the revised drought severity category (RVCI) proposed by us, 51% of years were under no drought, while 26%, 14%, 4% and 5% of years are under mild, moderate, severe, and extreme drought respectively. The percentage of years designated as no drought by VCI and RVCI along with the yield loss in cotton and groundnut is given in Fig. 5.

Despite no drought years, 22% and 26% of years showed more than 30% yield loss in the case of existing VCI for cotton and groundnut respectively, while only 8% and 12% of years showed more than 30% yield loss respectively by RVCI. The better significance of the RVCI threshold clearly emerged as, despite yield loss, a less number of years were under drought by existing VCI categories for both the crops as compared to RVCI categories. The percentage of drought years under various categories of mild/moderate/severe and extreme drought under each yield loss category is depicted in Figs. 6&7 for cotton and groundnut respectively.

A clearer link between mild and moderate drought years with comparatively less yield loss and moderate to severe drought years with higher yield loss is visible for RVCI compared to existing VCI. The percentage of drought years with 0 to 30% yield loss of cotton and groundnut was about only 2% for both the crops, while it was 12.1% and 8.3% for RVCI respectively for cotton and groundnut, with more percentage of years under mild droughts. If we combine years under 30% to 50% and 50 to 75% yield losses, only 8.5% and 3.3% years for cotton and groundnut respectively were defined as drought years by existing VCI while 21.5% and 13.2% for cotton and groundnut respectively by MVCI. While in the case of years with more than 75% yield loss, 3.3% and 8.3% years were under drought by VCI for cotton and groundnut respectively, while it was 4.7% and 12.9% respectively by MVCI. Overall, it can be stated that revised VCI categories define the yield losses and hence agricultural drought with better effectiveness as compared to existing VCI categories. The vegetation condition index with revised drought severity classification suggested in the study is recommended for agricultural drought assessment of areas with dominant crops such as cotton and groundnut. The single VCI drought severity categories mentioned in the Indian Drought Manual, 2016 (Anonymous, 2016) may not reflect the diverse climate, rainfall patterns, soils, and crops. Hence, our study recommends region and crop-specific agricultural drought categorization using long-term fine resolution satellite data like Landsat for comprehensive agricultural drought assessment. The research can be further enhanced by combining meteorological drought indices and estimation of crop yield loss by various machine learning techniques. The outcome of the study will guide the researchers, policymakers, and various stakeholders for efficient agricultural drought assessment and subsequent mitigation measures.

4. Conclusions

The agricultural drought analysis based on remote sensing-based vegetation indices NAI, VCI, and NDWI using the long term (33 years) and comparatively finer resolution Landsat and sentinel satellite data was carried out. The spatial and temporal drought analysis, drought severity maps, and correlations with crop yields revealed that remote sensing-based drought indices used in the study effectively quantified agricultural drought as well as corresponding yield anomalies. The VCI was found competent to quantify agricultural drought. However, the existing VCI drought severity thresholds resulted in an underestimation of droughts. The revised drought severity thresholds suggested in the study were found effective to categorize agricultural droughts with a corresponding crop yield loss of cotton and groundnut in comparison to existing thresholds. The study recommends to use long term, finer-resolution satellite data and region-specific drought severity thresholds of appropriate remote sensing-based vegetation drought indices for agricultural effective drought characterization.

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Data availability statement : The data used in the study will be available for the interested readers on request to author by email.

Disclaimer : The contents and views expressed in this study are the views of the authors and do not necessarily reflect the views of the organizations they belong to.

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