Development of multivariate integrated drought monitoring index (MIDMI) for Warangal region of Telangana, India

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ABSTRACT

Agricultural drought is one of the most frequent natural disasters in India’s southern part. Remote sensing-based drought indices give advantages in terms of continuous monitoring of land surface. The crop production in the Warangal region in India’s southern part is adversely affected due to insufficient rainfall and poor irrigation management. This study aims to develop a multivariate remote sensing-based composite drought index (CDI) to monitor the agricultural drought. Landsat-8 satellite data for all the 11 subregions of Warangal urban and 15 subregions of the rural district of Telangana from 2013 to 2020 for the month of May is used to obtain drought indices. The drought indices are used in this study to develop MIDMI and are compared according to the percentage area of the Warangal region under five different drought categories. In this study, the MIDMI is computed by a weighted average of five vegetation drought indices for the Warangal region as per the method developed by Iyengar and Sudarshan for the multivariate data. MIDMI for all the 26 subregions of the Warangal rural and Warangal Urban Districts is between 0.4 and 0.6, which makes the Warangal region moderately vulnerable to agricultural drought.

Key words: composite drought index (CDI), Landsat-8, soil moisture, vegetation drought indices

HIGHLIGHTS

- Multivariate Integrated Drought Monitoring Index (MIDMI) – a remote sensing-based index to measure the vulnerability of agricultural drought.
- Various drought indices were compared using unsupervised classification and percentage area calculation under each drought category.
- MIDMI is computed using the Landsat8 satellite data by assigning unequal weights to five drought indices as per Iyengar and Sudarshan method.

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INTRODUCTION

Drought is one of the least understood but most expensive natural disasters and affects water resources severely (Al-Najjar et al. 2020). It can occur in any climate regime. Specifically, in tropical and higher temperate zones, it impacts economic activities severely. The areas affected by droughts are much larger than other natural hazards (Fung et al. 2019). Drought monitoring has gained significance due to its frequency and severity, which involves developing several drought indices. Drought has been categorised into four different categories: agricultural, hydrological, meteorological, and socioeconomic drought. Droughts can be due to several hydrometeorological processes that affect precipitation and limit the availability of surface and groundwater, which creates drier situations than usual, thus causing reduced availability of moisture for crop growth (Heim 2002; Kartıpoglu et al. 2020; Das et al. 2021). The watershed located in India’s Telangana province shows a downward trend in rainfall and it is facing frequent droughts (Masroor et al. 2020). Approaches for monitoring drought and guiding early warning and assessment can be carried out using a single drought monitoring indicator, multiple indicators, or composite hybrid indicators. The Intergovernmental Panel on Climate Change (IPCC) report on extreme events and disasters cites a more considerable uncertainty in capturing recent drought trends than other natural hazards (Cardona 2005; Cardona et al. 2012; Limones et al. 2020). This study aims to determine the vulnerability of drought in the Warangal region of Telangana province of India using MIDMI.

Drought is a recurrent occurrence in India, with nearly one-third of cropland at risk. Within India, Andhra Pradesh (undivided) is the fourth largest state in terms of land area (27.4 million ha), fifth in terms of population (8.46 million), and third in terms of drought proneness (after Rajasthan and Karnataka). Agriculture, which accounts for 30% of the state’s gross domestic product (GDP), employs approximately 65% of the state’s population. Around 65% of the state’s net sown area is rainfed, making it susceptible to recurring droughts. While the state receives an average rainfall of 911 mm, its distribution is erratic, resulting in frequent droughts with a wide range of severity across the state (Kumar et al. 2019).

In this study, the Warangal region is selected for a case study; selecting the small area as a case study gives more accurate results for a particular drought index due to homogeneity in climatic conditions, geographical conditions, and cropping pattern.

Earlier research has quantified and analysed agricultural droughts by developing drought indices that combine the effects of rainfall, vegetation, and temperature variables. The vegetation index, soil moisture, land surface temperature, and precipitation are used as input variables to calculate these indices. These are gathered through a combination of ground observations and remote sensing data with varying spatiotemporal resolutions. Remote sensing data can cover large areas and enables the collection of data from previously unmeasured areas (Sur et al. 2019).
Integrated drought indices based on remote sensing data have the potential to describe drought conditions comprehensively, and multi-criteria combination analysis is increasingly being used to support drought assessment (Jiao et al. 2019; Limones et al. 2020). Besides climate change, the ever-increasing population and the fast-changing land-use patterns have left India’s major river basins in a dreary uncertainty to maintain the required runoff. The role of local reservoirs and water demand in coping with climate extremes is ignored by most existing drought indicators (Huang et al. 2016). Agricultural drought is a dynamic and subtle natural threat that is further exacerbated by impacts on crops. Univariate, bivariate, and multivariate analyses of drought have experienced some success, but there is still a lack of analysis of the evolution of agricultural drought and interaction with crop growth (Zhang et al. 2017). In the wake of climate change, the current water crisis seems to tighten its hold on the human race. Water resource estimation is an integral part of the country’s water resource planning, development, and management. Water resource estimation is based on several hydrological and meteorological parameters. The primary source of groundwater and surface-water resources is rainfall (Bhatt & Mall 2015). Various drought indices are developed for the more satisfactory spatial scale drought monitoring and the various remote sensing-based drought indices have been developed for the continuous monitoring of drought. The usefulness of these integrated, remotely-sensed drought indices is considerably limited because they were established and evaluated for a specific climate or geographic location. The preferred approach is to use different thresholds for specific data combinations. Ideally, this requires prior study to determine which drought indicator/indices are best suited to climate and drought timing, location, and form (AghaKouchak 2015).

Composite indicators are widely used to encapsulate a range of complex and multidimensional issues. The vulnerability indicators method is commonly used in vulnerability studies and is preferred by policymakers. The depiction of vulnerability over space provides policymakers the means to prioritise strategy and measures to manage disaster risk. The composite indicators method can provide an assessment of flood vulnerability in a particular geographical region.

Weighting techniques for normalised variables include the Iyengar–Sudarshan method, the doubt approach benefit, principal component analysis, and unobserved component model. Iyengar & Sudarshan (1982) combined the weights and uncertainties associated with multiple measures. The application of weights in this manner should ensure that significant changes in any of the indicators do not overwhelm the input from the remaining indicators, skewing the overall ranking of the countries. Analysis of the principal components, or, more precisely, factor analysis, combine collinear sub-indicators to create a composite predictor capable of extracting the maximum amount of general knowledge possible from such sub-indicators. The first step in using this approach to weight sub-indicators is to validate the data association structure. Second, no endogenous influences are detected.

The weights calculated using the four weighting methods described above are aggregated into a single composite global divide measure as three distinct grouping techniques. The 12 composite indices for each Asian region are calculated using linear aggregation, geometric aggregation, and the weighted displaced ideal method. Linear aggregation, geometric aggregation, and the weighted displaced ideal-form are all examples of specific aggregation techniques (Chakrabarty & Bhattacharjee 2016).

Various methods of combining drought indices are indicators or parameters used to characterise conditions of drought. Examples include precipitation, temperature, runoff, irrigation, river, soil moisture, and snowpack. Drought indices are usually simulated graphical depictions of the intensity of drought, calculated using climatic or hydrometeorological references, including the indicators mentioned above (Maity et al. 2013; Bhatt & Mall 2015).

The primary objectives of this study are: (1) to select the suitable drought indices for developing MIDMI and their computation for all the 26 subregions of the Warangal region; (2) to compare the selected drought indices for percentage area of the Warangal region into five different drought categories; (3) to develop MIDMI by giving unequal weights to selected drought indices and finding the vulnerability of agricultural drought in the Warangal region using MIDMI.

**STUDY AREA AND DATA COLLECTION**

The study was conducted in both Warangal rural and Warangal urban districts, as shown in Figure 1. Warangal region is in the southern part of India in the Telangana province. Warangal region is spread over an area of 3,480 km², consisting of Warangal urban district at 1,504 km² area and Warangal rural district at 2,176 km² area. Warangal rural district is divided into 15 subregions locally called Mandals. Raiparthy is the largest Mandal of the Warangal rural district with an area of 219 km², whereas Atmakur is the smallest Mandal with a total area of 99 km². Warangal urban district is divided into 11 Mandals.
Dharmasagar is the largest Mandal of the Warangal urban district with an area of 167 km², whereas Warangal Mandal is the smallest Mandal with a total area of 38 km², as shown in Figure 1.

The database utilised in this study consists of the most recently launched LANDSAT 8 satellite data available from February 2013. The Landsat-8 satellite consignment contains two scientific instruments: the operational land imager (OLI) and the thermal infrared sensor (TIRS). These two devices offer seasonal exposure of the global landmass at 30 meters spatial resolution for visible, NIR, and SWIR bands; 100 meters thermal resolution; and 15 meters panchromatic resolution. Landsat-8 consists of 11 bands which is the modification over Landsat-7, which consists of eight bands. Landsat-8 band 1, known as
coastal and having 30 meters resolution, is helpful in various aerosol and coastal studies. Band 2, known as visible blue with 30 meters resolution, is helpful in Bathymetric mapping, distinguishing soil from vegetation and deciduous from coniferous vegetation. Band 3, known as visible green with 30 meters resolution, emphasises peak vegetation, useful for assessing plant vigour. Band 4, known as visible red with 30 meters resolution, helps discriminate vegetation slopes. Band 5, known as near-infrared with 30 meters resolution, emphasises biomass content and shorelines. Band 6, known as short wavelength infrared-1 with 30 meters resolution.

**METHODOLOGY**

In this study, the Landsat-8 data is used to calculate various drought indices and processing of MIDMI. In India’s southern part, the latter part of May and early June are generally drought-prone months that are more susceptible to agricultural drought. Hence, we have used path 143 and row 48 of Landsat-8 data for this study, mainly 20–30th of May from May 2013 to May 2020. Other than the latter part of May or early June, this may not necessarily indicate the vulnerability of agricultural drought in the southern part of India.

The drought indices based on the prior study as per the literature review (Cardona 2005; Cardona et al. 2012; Kumar et al. 2019; Limones et al. 2020) are selected for the computation of MIDMI. The flowchart of the methodology is as shown in Figure 2.

**Processing of drought indices**

The following drought indices are selected as per the literature review (Cardona 2005; Cardona et al. 2012; Kumar et al. 2019; Limones et al. 2020) are processed in various geographic information system (GIS) software such as QGIS, ArcGIS, ERDAS Imagine for different operations such as processing of drought indices, zonal statistics, unsupervised classification, and percentage area calculation.

**Normalised difference vegetation index (NDVI)**

NDVI is one of the most common and extensively utilised remote sensing-based drought indicators (Bhandari et al. 2012). NDVI values range from +1.0 to −1.0. Areas of barren rock, sand, or snow usually show shallow NDVI values (for example, 0.1 or less). Sparse vegetation such as shrubs and grasslands or senescing crops may result in moderate NDVI values (approximately 0.2–0.5). High NDVI values (approximately 0.6–0.9) correspond to dense vegetation such as that found in temperate and tropical forests or crops at their peak growth stage. NDVI quantifies vegetation by measuring the difference between near-infrared (which strongly reflects vegetation) and red light (which absorbs sunlight). The NDVI of a densely vegetated area tends toward positive values, whereas water and built-up areas are represented by near-zero or negative values. However, there is no clear border for each type of ground cover. By altering basic satellite information into NDVI values, scientists can interpret a rough amount of plant category, quantity, and state on terrestrial surfaces worldwide. NDVI is particularly valuable for continental- to global-scale vegetation monitoring as it can compensate for varying illumination situations, land slope, and observing angle. It can be noted that the NDVI does tend to saturate over compact vegetation and is sensitive to beneath soil colour. NDVI is calculated using Equation (1) (NDVI, the Foundation for Remote Sensing Phenology n.d.): 

\[
NDVI = \frac{NIR - RED}{NIR + RED}
\]

**Normalised difference water index (NDWI)**

The normalised difference water index (NDWI) is strongly related to plant water content. The sources near-infrared (NIR) and short-wave infrared (SWIR) are used to find the normalised difference water index (NDWI). SWIR reflectance reflects variations in plant water content as well as spongy mesophyll composition in vegetation canopies. In contrast, NIR reflectance is determined by internal leaf structure and leaf dry matter content but not water content. NIR and SWIR remove changes caused by the composition of the inner leaf and the dry leaf matter quality, improving soil water recovery accuracy. NDWI value ranges from +1 to −1. An NDWI value near +1 means more plant water content available, whereas an NDWI value near −1 indicates no plant water content (Gao 1996; Bhangale et al. 2020). NDWI is
calculated by using Equation (2):

\[
NDWI = \frac{NIR - SWIR}{NIR + SWIR}
\]
Normalised multiband drought index (NMDI)

NMDI was planned for remote sensing data in cooperation with soil and plants moisture content from space utilising three bands as NIR, SWIR6, and SWIR7. The pilot results indicated that for bare soil or inadequately vegetated region, a pixel indicates dry soil condition if the value of NMDI is greater than or equal to 0.7. The pixel records soil as intermediate dry if the NMDI is between the value of 0.6–0.7. The soil is recorded as wet if the value of NMDI is less than 0.6, while for densely vegetated regions, the operation of NMDI is like NDWI. Hence, by the combination of statistics from many NIR and SWIR channels, NMDI has improved the understanding of drought severity and is well suitable for the estimation of moisture content for soil and vegetation (Wang & Qu 2007). NMDI is given by the relation given in Equation (3):

\[
NMDI = \frac{NIR - (SWIR_6 - SWIR_7)}{NIR + (SWIR_6 + SWIR_7)}
\] (3)

Surface water content index (SWCI)

The regeneration of land and plant water quality is assessed in the analysis of drought control, respectively. It is challenging to acquire soil water influence directly through optical remote sensing with the effect of vegetation distribution on the earth’s surface. Considering the water reflectance spectrum, a new model is proposed called SWCI (surface water content index), which combines the spectrum characteristic of both soil and water. China Meteorological Administration (CMA) data on rainfall and soil water states that the model is compatible with soil water content and shifts. SWCI is very useful for tracking the rapid soil water content over a broad region (Hong et al. 2018). SWCI can be computed using Equation (4):

\[
SWCI = \frac{SWIR_6 - SWIR_7}{SWIR_6 + SWIR_7}
\] (4)

Moisture stress index (MSI)

The moisture stress index for maize and soybean crops calculates the impact of drought and extreme wetness on national crop yield, measured using a drought index. Moisture stress, either a shortage or an excess of soil moisture during crucial phases of the crop growth and development process, affects the average crop yield in the United States, mainly when moisture stress exists in the most crucial crop growing areas. The soil moisture levels were considered the most vital measures of average crop yields for maize and soybeans in July and August and are thus included in creating a moisture stress index (Welikhe et al. 2017). MSI is computed using Equation (5):

\[
MSI = \frac{SWIR_6}{NIR}
\] (5)

The value of MSI indicates the inverse behaviour as compared to the other mentioned four drought indices. Thus, to unify all the indices' behaviour, MSI inverse (MSI') is used in this study, representing similar behaviour in terms of severity of the agricultural drought. All the five drought indices mentioned above indicate the lower severity of agricultural drought and vice versa.

The basic prior operations required to calculate any drought index for the particular region are shown in Figure 3. Layer stacking is a mechanism by which several images are merged into a unique image. For this, the raster images should have the
same scale (number of rows and number of columns), so it needs to resample certain bands that have the specific spatial resolution to the target. Mosaic is helpful when it is essential to merge more than one neighbouring raster dataset into one object. Several mosaic strategies may help eliminate sudden shifts along the conflicting raster boundaries. The multiple combined images are then clipped by overlapping the study area shapefile to obtain the required calculation area. It also serves the purpose of saving time by a reduction in the number of pixels calculation. All the drought indices are then calculated in the raster calculator in GIS software with the appropriate formula. A pictorial representation stepwise calculation of drought indices is shown in Figure 3.

**Scaling down of drought indices**

The various drought indices used in this study have different extreme values, for example NDVI ranges from –1 to 1, whereas MSI ranges from 0 to more than 3. These drought indices are scaled-down by normalisation from zero to one. The normalized NDVI, NMDI, SWCI, MSI', NDWI is represented by NDVIZ, NMDIZ, SWCIZ, MSI'Z, NDWIZ. The sample representation of NDVI and NDVIZ is discussed further. Equation (6) represents NDVI, whereas Equation (7) represents the normalised value of NDVI (NDVIZ). The variation in units and forms of the indices was resolved through scaling down indicators into normalised positive values that range from zero to one.

\[
\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}} \tag{6}
\]

\[
\text{NDVIZ} = \frac{\text{NDVI} - \text{NDVI}_{\text{min}}}{\text{NDVI}_{\text{max}} - \text{NDVI}_{\text{min}}} \tag{7}
\]

**Drought categorisation and percentage area calculation**

Drought indices have long been used to characterise various types of drought, and the importance of combining multiple drought indices for accurate drought monitoring has long been recognised. Recently, a variety of multivariate drought indices based on linear combinations of multiple drought indices have been developed for comprehensive drought monitoring, integrating drought data from multiple sources. For operational drought management, it is generally necessary to establish drought severity thresholds that trigger a mitigation response during a drought event. This assists stakeholders and policymakers in making informed decisions.

Agricultural drought is categorised into five classes: Extreme Drought, Severe Drought, Moderate Drought, Slight Drought, and No Drought, to compare the five drought indices. Unsupervised classification is carried out using Erdas Imagine software for each drought index. The percentage area of the Warangal region in India’s Telangana province of each drought category is computed using zonal statistics.

**Iyengar and Sudarshan’s method of assigning unequal weight to multivariate data**

Assigning the equal weightage to various drought indices may not necessarily be correct. Hence it is advisable to give weights to the indices. Iyengar and Sudarshan established a technique for obtaining a composite index from multivariate data. Iyengar and Sudarshan used this technique to rank the districts for their economic performance. This technique is statistically sound and appropriate for developing a composite index of vulnerability to agricultural drought. The details of this technique are explained in the following paragraph. A composite index is commonly used to measure development in regional studies. The goal of this note is to define a composite index for measuring spatial differences in development levels. The construction and application of such indices are demonstrated using district-level data from the states of Andhra Pradesh and Karnataka.

For instance, there are M regions or subregions of a specific district, and there are K indices of vulnerability, and \(X_{ij} (i = 1, 2, \ldots; M; j = 1, 2, \ldots, K)\) is the normalised value. The level or stage of progress of the \(i\)th zone, \(Y_i\) is assumed to be a linear summation of \(X_{ij}\), as shown in Equation (8):

\[
Y_i = \sum_{j=1}^{K} W_j X_{ij} \tag{8}
\]

where \(W (0 < W < 1 \text{ and } \sum_{j=1}^{K} W_j = 1)\) is the weight. In Iyengar and Sudarshan’s method, the weights are expected to differ inversely with the regions’ variance in the respective indicators of vulnerability. The weight \(W_j\) can be determined as shown in
Equation (9):

\[ W_j = \frac{C}{\sqrt{\text{Var} (X_{ij})}} \]  

In Equation (9), \( C \) is a normalising constant and can be obtained as shown below in Equation (10):

\[ C = \left[ \sum_{j=1}^{j=k} \frac{1}{\sqrt{\text{Var} (X_{ij})}} \right]^{-1} \]  

The calculation of the weights using this technique ensures that considerable variation in any one of the indices would not unduly govern the rest of the indicators' contribution and distort inter-regional comparisons. The vulnerability index calculated using this technique lies between zero and one, with one value indicating maximum vulnerability and zero value indicating no vulnerability (Iyengar & Sudarshan 1982; Duong et al. 2017).
Corrected weightages of drought indices by considering relative error

All the weightages of drought indices found out by the Iyengar and Sudarshan’s method of assigning unequal weight to multivariate data are checked for error. The summation of all the weightages should be equal to one. The error occurring in the calculation is distributed to every index weightage as per their significance of weightage.

\[
Total Error (E_T) = 1 - \sum \text{Weightages of all drought indices (Xi)} \tag{11}
\]

\[
Relative Error (E_{Ri}) = E_T \times \frac{Xi}{\sum Xi} \tag{12}
\]

\[
Corrected Weightage of Drought Index (Xi') = E_{Ri} + Xi \tag{13}
\]

Total error \((E_T)\) in the combined drought index is calculated using Equation (11). This error is further divided relatively into all the considered drought indices as per their relative weightages using Equations (12) and (13).

\[\text{Figure 5} \mid \text{Graphical representation of scaled-down NDVI.}\]
RESULTS AND DISCUSSION

Various values of scaled-down MSI, NDVI, NDWI, and SWCI are discussed below.

Scaled-down moisture stress index

The MSI value varies from 0.6 to 2.2 from May 2013 to May 2020 for several subregions of the Warangal region of Telangana, India, whereas the value of MSI' varies from 0.45 to 1.67, with 0.45 indicating more vulnerability to agricultural drought and 1.67 indicating less vulnerability. To compare MSI' with other drought indices and determine the weightage of MSI' in MIDMI, MSI' is scaled down to 0 to 1 by normalisation for the month of May and analysed from May 2013 to May 2020, as shown in Figure 4. The maximum value of scaled-down MSI' for the Warangal region was observed as 0.39 in 2017 and 2019 at Nallabelli Mandal. The minimum value of scaled-down MSI for the Warangal region was observed as 0.26 in 2016 at Khila Warangal Mandal. The higher values of scaled-down MSI at Nallabelli Mandal show comparatively more significant plant water stress and, in inference, less soil moisture content in that part of the Warangal region. The lower value of scaled-down MSI at Khila Warangal Mandal shows comparatively less water stress in that part of the Warangal region of Telangana, India (Welikhe et al. 2017).

Figure 6 | Graphical representation of scaled-down NDWI.
Scaled-down normalised difference vegetation index

The NDVI value varies from −1 to 1 for the Warangal region of Telangana, India. To compare NDVI with other drought indices and determine the weightage of NDVI in MIDMI, NDVI is scaled down to 0 to 1 by normalisation for the month of May and analysed from May 2013 to May 2020, as shown in Figure 5. The maximum value of scaled-down NDVI for the Warangal region was observed as 0.61 in 2015 and 2018 at Shayampet, Khila Warangal, and Khanapur Mandal. The minimum value of scaled-down NDVI for the Warangal region was observed as 0.35 in 2014 at Wardhannapet Mandal. The higher values of scaled-down NDVI at Shayampet, Khila Warangal, and Khanapur Mandal show comparatively healthier vegetation in that part of the Warangal region. The lower value of scaled-down NDVI at Wardhannapet Mandal shows comparatively poor vegetation health in that part of the Warangal region of Telangana, India (NDVI, the Foundation for Remote Sensing Phenology n.d.).

Scaled-down normalised difference water index

The NDWI value varies from −1 to 1 for the Warangal region of Telangana, India. To compare NDWI with other drought indices and determine the weightage of NDWI in MIDMI, NDWI is scaled down to 0 to 1 by normalisation for the month of May and analysed from May 2013 to May 2020, as shown in Figure 6. The maximum value of scaled-down NDWI for the Warangal region was observed as 0.56 in 2016 at Wardhannapet Mandal. The minimum value of scaled-down NDWI for the Warangal region was observed as 0.35 in 2014 at Wardhannapet Mandal. The higher values of scaled-down NDWI at Wardhannapet Mandal show comparatively healthier vegetation in that part of the Warangal region. The lower value of scaled-down NDWI at Wardhannapet Mandal shows comparatively poor vegetation health in that part of the Warangal region of Telangana, India (NDWI, the Foundation for Remote Sensing Phenology n.d.).

Figure 7 | Graphical representation of scaled-down NMDI.
down NDWI for the Warangal region was observed as 0.46 in 2017 at Nallabelli Mandal. The higher values of scaled-down NDWI at Wardhannapet Mandal show more plant water content in that part of the Warangal region. The lower value of scaled-down NDWI at Nallabelli Mandal shows comparatively poor plant water content in that part of the Warangal region of Telangana, India. (Gao 1996; Bhangale et al. 2020).

**Scaled-down normalised multiband drought index**

The NMDI value varies from –1 to 1 for the Warangal region of Telangana, India. To compare NMDI with other drought indices and find the weightage of NMDI in MIDMI, NMDI is scaled down to 0 to 1 by normalisation for the month of May and analysed from May 2013 to May 2020, as shown in Figure 7. The maximum value of scaled-down NMDI for the Warangal region was observed as 0.68 in 2016 at Wardhannapet and Khila Warangal Mandal. The minimum value of scaled-down NMDI for the Warangal region was observed as 0.61 in 2018 at Nallabelli Mandal. The higher values of scaled-down NMDI at Wardhannapet and Khila Warangal Mandal show more wet soil in that part of the Warangal region. The lower value of scaled-down NMDI at Nallabelli Mandal shows comparatively less wet soil in that part of the Warangal region of Telangana, India (Wang & Qu 2007).

*Figure 8* | Graphical representation of Scale-Down SWCI.
Scaled-down surface water content index

The SWCI value varies from –1 to 1 for the Warangal region of Telangana, India. To compare SWCI with other drought indices and determine the weightage of SWCI in MIDMI, SWCI is scaled down to 0 to 1 by normalisation for the month of May and analysed from May 2013 to May 2020, as shown in Figure 8. The maximum value of scaled-down SWCI for the Warangal region was observed as 0.59 in 2014 at Velair Mandal. The minimum value of scaled-down SWCI for the Warangal region was observed as 0.53 in 2016 at Khila Warangal Mandal. The higher values of scaled-down SWCI at Velair Mandal show comparatively higher soil water content in that part of the Warangal region. The lower value of scaled-down SWCI at Khila Warangal Mandal shows comparatively lower soil water content in that part of the Warangal region of Telangana, India.

Comparison of drought indices

The Warangal region is classified into five different drought categories. MSI, NDVI, NDWI, NMDI, and SWCI are used to categorise the Warangal region into Extreme Drought, Severe Drought, Moderate Drought, Slight Drought, and No Drought categories. Figure 9 represents the percentage area under five categories for all the drought indices. The Warangal region’s percentage area under the Extreme Drought category remains constant for all the five drought indices from 2013 to 2020. The study indicates shows almost 8.81% area has no vegetation cover at all, which may be occupied by the water bodies. On the other side, the percentage area under the No Drought category shows extreme dense vegetation varying between 3.54 and 9.95% from 2013 to 2020 for the five different drought indices.

Raster images output

MSI, NDVI, NDWI, NMDI, SWCI indices are obtained by Landsat-8 satellite data for all the 26 Mandals of Warangal urban and rural districts of Telangana from 2013 to 2020, particularly for the 20–30th of May, as shown in Figure 10. The MIDMI is computed by giving weightage to these indices as per the Iyengar and Sudarshan method. Values of variance \((X_{ij})\), as discussed in Equation (8), varies from \(9.61571 \times 10^{-6}\) to \(0.001588\). The average value of variance for all the years for MSI is 0.00022. The average value of variance for all the years for NDVI is \(7.5384 \times 10^{-5}\). The average value of variance for all the years for SWCI is \(1.61535 \times 10^{-5}\). The average value of variance for all the years for NDWI is 0.00013. The average value of variance for all the years for NMDI is 0.00024. The average value of variance for all the years for MIDMI is 0.00042.
| YEAR | SWCI | NDWI | MSI | NDVI | NMDI |
|------|------|------|-----|------|------|
| 2013 |      |      |     |      |      |
| 2014 |      |      |     |      |      |
| 2015 |      |      |     |      |      |
| 2016 |      |      |     |      |      |
| 2017 |      |      |     |      |      |
| 2018 |      |      |     |      |      |
| 2019 |      |      |     |      |      |
| 2020 |      |      |     |      |      |

**Figure 10** | Raster operations output.
The weightage of NDVI is maximum for the Khanapur Mandal and minimum for the Hasanparthy Mandal. The weightage of NDWI is maximum for the Elkathurthi Mandal and minimum for the Damera Mandal. The weightage of NMDI is maximum for the Shayampet Mandal and minimum for the Damera Mandal. The weightage of SWCI is maximum for the Sangem Mandal and minimum for the Damera Mandal. The weightage of MSI is maximum for the Hanamkonda Mandal and minimum for the Damera Mandal, as shown in Figure 11. All these drought indices are then scaled down by normalisation to compare and categorised in zonal statistics for percentage area calculation under each drought category. The weights of the drought indices are corrected by distributing the total amount of error into all the five drought indices relatively as per their weightage. The weightage of NDVI is highest among all (33%), followed by NMDI (29%), NDWI (18%), MSI (12%), and SWCI (8%), as shown in Table 1. The range of MIDMI is 0 to 1, with 0 indicating Extreme Drought and 1 indicating No Drought condition.

The vulnerability of agricultural drought is accessed using MIDMI for the Warangal region of Telangana, India, for all the 26 subregions. MIDMI is classified into five drought categories: Extreme Drought, Severe Drought, Moderate Drought, Slight Drought, and No Drought. In Figure 12, the vulnerability of agricultural drought in five different drought categories are shown. The Mandal-wise variation of agricultural drought vulnerability is represented from May 2014. All Mandals of Warangal urban and Warangal rural districts come under the Moderate Drought category as per the analysis carried out with NDWI and SWCI. All the Mandals of Warangal urban and rural districts come under the severe drought category as per MSI. On the other hand, all the Mandals of Warangal urban and rural districts comes under the Slight Drought category as per NMDI analysis. As per analysis carried out with NDVI, Khila Warangal and Khanapur Mandal is under the Slight Drought category, and Wardhannapet Mandal is under the Severe Drought category. All the other Mandals of Warangal urban and rural regions are under Moderate Drought category as per NDVI for May 2014. This variation in the analysis of agricultural drought with different drought indices is because these drought indices were developed for different climatic and geographical conditions as well as different input data. In Figure 12, Mandals of the Warangal urban and rural regions are numbered alphabetically as: 1. Atmakur, 2. Bheemadevarappalli, 3. Chennaraopet, 4. Damera, 5. Dharmasagar, 6. Duggondi, 7. Elkathurthi, 8. Geesugonda, 9. Hanamkonda, 10. Hasanparthy, 11. Inavolu, 12. Kamalapur, 13. Khaazipet, 14. Khanapur, 15. Khila Warangal, 16. Nallabelli, 17. Narsampet, 18. Nekkonda, 19. Parkal, 20. Parvathagiri, 21. Raiparthy, 22. Sangem, 23. Shayampet, 24. Velair, 25. Warangal and 26. Wardhannapet.

![Figure 11](image-url) | Distribution of weightages of drought indices.

| Table 1 | Corrected weightages of drought indices by considering relative error |
|---------|-------------------------------|
| Title   | MSI   | SWCI  | NDWI  | NMDI  | NDVI  | SUM   |
| Weightage to drought index | 0.114654 | 0.076482 | 0.16799 | 0.272173 | 0.310378 | 0.941678 |
| Relative error in drought index | 0.007101 | 0.004737 | 0.010404 | 0.016857 | 0.019223 | 0.058322 |
| Corrected weightage to drought index | 0.121755 | 0.081219 | 0.178395 | 0.289030 | 0.329601 | 1.000000 |
Figure 12 | Agricultural drought vulnerability of the Warangal region for May 2014.
Computation of MIDMI

MIDMI is computed using the above-mentioned unequal weights for all the 15 subregions of the Warangal rural district and all the 11 subregions of the Warangal urban district for the drought-prone month of May from 2013 to 2020. The maximum, minimum, and mean values of MIDMI of the entire Warangal region from 2013 to 2020 are shown in Figure 13. The maximum value of MIDMI was observed in Atmakur and Damera Mandal for 2018, indicating that regions are less vulnerable to agricultural drought. The minimum value of MIDMI was observed in Wardhannapet Mandal for 2014, indicating that the region is more vulnerable to agricultural drought. Overall, the MIDMI average for the entire Warangal region varies from 0.52 to 0.56 for May 2013 to 2020, indicating the Warangal region is moderately susceptible to agricultural drought.

CONCLUSIONS

This study developed a multivariate integrated drought monitoring index (MIDMI) using the Landsat8 satellite data for the Warangal region of Telangana, India, by assigning unequal weights to MSI, NDVI, NDWI, NMDI, and SWCI as per the Iyengar and Sudarshan method. The Warangal region’s percentage area under the Extreme Drought category remains constant for all the five drought indices for the Warangal region. The percentage area under the Extreme Drought category remains constant for MIDMI. NDWI and NDVI show more percentage area under the Severe Drought and Moderate Drought region than other drought indices for the Warangal region of Telangana, India. MSI shows the least percentage of area under the Severe Drought category compared to other drought indices for the Warangal region of Telangana, India. MSI gives the maximum percentage of area under the Slight Drought and No Drought category for the Warangal region of Telangana, India. NDVI carries maximum weightage in MIDMI as the growth of vegetation is limited by water availability in the Warangal region (NDVI, the Foundation for Remote Sensing Phenology n.d.).

As per the results obtained by considering the average data of all the 26 subregions of Warangal urban and Warangal rural district, the Warangal region is moderately susceptible to the agricultural drought. MIDMI effectively combines drought information from different single drought indices (the use of these integrated, remotely-sensed drought indices is limited considerably by the fact that they were established and evaluated for a specific climate or geographic location), thereby overcoming some of the shortcomings of single drought indices, which cannot always capture aspects of agricultural drought. Because it does not rely on expert knowledge or station data, it has strong potential to progress ‘holistic’ drought monitoring in areas without robust meteorological station networks and across diverse climate conditions. The limitation of this study is the consideration of the comparatively short span of Landsat 8 satellite data. Also, there is further scope of comparing MIDMI with field data such as crop area sown. The net area under irrigation can be compared with MIDMI and the vulnerability of agricultural drought to a particular region under study.

Figure 13 | MIDMI for Warangal region from May 2013 to May 2020.
DATA AVAILABILITY STATEMENT

All relevant data are available from an online repository or repositories.

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