
# Journal of Agrometeorology

*ISSN : 0972-1665 (print), 2583-2980 (online)*
*Vol. No. 24 (4) : 384-392 (December- 2022)*

*https://journal.agrimetassociation.org/index.php/jam*

***Research Paper***

# Development of PCA-based composite drought index for agricultural drought assessment using remote sensing

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## ABSTRACT

The present study was conducted in the Saurashtra region of Gujarat to demonstrate the development and validation of location and crop-specific composite drought index (CDI) using a linear combination of three parameters including meteorological drought index, vegetation drought index and inverse of maximum consecutive dry days % for major *Kharif* crops of the region *i.e.* cotton and groundnut. The performance of nine drought indices including six meteorological and three remote sensing-based vegetation indices was evaluated in terms of correlation with district scale crop yields.The district-wise expressions of CDI were developed by assigning principal component analysis (PCA) based weights to parameters. Standardized Precipitation Evapotranspiration Index (SPEI)/ Reconnaissance Drought Index (RDI) among meteorological indices and NDVI Anomaly Index (NDVIA)/ Vegetation Condition Index (VCI) among vegetation indices were found suitable for generating district specific CDI expressions. The developed CDI showed higher correlation with *Kharif* Cotton and Groundnut crop yields as compared to various meteorological as well as vegetation indices used in the study and effectively quantified major historic agricultural droughts.The average correlation coefficients of developed CDI with cotton and groundnut yields were 0.71 and 0.77 respectively. The correlations of CDI and crop yields for all CDI expression were highly significant with $p<0.01$. The method developed in the study will be useful to generate crop and region-specific multi-scalar drought indices by the amalgamation of multiple drought indices for assessing crop production losses.
***Key Words:*** Drought monitoring, cotton, groundnut, SPEI, NDVI, VCI

The droughts are the recurring and multifaceted phenomenon affecting agriculture, water resources and the overall socio-economic condition of the arid and semiarid region. Inappropriate agroecosystem management and frequent droughts have made the drylands increasingly susceptible and prone to rapid degradation (Rathore, 2020). Bandyopadhyay *et al.* (2020) suggested the revision and up gradation in post-drought assessment while observing some drawbacks and in-adequacy of present drought mitigation policies in Gujarat.

Agricultural drought characterized by significant yield loss in major crops is more difficult to assess as compared to meteorological and hydrological drought due to the complex relationship between crop genotype, soil moisture availability and climate. The ordinary method to quantify agricultural droughts is relying on a single index or several indices with different ranges and thresholds for classifying droughts. However, Zargar *et al.* (2011) emphasized the need to develop customized indices for specific climatic and hydrologic regimes through the assimilation of data from various indicators into a single numerical value. Hao and Singh (2015) exhaustively reviewed the development of drought indices based on multiple drought-related variables and indices based on various technics e.g. blending objective and subjective indicators, water balance model, linear combination, joint distribution, principal component analysis, *etc.* Sridhara *et al*. (2021) used various drought indices (SPI, CZI, ZSI etc) to assess the drought situations in Karnataka. Chhajer *et al.* (2015) developed composite drought index using Soil based Vegetation Condition Index (SVCI), Temperature Condition Index (TCI) and SWI Standardized Water-Level Index (SWI) for Jaisalmer district of Rajasthan, Mlenga *et al.* (2019) combined NDVI, SPI and Temperature to quantify agriculture drought in Eswatini, Southern Africa using step wise regression. The liner combinations by assigning principle component analysis (PCA) based weights to parameters was attempted by Mansour *et al.* (2019) while developing agricultural drought condition index (ADCI) for millet crop using Precipitation Condition index (PCI), Evapotranspiration Condition Index (ETCI), VCI and TCI. PCA based CDIs were developed by Kulkarni *et al.* (2020) using SPI, land surface temperature, soil moisture (SM), and NDVI and Prajapati *et al.* (2022) using SPI, streamflow drought index (SDI), and vegetation condition index (VCI) for Marathwada region of Maharashtra, Kamble *et al.* (2019) compared SPI and

***Article info - DOI***: *https://doi.org/10.54386/jam.v24i4.1738*
*Received: 13 July 2022; Accepted: 15 November 2022; Published online : 1 December 2022*

VCI performance with productivity index in Uttar Pradesh. Lim *et al.* (2019) proposed a crop-specific index such as standardized agricultural drought index (SADI) for rice and maize.

The study conducted by Moharana *et al.* (2016) showed that west Rajasthan, Saurashtra & Kutch cover most of the hot arid zone of northwest India. Manual for Drought Management, Govt. of India (Anonymous, 2016) quoted that many states in India still rely on the traditional practice such as eye estimation and crop cutting experiments to assess the extent of crop damage for drought declaration. The above-mentioned facts lead to the development of a crop-specific composite drought index for the semiarid and drought-prone Saurashtra region of Gujarat (India) by incorporating meteorological and vegetation drought indices. The findings of the present study are expected to improve the assessment of impact of drought on agriculture by much quicker estimates of drought impact on agriculture, which will be highly valuable to researchers, policy makers, insurance companies, development agencies and other stakeholders for taking appropriate measure mitigate the drought impact.

## MATERIALS AND METHODS

The present study was carried out in the Saurashtra region of Gujarat, India. The daily rainfall and monthly minimum & maximum temperature data of 34 years (1986 to 2019) were used to compute meteorological drought indices. Out of 36 stations, rainfall data for 27 stations were obtained from State Water Data Centre, Govt. of Gujarat, Gandhinagar, 7 stations from various centers of Junagadh Agricultural University and 2 stations of IMD. The minimum and maximum temperature data were obtained from NASA/POWER, National Center for Environmental Prediction (NCEP) global reanalysis, also recommended by Srivastava *et al.* (2020) for estimating potential evapotranspiration. The satellite images of Landsat with a spatial resolution of 30 meters were used for estimating vegetation indices. The district-wise crop yield data of two major *Kharif* crops of the region*i.e.* cotton and groundnut obtained from the Department of Agriculture Government of Gujarat were used. The total growth period for groundnut is considered 120 days, flowering, peg penetration and pod development are critical crop stages with respect to water needs. The crop growth period of cotton in the region is 135 days, the most critical stage for water requirement is the first seed to ball formation followed by ball formation to ball maturity (Pandya *et al.*, 2020).

### *Computation of drought indices*

The drought analysis was carried out by computing six meteorological drought indices and three remote sensing-based vegetation indices. The details of indices used along with brief computation procedure are given in below.

### *Standardized precipitation index (SPI)*

$$g(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta}$$

Fitting gamma probability distribution to the long-term precipitation at various time scales. The gamma distribution is defined by its frequency or probability density function (McKee *et al.* 1993)

Where, α, β and x>0, α is a shape parameter, β is the scale parameter and x is precipitation. The cumulative probability is then transformed to the standard normal random variable Z with a mean zero and variance of one.

### *Rainfall anomaly index (RAI)*

$$\mathrm{RAI} = 3\,\frac{\mathrm{P}-\overline{\mathrm{P}}}{\overline{\mathrm{M}}-\overline{\mathrm{P}}} \text{ if } \mathrm{P} > \overline{\mathrm{P}} \text{ or } \mathrm{RAI} - 3\,\frac{\mathrm{P}-\overline{\mathrm{P}}}{\overline{\mathrm{N}}-\overline{\mathrm{P}}} \text{ if } \mathrm{P} < \overline{\mathrm{P}}$$

Where P is the precipitation of the period for which RAI is to be computed and $\overline{\mathrm{P}}$ the mean precipitation of all the records. $\overline{\mathrm{M}}$ and $\overline{\mathrm{R}}$ are the means of the ten highest and lowest precipitation (Van Rooy, 1965).

### *Drought area index (DAI)*

$$\mathrm{I_k} = 0.5\,\mathrm{I_{k-1}} + \frac{\mathrm{M_k}}{48.55}\ .\ \text{Where } \mathrm{M_k} = 100\,\frac{\mathrm{P_k}-\bar{\mathrm{I}}_\mathrm{k}}{\sigma_\mathrm{k}}$$

Where I is the intensity of drought (dimensionless), k is the month number, P is monthly precipitation (mm), is average of precipitation for the month (mm), is intensity of drought for the previous month and is the precipitation standard deviation (mm) (Bhalme and Mooley, 1980).

### *Decile index (DI)*

Long-term rainfall records are arranged in descending order to construct a cumulative frequency distribution and the distribution is then split into ten parts (or deciles) based on equal probabilities (Gibbs and Maher, 1967)

### *Standardized precipitation evapotranspiration index (SPEI)*

The precipitation term in SPI is the term Di= P - PET. The PET (Potential Evapotrapiration) is calculated by Thornthwaite (1948) method. Instead of gamma distribution used in SPI, the log logistic distribution is fitted in SPEI (Vicente-Serrano *et al.*, 2010).

### *Reconnaissance drought index (RDI)*

The initial value of the index for a certain period, indicated by a certain month (k) during a year, is calculated by (Tsakiris and Vangelis, 2005)

$${\alpha_k}^{(i)} = \frac{\sum_{j=1}^{k} P_{ij}}{\sum_{j=1}^{k} PET_{ij}}$$

Where $P_{ij}$ and $PET_{ij}$ are the precipitation and potential evapotranspiration by Thornthwaite (1948) method of month j of year i, and N is the total number of years of the available data. The calculation of the $RDI_{st}$ could be performed better by fitting the gamma probability density function to the given frequency distribution of the $\alpha_k$, same as SPI.

***NDVI anomaly index (NAI)*** was calculated following Anyamba *et al.*, (2001)

**Table 1:** Drought severity classifications by various drought indices

| Category | SPI/SPEI / RDI | RAI | DAI | DI | NAI | VCI | NDWIA |
|---|---|---|---|---|---|---|---|
| No Drought | >0.49 | >0.49 | >0.99 | >40 | >0 | >40 | >0 |
| Near normal | -0.49 to 0.49 | -0.49 to 0.49 | -0.99 to 0.99 | 40 to 60% | - | - | - |
| Mild drought | -0.5 to -0.99 | -0.5 to -0.99 | -1 to -1.99 | 30% to 40% | 0 to -10 | 30 to 40 | 0 to -1 |
| Moderate drought | -1.0 to -1.49 | -1.0 to -1.99 | -2 to -2.99 | 20% to 30% | -10 to -25 | 20 to 30 | -1 to -2 |
| Severe drought | -1.5 to -1.99 | -2.0 to -2.99 | -3 to -3.99 | 10% to 20% | -25 to -50 | 10 to 20 | -2 to -3 |
| Extreme drought | ≤ -2.0 | ≤ -3.0 | ≤ -4 | ≤ 10 | Below -50 | <10 | -3 to -4 |

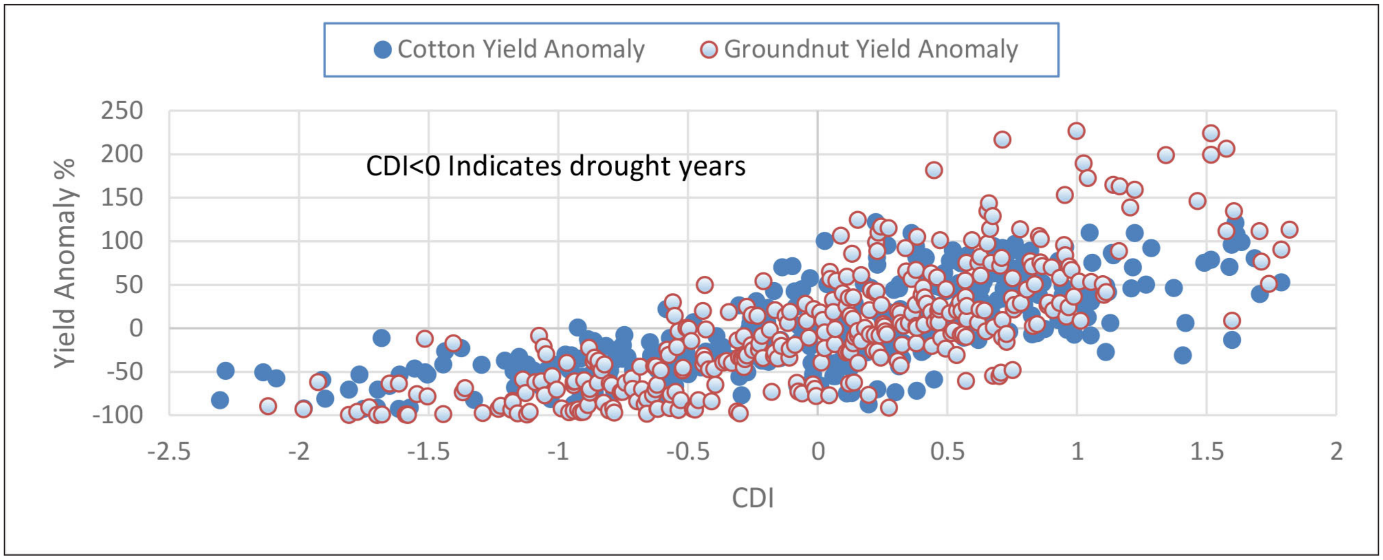


**Fig. 1:** Yield anomaly of cotton and groundnut for various CDI

The NDVI is given by $NDVI = \frac{(NIR-RED)}{NIR+RED}$

Where NIR and RED are reflectance in the near-infrared and red bands.

$$\text{NAI} = \frac{NDVI_i - NDVI_{mean}}{NDVI_{mean}} \text{ X } 100$$

*NDVI* is NDVI for a particular month, $\text{NDVI}_{mean}$ is the long-term mean NDVI.

***Vegetation condition index (VCI)*** was calculated using following formula given by Kogan (1995).

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

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

***NDWI anomaly index*** **(NDWIA)**

$$NDWI_t = \frac{NIR_t - SWIR_t}{NIR_t + SWIR_t}$$

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

$NDWI = \frac{X_t - \bar{X}}{\delta}$ Where= 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 (Gao, 1996).

The ranges to classify various drought categories such as no drought or mild/moderate/severe and extreme drought is given in Table 1. All meteorological indices were computed for monthly, 3 monthly and seasonal rainfall period for the months June to September. The Landsat satellite images were processed in QGIS open-source environment. The sowing of *Kharif* crops in the region starts in the middle of June as soon as sufficient rainfall occurs. The drought situation can be evaluated by analyzing the crop situation at the crop stage of highest NDVI occurrence as any departure from maximum NDVI reflects the poor crop health and can be directly linked with moisture deficiency. Kaushalya *et al.* (2015) reported that maximum NDVI occurred in the months of September–October annually reflecting the southwest monsoon across India. Therefore, estimation of vegetation indices at late September is useful to link crop yield anomalies to droughts resulting from deficient rainfall in the southwest monsoon as well as insufficient rainfall at critical crop growth stages. Moreover, it was uncertain to obtain cloud-free satellite images during the same crop period for 34 years during June, July and August. Hence high-quality cloud-free images available during late September were used for generating satellite-based indices when crops are at the stage of about 90 to 100 days after sowing. The crop masking was performed to eliminate non-cropped area for precise estimation of vegetation indicesusing crops class of the ESRI land cover of 10m x 10m resolution (vector separated) based on Sentinel-2 imagery of 2019. District-wise mean values of vegetation indices were extracted using the zonal statistics tool in QGIS.

As meteorological indices only consider accumulated rainfall depth over 1, 3 or 6 months' time scales, the highest number of consecutive dry days in percentage of total days of the crop season was used as third parameter to formulate CDI. Frich *et al.* (2002) defined the maximum number of consecutive days (MCDD) with precipitation less than 1 mm to assess seasonal droughts. Haensel *et al.* (2019) also used the same MCDD for drought quantification. As the crop yield is inversely proportional to maximum consecutive dry days % (MCDD %), hence inverse of MCDD% was also used as a parameter in CDI

***Development of composite drought index (CDI)***

Composite Drought Index (CDI)) was developed by combination of three parameters *i.e.* meteorological drought index (x), vegetation index (y) and $\frac{1}{MCDD\%}$(Z) . The district average drought severity series of all indices were correlated with cotton and groundnut crop yields to select meteorological and vegetation index for CDI formulation. As CDI parameters were having different ranges of values (Table 1), the indices values were converted into z score to bring all indices at same range level.

Z score= $\frac{x-\mu}{\sigma}$

Where x is the parameter value, μ is its mean, and σ is its standard deviation.

The proposed composite drought index for the Saurashtra region was articulated as

$$CDI = \alpha\, z_x + \beta z_y + \gamma z_z (10)$$

$$\alpha + \beta + \gamma = 1$$

Where, $z_x$, $z_y$ and are Z scores of x, y and z parameters. The α, β, γ are weights of the respective parameter.

The decision on the contribution of an individual parameter in CDI in terms of weights is very crucial. The Principal Component Analysis (PCA) was used by constructing a matrix with rows as years and three columns as parameters of CDI. The eigenvectors and eigenvalues were obtained for each principal component; the percentage contribution of the individual parameter (weight) was assigned as the square of eigenvectors for the first principal component which explains the highest variance. Considering 11 districts and 2 crops (cotton and groundnut), total 22 expressions of CDI were worked out (11 x 2 =22). The developed CDI was validated using two approaches, (i) correlation with crop yields (ii) observing the CDI values and corresponding crop yield anomalies for major historic dry and wet years. The yield anomalies of cotton and ground for each of the 34 years was computed as below.

Yield anomaly (%) = $\frac{Y_i - Y_a}{Y_a}\, x\ 100$

Where $Y_i$ is crop yield of a specific year, Ya is district average crop yield

## RESULTS AND DISCUSSION

***Selection of parameters to formulate CDI***

The metrological drought index (x) and vegetation index (y) selected based on the strongest correlation for each district are presented in Table 2. The significance of the correlation was tested for selected indices as well as the inverse of MCDD%(z). Only parameters having significant correlation were used to formulate the CDI. Table 2 shows that all metrological and vegetative indices were significantly correlated with yields of both crops for all the 11 districts. The correlation of inverse of MCDD% was found non-significant for 4 districts in the case of cotton and 1 district in the case of groundnut. Therefore, for these five CDI expressions, only two parameters *i.e.* the metrological and agricultural drought index were used. Botad and Surendranagar are major cotton growing districts with better canal irrigation facilities compared to other districts, while Junagadh and Porbandar districts have groundnut as major crop and cotton is grown only ~~a~~ in small pockets with assured irrigation facilities. Non-significant correlations between MCCD and crop yields might be due to the fact that better irrigation facilities that provided supplement irrigation at critical crop growth stages which might had reduced the crop yield loss due to continuous dry spells. While comparing six meteorological drought indices based on correlations with crop yields, SPEI and RDI were proven better than SPI, RDI, DAI and DI to explain crop yield anomalies of cotton and groundnut. The SPEI at the seasonal time scale was observed with highest correlation for seventeen CDI expressions and RDI at the seasonal time scale for five CDI expressions. The indices SPI, RAI, DAI and DI are based only on rainfall and explain the soil moisture anomalies due to rainfall, While SPEI and RDI take in to account anomalies in climatic water demand due to the inclusion of PET. The rainfall deficiency accompanied by higher temperatures and consequent evapotranspiration may worsen the drought effects on agriculture which can be reflected in SPEI and RDI. Hence, in present study better correlation for SPEI and RDI is observed than rest of the indices. Between SPEI and RDI, better performance in terms of correlation with crop yields was observed for SPEI. The SPEI is based on difference between precipitation and PET and RDI is based on the ratio of precipitation and PET. Sergio *et al.* (2015) pointed that SPEI shows the largest sensitivity to ETo variation, with clear geographic patterns mainly controlled by aridity in comparison to RDI which is only sensitive to the variance but not to the average of P and ETo. Researchers advocated the superiority of SPEI across the globe including India (Mujumdar *et al.*, 2020). In addition, considering climate change and global warming, the inclusion of temperature term in drought indices is more important (Vicente-Serrano *et al.*, 2010). The correlation of SPI/RDI with crop

**Table 2:** Selected indices for CDI and its correlation with groundnut and cotton yield

| Sr. No | District | Cotton | | | | | Groundnut | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | x | $r_x$ | y | $r_y$ | $r_z$ | x | $r_x$ | y | $r_y$ | $r_z$ |
| 1 | Amreli | RDI | 0.69 | VCI | 0.50 | 0.63 | RDI | 0.58 | NDVIA | 0.48 | 0.58 |
| 2 | Bhavnagar | RDI | 0.74 | VCI | 0.43 | 0.36 | SPEI | 0.66 | VCI | 0.61 | 0.46 |
| 3 | Botad | SPEI | 0.74 | NDVIA | 0.52 | $0.14^{NS}$ | SPEI | 0.65 | NDVIA | 0.73 | 0.52 |
| 4 | Dwarka | SPEI | 0.61 | VCI | 0.53 | 0.44 | SPEI | 0.71 | NDVIA | 0.62 | 0.38 |
| 5 | Gir Somnath | RDI | 0.44 | VCI | 0.45 | 0.40 | RDI | 0.48 | NDVIA | 0.55 | 0.50 |
| 6 | Jamnagar | SPEI | 0.60 | NDVIA | 0.53 | 0.56 | SPEI | 0.69 | NDVIA | 0.70 | 0.57 |
| 7 | Junagadh | SPEI | 0.46 | VCI | 0.32 | $0.24^{NS}$ | SPEI | 0.64 | VCI | 0.33 | 0.58 |
| 8 | Morbi | SPEI | 0.59 | VCI | 0.65 | 0.36 | SPEI | 0.69 | NDVIA | 0.57 | 0.67 |
| 9 | Porbandar | SPEI | 0.31 | VCI | 0.34 | $0.02^{NS}$ | SPEI | 0.45 | NDVIA | 0.45 | 0.40 |
| 10 | Rajkot | SPEI | 0.65 | NDVIA | 0.43 | 0.47 | SPEI | 0.70 | NDVIA | 0.46 | 0.57 |
| 11 | Surendranagar | SPEI | 0.62 | NDVIA | 0.74 | $0.20^{NS}$ | SPEI | 0.57 | NDVIA | 0.77 | $0.27^{NS}$ |

NS= Non-Significant, except NS, all were significant at 0.05% level of significance

**Table 3:** PCA-based weights of various indices for CDI

| Sr. No | District | Cotton | | | Groundnut | | |
|---|---|---|---|---|---|---|---|
| | | α | β | γ | α | β | γ |
| 1 | Amreli | 0.42 | 0.30 | 0.29 | 0.45 | 0.20 | 0.35 |
| 2 | Bhavnagar | 0.45 | 0.26 | 0.29 | 0.45 | 0.27 | 0.29 |
| 3 | Botad | 0.59 | 0.41 | - | 0.42 | 0.41 | 0.17 |
| 4 | Dwarka | 0.46 | 0.31 | 0.24 | 0.46 | 0.29 | 0.24 |
| 5 | Gir Somnath | 0.47 | 0.32 | 0.20 | 0.46 | 0.32 | 0.22 |
| 6 | Jamnagar | 0.44 | 0.24 | 0.32 | 0.44 | 0.24 | 0.32 |
| 7 | Junagadh | 0.59 | 0.41 | - | 0.55 | 0.10 | 0.34 |
| 8 | Morbi | 0.42 | 0.29 | 0.30 | 0.41 | 0.30 | 0.29 |
| 9 | Porbandar | 0.48 | 0.52 | - | 0.47 | 0.37 | 0.16 |
| 10 | Rajkot | 0.46 | 0.25 | 0.30 | 0.46 | 0.25 | 0.30 |
| 11 | Surendranagar | 0.45 | 0.55 | - | 0.42 | 0.58 | - |

yields was ranging from 0.31 to 0.74 for cotton and 0.45 to 0.71 for groundnut crops. Out of three vegetative indices, the NDWIA was found unsuitable for all the districts to generate CDI. The NDWI is based on the shortwave infrared band and is sensitive to soil and canopy moisture which is more useful in crop health monitoring at the beginning of the cropping season. In the present study, the vegetation indices were estimated at about 90 to 100 days after sowing, hence NDVI based NDVIA and VCI showed a greater association with crop yields as compared to NDWIA. The correlation between vegetation indices NDVIA/VCI and crop yields was ranging from 0.32 to 0.74 for cotton and 0.33 to 0.77 for groundnut. A study conducted by Lunagaria and Sur (2019) in various districts of Saurashtra using MODIS satellite data from 2000-2019 observed a correlation between VCI and yield anomalies of cotton and groundnut between 0.15 and 0.26. They noticed that MODIS-derived VCI could not reveal the relation between cotton and groundnut precisely for Saurashtra due to coarse resolution (0.5 km x 0.5 km) and only gave a synoptic view. In comparison to these, the present study observed a reasonably high correlation between VCI and NDVIA using Landsat data of fine-resolution (30m x 30m) and comparatively long-term (34 years). These findings advocate the importance of fine resolution and long-term data for agricultural drought analysis with proper crop masking.

***PCA based weights and formulation of CDI***

The first component of PCA could explain the maximum variability of crop yields and therefore weights of individual parameters were equal to a square of eigenvectors of the first principal component (Table 3). For all the districts except Surendranagar for cotton & groundnut and Porbandar for cotton, the metrological drought index outperformed the rest of the two parameters and was found to have the highest share in CDI in terms of its weight. The dominance of the meteorological drought index in the formulation of composite drought indices by blending different parameters was also reported by Kulkarni *et al.* (2020) and Prajapati *et al.* (2022). The crop yield variability depends on several factors such as climate, genotype, crop management practices, and disease outbreak etc. As mentioned by Matiu *et al.* (2017), out of various factors influencing crop yield, climate explains almost 60% of yield variability and is a crucial factor in crop production. The meteorological drought indices are capable of explaining the yield variability due extreme

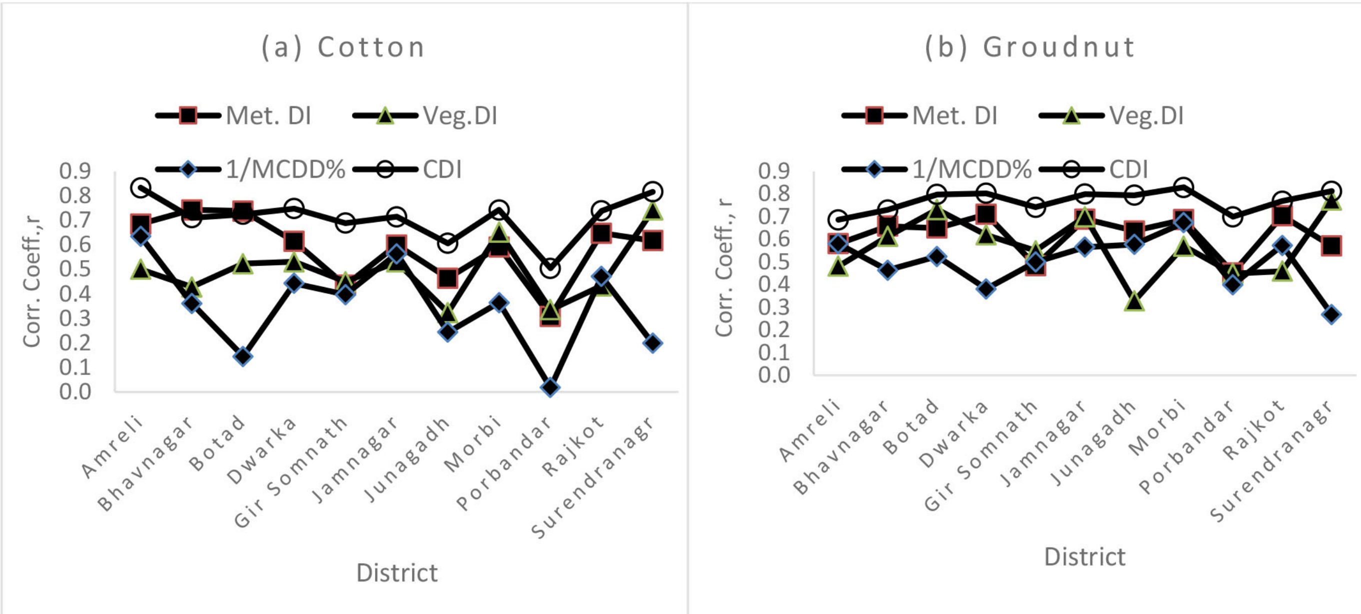


**Fig. 2:** Correlation of various indices and CDI with crop yields of(a) cotton and (b) groundnut

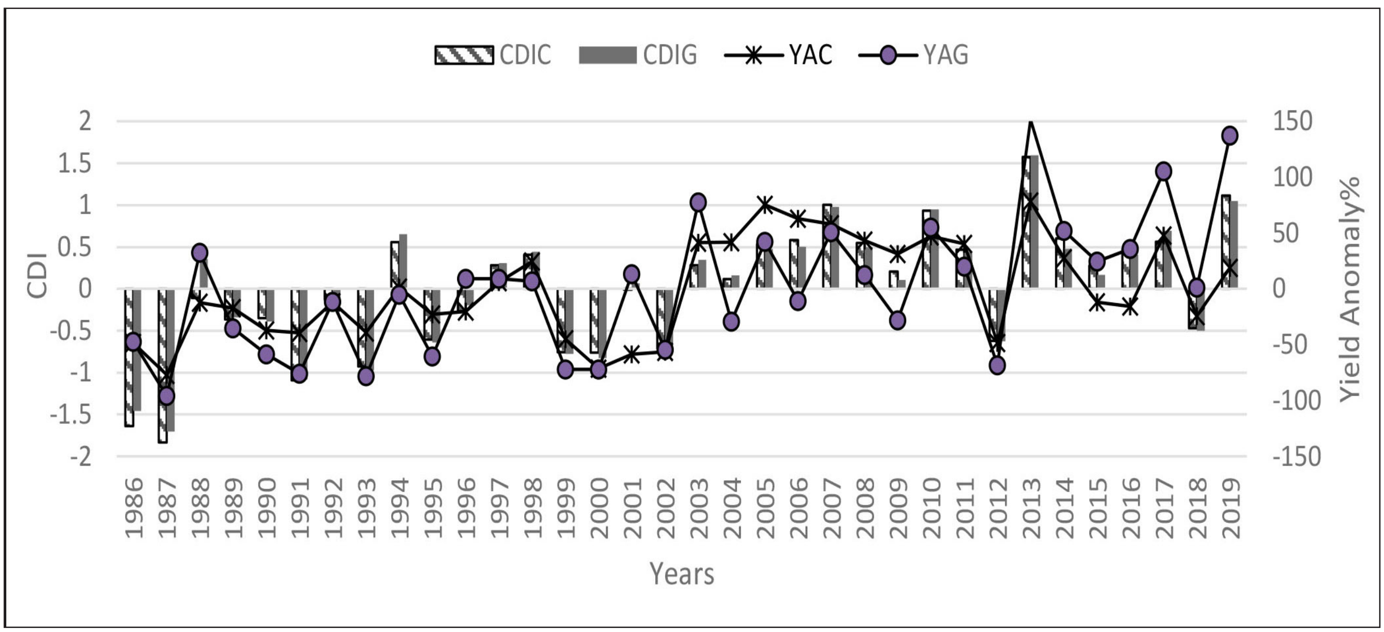


**Fig.3:** Average CDI and crop yield anomalies for historic drought years in Saurashtra (CDIC is CDI for cotton, CDIG is CDI for groundnut, YAC is yield anomaly of cotton, YAG is yield anomaly of groundnut. CDI<0 indicates drought years)

events like droughts to a certain extent. However, complementing the meteorological indices, crop health assessment by satellite derived vegetation drought indices can produce clearer picture.

The values of parameters were converted in the Z scores and CDI was formulated by a linear combination of Z scores with weights assigned as per Table 3. For example, the expression of CDI for Amreli district for cotton crop would be CDI= 0.42 $Z_{RDI}$ + 0.30 $Z_{VCI}$+0.29 $Z_{(1/(MCDD\%)}$. Similarly, expressions for other districts can be obtained.

***Drought categories of CDI***

The CDI and crop yield anomalies are plotted in Fig. 1 based on data from 11 districts with a total of 374 (11x34) data points for each cotton and groundnut. It can be observed that for negative CDI, the yield anomalies were negative and vice versa. The higher yield loss (high negative yield anomalies) was clearly visible corresponding to more negative CDI. Additionally, for most of the points with less than -0.5 CDI the yield anomalies were negative which reflect the effectiveness of developed CDI to quantify yield loss induced by droughts. The yield loss in groundnut was higher as compared to cotton for the same value of CDI. As cotton is a long-duration crop of about 135 days with high irrigation requirement (700-1000 mm) as compared to groundnut (120 days and 400 to 600 mm) with multiple pickings; therefore, cotton is mostly grown by the farmers due to better irrigation facilities. For instance, In the year 2018-19, out of the total area under cotton cultivation in Saurashtra 83% was irrigated while for groundnut only 18.7% was irrigated (Anonymous, 2020). Better irrigation facilities had reduced the vulnerability to drought for the cotton-growing area. Moreover, the deep-rooted system of cotton crop could be able to extract moisture from deeper layers hence it withstands dry spells of longer duration compared to groundnut crop.

***Performance evaluation of CDI***

The validation of developed indices is an essential step to demonstrate its applicability. There lies the unavailability of "ground truth" for the exact validation of drought indices. Comparing the developed index with a well-accepted index in terms of classification in various drought categories using secondary data is suggested for validating the new drought index (Hao and Singh, 2015; Kulkarni *et al.* 2020; Prajapati *et al.* 2022). The correlation of the best of the meteorological drought index, agricultural drought index and CDI with cotton and groundnut can be observed in Fig. 2. The developed CDI showed a stronger correlation as compared to the best of the individual metrological or vegetative indices under the study. The correlation coefficients for all 22 CDI expressions were highly significant with $p<0.01$. The CDI for cotton showed r values between 0.7 to 0.8 for seven districts and more than 0.8 for two districts. While for Junagadh r was 0.61 and for Porbandar, a low value of r, i.e. 0.50 was observed. The correlation coefficient of CDI and groundnut yield was observed between 0.69 and 0.83 for various districts. The CDI for groundnut recorded r between 0.7 and 0.8 for 6 districts and r more than 0.8 for 5 districts. A substantial improvement in the correlation for the majority of CDI expressions over the existing indices was observed for both cotton and groundnut. Several crops and region-specific drought indices were developed with various technics. The correlation for various crops for such indices was 0.62 with millet (Mlenga *et al.*, 2019) and 0.67 for cotton (Kulkarni *et al.* 2020). Hence, the correlation ranges for developed CDI expression in the present study are found satisfactory to explain the agricultural drought conditions in respect of cotton and Ground nut crops of the Saurashtra region.

The average values of developed CDI and average yield anomalies of cotton and groundnut were computed for the duration of 1986 to 2019 to analyze the historical droughts (Fig. 3). The major dry and wet years were observed to show the effectiveness of CDI to identify agricultural droughts. The five major historic drought years in the sequence of highest to lowest drought severities in the Saurashtra region emerged as years 1987, 1986, 1991, 1993 and 2000. The average CDIs of these drought years were ranging from -1.83 to -0.76 for cotton with yield anomalies of -77% to -39% respectively. In the case of groundnut, the CDIs for these five major drought years were between -1.71 to -0.82 with yield anomalies in the tune of -96% to -47%. As mentioned earlier, cotton is mostly grown by farmers having irrigation facilities, the yield loss for the same drought category was high for groundnut as compared to cotton. The correlation and its significance for MCDD% (Table 2) also confirm this fact as MCDD% was more relevant for groundnut as compared to cotton. The recorded major wet years with higher positive values of CDI in the sequence of lowest to highest positive CDI were 2014, 2010,2007,2019 and 2013 with CDI values between 0.60 to 1.58 for cotton and 0.48 to 1.60 for groundnut. The corresponding crop yield anomalies ranged from 19% to 78% for cotton and 51 to 152% for groundnut. These results confirm that developed CDI and its expressions are in close agreement with drought-induced yield loss. Not only this, but CDI was also able to capture the wet climatic condition also for years recorded with a satisfactory yield of cotton and groundnut yield. The better performance of CDI for both the crops and both the dry and wet conditions proves the robustness of developed CDI. To enhance the applicability of developed CDI, a web-based app has been developed which can be assessed through http://150.242.17.6/pap/. Selecting district and crop and entering the required input values, the CDI value and drought severity category can be obtained. The expected yield loss in cotton and groundnut for various drought categories is also displayed the tabular form based on historic average values of yield losses.

As limited water availability is not the only factor for crop yield reduction, several other factors like pest/disease infestation, genotypes, etc. may also be responsible for low yield in non-drought years in some cases. The developed CDI with multiple expressions is recommended for quantifying agricultural drought in the Saurashtra region. As agricultural drought is a regional phenomenon, general indices have limited effectiveness to capture region-specific climate, crops other factors affecting crop production. The variables like soil moisture, land surface temperature, vegetative indices at various stages, irrigation level *etc.*may be attempted for developing such composite drought indices to improve their effectiveness. The method demonstrated in the study will be useful to develop such location and crop-specific agricultural drought indices.

## CONCLUSION

The composite drought index was developed using a linear combination with PCA based weights of three parameters including meteorological drought index, vegetation drought index and inverse of maximum consecutive dry days. The district-wise CDI expressions using SPEI/RDI among meteorological drought indices and VCI/NDVIA among vegetation drought indices showed a higher correlation with cotton and groundnut crop yields as compared to existing indices and detected crop yield anomalies of historic dry and wet years effectively. The study recommends the development of such location and crop specific composite drought indices for regional agricultural drought assessment.

**ACKNOWLEDGEMENT.** The Authors are thankful to State Water Data Centre, Gandhinagar and Agrometeorological Cell, Junagadh Agricultural University, Junagadh for providing meteorological data.

***Conflict of Interest Statement:*** The author(s) declare(s) that there is no conflict of interest.

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