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RESEARCH ARTICLE

Drought vulnerability assessment by employing the Geographical Information System and Analytical Hierarchy Process for the Kurnool district of Andhra Pradesh, India

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Abstract – Droughts are recurring events that adversely affect agricultural activities, population density, and irrigated land. The consequences vary from region to region and are called a ‘creeping phenomenon’. It is necessary to map drought vulnerability comprehensively in order to develop and implement drought mitigation strategies. In this regard, remote sensing-based studies are most robust, effective, and efficient at monitoring and mapping droughts compared to conventional ground survey methods. The purpose of this study was to develop a comprehensive drought vulnerability map using geospatial techniques and remote sensing to assess the spatial extent of drought vulnerability in Kurnool district, Andhra Pradesh, India. A total of 13 drought-influencing parameters such as Slope, Elevation, Aspect, Soil texture, Geology/Lithology, Land Use & Land Cover, Drainage density, Distance from water bodies, Groundwater fluctuation, Normalised Difference Vegetation Index, Rainfall, Land Surface Temperature and Topographic Wetness Index were selected for the assessment of drought vulnerability. These indices were integrated to create drought maps of both spatial and temporal extent in ArcGIS. Using pairwise comparison matrices, the Analytical hierarchy process (AHP) calculates weights for each criterion. The Drought Vulnerability Assessment map is generated by analysing the parameters through spatial analysis. The results revealed that the drought vulnerability index of Kurnool is 42.5. This finding has been successfully validated by historical drought records of the region. Decision-makers can use the results to develop and apply proactive drought mitigation strategies.

Keywords – Analytic Hierarchy Process (AHP), Geospatial Techniques, Geographic Information System (GIS) Remote Sensing, Drought vulnerability

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INTRODUCTION

Over time, the prolongation of dry weather impacts the social, economic and environmental aspects as a slow natural hazard (Palchaudhuri and Biswas, 2016). Recent decades have seen the term “drought” gained worldwide attention due to its devastating effects. Depending on the individual climatic circumstances, drought may also happen in locations with heavy precipitation or humidity, therefore it’s not just a risk in dry or arid areas (Erdem et al., 2021; Ideki and Weli, 2019; Khampeera et al., 2018). Food security in our country is at serious risk due to severe droughts, which severely threaten agricultural and water resources (Mohammad Ekrami et al., 2016; A. Zarei et al., 2021) (Ramu et al., 2022). However, agriculture’s qualitative and quantitative impacts intervene with climatic conditions and allied factors. Drought risk, severity, and duration vary by location, with different forecasts worldwide (Erdem et al., 2021; Khampeera et al., 2018). Every year, many people are affected by recurring drought events, which are common in many parts of the world. The effects of drought can vary by crop type, growth conditions, and local conditions in a region and can have devastating impacts on crop yield and production (Abuzar et al., 2019; Belal et al., 2014; Ramu et al., 2022). Droughts are difficult to monitor because they are complex phenomena affected by several variables. Hydrological droughts are brought on by variations in the availability of surface or groundwater, whereas meteorological droughts happen when there is a lack of precipitation and changes in relative humidity in a region (Belal et al., 2014; Hagenlocher et al., 2019; Sivakumar et al., 2021). As a result of changes in land use/land cover, soil texture, slope, and water insufficiency, crop health, growth, and production, population density and economic status are adversely affected (socioeconomic drought) (Kampragou, 2015; Sivakumar et al., 2021; Srinivasareddy et al., 2021).

According to many authors' research, the ideal strategy for drought management is a comprehensive, cost-effective, and timely system. While drought crisis management happens as the drought develops, drought preventive measures may be performed prior to the drought's commencement. A number of measures have been implemented to lower the likelihood of droughts, with the main emphasis being on controlling drought risks and emergencies. These programmes also take into account how droughts might coexist with other elements that may amplify their effects, such as population expansion, urbanisation, and changes in land use (M. Ekrami et al., 2016; Saha et al., 2021; A. R. Zarei et al., 2021). It is possible to integrate and analyse different data sources using GIS techniques as part of catastrophe monitoring (N. Zagade and Umrikar, 2021). A multidisciplinary approach is required for predicting and mitigating drought hazards due to their complexity and importance (Raheem et al., 2019; Sultana et al., 2021a). Numerous studies have focused on creating hydro-meteorological drought indices for assessment and monitoring (Belal et al., 2014; Zagade and Umrikar, 2021). Droughts being non-structural and recurring phenomena, require conscientious monitoring and management practices to ensure that an agrarian country like India has high productive potency (Savari et al., 2022). Such is a Drought assessment through AHP. AHP is thought to help rank factors and criteria in a hierarchical order and analyse data using pairwise comparisons (Palchaudhuri and Biswas, 2016; Penki et al., 2022a; Ramu et al., 2022).

Droughts can have a detrimental effect on an economy and have serious effects on the forestry, fishing, and agriculture industries (Raheem et al., 2019). A water shortage causes drought events to decrease crop and livestock production (Berger et al., 2018). Drought can have wide-ranging and far-reaching impacts on the environment. Some of the ways in which drought affects the environment are Loss of vegetation, Wildfires, Soil erosion, Water scarcity and Changes in land use. Overall, the impact of drought on the environment can be significant and long-lasting, affecting ecosystems, wildlife, and human communities in many different ways (Hagenlocher et al., 2019). Moreover, the social impact is also evident because the drought persists for such a long time and is so severe (Alston and Kent, 2004).

A vast area is subject to unpredictable drought, so using powerful- robust technologies such as remote sensing is necessary to monitor and map droughts. Satellite image-based spatial monitoring of droughts can help reduce the impacts of drought (Penki et al., 2022a; Ramu et al., 2022, 2022; Savari et al., 2022). It has become more popular and widespread to monitor agricultural droughts using satellites in recent years (Kundu et al., 2021). The use of remote sensing and GIS to monitor environmental problems, including drought, has proliferated over the past few decades (Sultana et al., 2021a).

Drought monitoring is the most reliable approach to mitigating drought-related challenges on both a local and global scale, ensuring sustainable improvements in agricultural production efficiency and improving livelihoods (M. Ekrami et al., 2016; Savari et al., 2022, 2022; Sultana et al., 2021b). Drought has a negative impact on environmentally sustainable practices, so it is critical to conduct research in this area to recognise better the characteristics, occurrence, and effects of drought at the regional and local scales (Senamaw et al., 2021; Sultana et al., 2021b; Wijitkosum, 2018). The current research closely monitored droughts with several drought indices for sustainable agricultural production and land-use planning throughout the study area.

The multicriteria decision analysis technique (MCDA) offers a variety of techniques and procedures for analysing and structuring decision problems, evaluating alternative decisions, and prioritising them (Penki et al., 2022a, 2022b; Ramu et al., 2022, 2020; Wijitkosum, 2018). The pairwise comparison method created by Saaty (1990) in the framework of such decision-making procedure, termed as the Analytic Hierarchy Process, represents one of the collection's most promising strategies (AHP) (Saaty, 1990; Saaty and Vargas, 1991).

DATA COLLECTION & METHODOLOGY

Study area

Kurnool is a district in Andhra Pradesh, India, with an area of 8,507 km2. The study region map of the Kurnool district is shown in Fig. 1. It has an average elevation of 273 meters (898 feet) and is located at 15.8333°N 78.05°E. According to the 2011 census, Kurnool has 4,053,463 residents. Tungabhadra River runs along Kurnool's banks. Several rivers run through the city, including Hundri and Neeva. Kurnool has a hot savanna climate with summer temperatures ranging from 26 °C to 46 °C and winter temperatures ranging from 12°C to 31°C. The annual rainfall averages around 920 mm.

The impact of droughts on agriculture must be evaluated, and a drought vulnerability map must be made in order to pinpoint drought-prone regions in the Kurnool region. Using geographic information systems and multicriteria decision models (AHP) can yield more realistic and accurate results (Penki et al., 2022a). A variety of factors cause agricultural drought vulnerability. Data availability and reliability in different regions play a role in mapping agricultural drought vulnerability. Based on the literature, it was found that several parameters and factors in the current study can predict agricultural drought vulnerabilities. Slope, Elevation, Aspect, Soil Texture, Geology/Lithology, Land Use & Land Cover (LULC), Drainage Density, Distance from Water Bodies, Ground Water Fluctuation, Normalised Difference

Vegetation Index (NDVI), Rainfall, Land Surface Temperature (LST), and Topographic wetness index (TWI) were then specified as the leading indices, making a total of thirteen parameters. Thematic maps were then produced for each of them. Section 3.1 discusses how relevant data collected from different sources were utilised to produce maps derived from parameters other than land use/land cover parameters. Multispectral classification techniques were used to prepare the land use/landcover map derived from remotely sensed data (Penki et al., 2022a; Ramu et al., 2022). During this study, the supervised classification technique has been used to classify multispectral LULC maps using the prior probabilities calculated from the ground data (Penki et al., 2022a; Ramu et al., 2022). An initial step in supervised classification is identifying the information classes corresponding to the spectral classes. These maps are divided into different drought risk intensities based on the ratings. The criteria are then prioritised in order of priority for categorising the study area into the several drought-influencing parameters depicted in the table5.

Thematic maps preparation

Landsat8 OLI-TIRS C1 Level-1 data was taken from the USGS Earth Explorer to produce the region's NDVI and Land surface temperature layers (Penki et al., 2022a; Ramu et al., 2022; N. Zagade and Umrikar, 2021). Slope & elevation layers have been developed using SRTM-DEM downloaded from USGS earth explorer, with 30m resolution by application of spatial analyst tool (Penki et al., 2022a). TWI is derived from the SRTM DEM by using a raster calculator. Soil texture and geology maps are framed by referring to the FAO/UNESCO Soil map of the world and USGS world geologic maps, respectively (Ramu et al., 2022). Using the hydrology tool, the stream flow lines were removed from the Digital Elevation Model (DEM), and a drainage density map was produced in GIS using a line density command. To understand the (LULC) pattern in the area, a global map of LULC is derived from landsat8 at 30m resolution (Penki et al., 2022a; Ramu et al., 2022). Groundwater fluctuation level data is obtained from the India-WRIS for generating groundwater depth maps. To validate the drought zonation model, the existing surface water bodies were manually digitised using Google Earth images to prepare the Distance from the water body's map. The methodology implemented for this study is shown in Fig. 2, and for easy visibility, the data source is shown in table 1.

Prolonged dry periods, a considerable increase in entire dry days, and fewer rainfall events characterise drought rainfall variability. Hence, annual rainfall data have been utilised to understand the features of drought better. For the drought assessment, rainfall data is collected from the Andhra Pradesh Water Resources Information & Management System (Gaddam and Sampath, 2022) to develop a yearly-rainfall map using "The IDW Interpolation method".

Tab. 1 Data Source

S.no	Parameters	Data Description	Source	Resolution
1	LULC, LST, NDVI	Landsat 8	USGS Earth Explorer	30m
2	Elevation, Slope, Aspect, TWI, Drainage density	SRTM DEM	USGS Earth explorer	30m
3	Rainfall	Annual Rainfall data	APWRIMS	-
4	Soil Texture	Soil Shapefiles	Food and Agriculture Organization (FAO)	1:500000
5	Lithology	Lithology	Geological Survey of India (GSI)	1:500000
6	Groundwater	Groundwater depth	Indian Water Resource information system	-
7	Distance from the water bodies	Shapefile	-	-

The NDVI monitors vegetation cover, crop identification, plant health, and agricultural growth patterns. Vegetative reflectance in red and near-infrared wavelengths is used to calculate the intensity and the density of the green cover shown in Eq. (1) (Penki et al., 2022a):

$$NDVI=(Nir-Red)/(Nir+Red) \qquad (1)$$

Here, Nir and Red are the spectral reflectances attained in the near-infrared regions & red (visible).

The Topographic Wetness Index measures how much water is distributed across the landscape. It estimates the possibility of water accumulation in reliable areas. If the index number is high, much water may be collected from the slope, and vice versa. TWI is calculated using Eq. (2), shown below:

$$TWI = \ln(\alpha / \tan\beta) \qquad (2)$$

Where α = catchment area and β = slope.

Several parameters should be picked up in order to compute Land Surface Temperature. Converting top atmosphere radiance values was one of the steps. Then, using temperature constants, calculate Atmosphere Brightness Temperature (BT) as a key in the final equation. Vegetation coverage is used to calculate NDVI and Land Surface Emissivity. To end, the results are utilised to calculate the land surface temperature shown in Eq. (3):

$$LST= BT/ (1+(\lambda*BT/c2) * \ln(\mathcal{E})) \qquad (3)$$

Where LST= Land Surface Temperature in Celsius (°C), BT= Brightness Temperature in (°C), λ= Wavelength of Band, Ɛ= Land surface Emissivity.

AHP Approach

An AHP is a multicriteria decision-making process based on pairwise comparisons between elements in a hierarchy (Saaty, 1990; Saaty and Vargas, 1991). AHP is evaluated using a hierarchical approach, and the expertise/experience of critical decision-makers is explicitly incorporated into the evaluation (Saaty, 1990). In order to determine how drought-prone the area is, AHP was employed to identify the zones. Weights have been assigned to influencing factors following the steps described below in the hierarchical dominance framework shown in sections 2.2.1 to 2.2.4. Based on this premise, our research utilised AHP and GIS techniques to evaluate drought vulnerability in the Kurnool province from a socioeconomic perspective. In one instance, we combined relevant socioeconomic data with satellite-derived insights to assess drought vulnerability (Gaddam and Sampath, 2022; Gibney and Shang, 2007; N. Zagade and Umrikar, 2021).

Generation of a hierarchy structure

Establishing a value structure of assessment criteria with a hierarchical relationship between the objectives and the appropriate alternative is part of the process for geospatial multicriteria decision problems. The overall objective is placed at the top of the hierarchy in AHP, and the criteria, sub-criteria, and alternatives are placed at each descending level (Gibney and Shang, 2007). At each level, the user creates a comparison matrix to apply the principle of comparative judgments by comparing pairs of criteria or alternatives.

Pairwise Comparison matrix

The pairwise comparison matrix (PWCM) assigns a rating to each component based on how strongly (or weakly) they relate to other factors and how much of an impact they exert on the severity of a drought. A scaling of attributes from 1 to 9 is used to generate PWCM for dimensions n × n (no of criteria contrasted) and is displayed in the table3.

Once the matrix of pairwise comparisons has been formed, the relative priority of each alternative in terms of the specific criterion can be estimated. Each alternative's combined weight is calculated based on preferences derived from criteria or sub-criteria matrix. The option with the highest overall rating is typically chosen as the final solution.

Consistency ratio (CR)

A consistency ratio is examined as the final step. When the consistency ratio (CR) is less than 10%, the hierarchy and ranks are considered consistent in PWCM; otherwise, the hierarchy and ranks are not considered consistent and should not be considered. A CR value of greater than 1 should be revised by the expert's knowledge and experience (Saaty, 1990; Saaty and Vargas, 1991). The consistency ratio (CR) for this study is 0.043 (i.e., 4.3%), which is less than 10%, and as a result, the ranks are considered consistent and suitable for modelling. The numerical form for calculating the consistency ratio (CR) is represented by Eq. (4):

$$CR = CI/RI \qquad (4)$$

CI is the consistency index, and RI is the mean consistency index, which varies with matrix size. Eq. (5) specifies the formula used to calculate the CI.

$$CI = (\lambda max-n)/n-1 \qquad (5)$$

Where n is the size of the matrix and λmax is the principal-eigen-value. Table 4 shows the values for the Random index.

Eigenvalues are computed by averaging and normalising the weights of the evaluating criterion. Additionally, the greatest eigenvalue is considered as λmax, which verifies the PWCM's consistency in decision-making.

RESULTS

Drought in the study area has been assessed by the indices (Slope, Elevation, Aspect, Soil texture, Geology/Lithology, LULC, Drainage density, Distance from the Streams, Groundwater depth, NDVI, Rainfall, LST and TWI) to monitor the drought severity. Thirteen "pairwise comparison matrices" for the criteria regarding the goal were generated in this study, shown in Table 5.

Slope

The slope of the land is an essential feature in determining the "rainfall to runoff" and "rainfall to recharge" ratios. Because rainwater has a short residence time on land with steep slopes, there is little chance of Infiltration (Penki et al., 2022a). The land slope has been classified into five categories: flat-gentle (2°), low slope (2°-5°), moderate (5°-10°), high (10°-20°), and very high (> 20°). As a result, as the slope increases, the rate of water infiltration decreases, likely to result in much more runoff. Slopes are also essential in determining land-use patterns and varying the natural recharge rate. Most of the area is covered by a gentle to flat slope, i.e., the plateau region depicted in Fig. 3. The slope tends to increase toward the NE and SE, particularly in the peripheral hilly region where high runoff is generated; thus, low ranks and high weights are assigned to the very high slope category, where there is a more significant impact on drought vulnerability. As a result, despite high rainfall, the hamlets and small settlements in hilly areas face drinking water scarcity yearly.

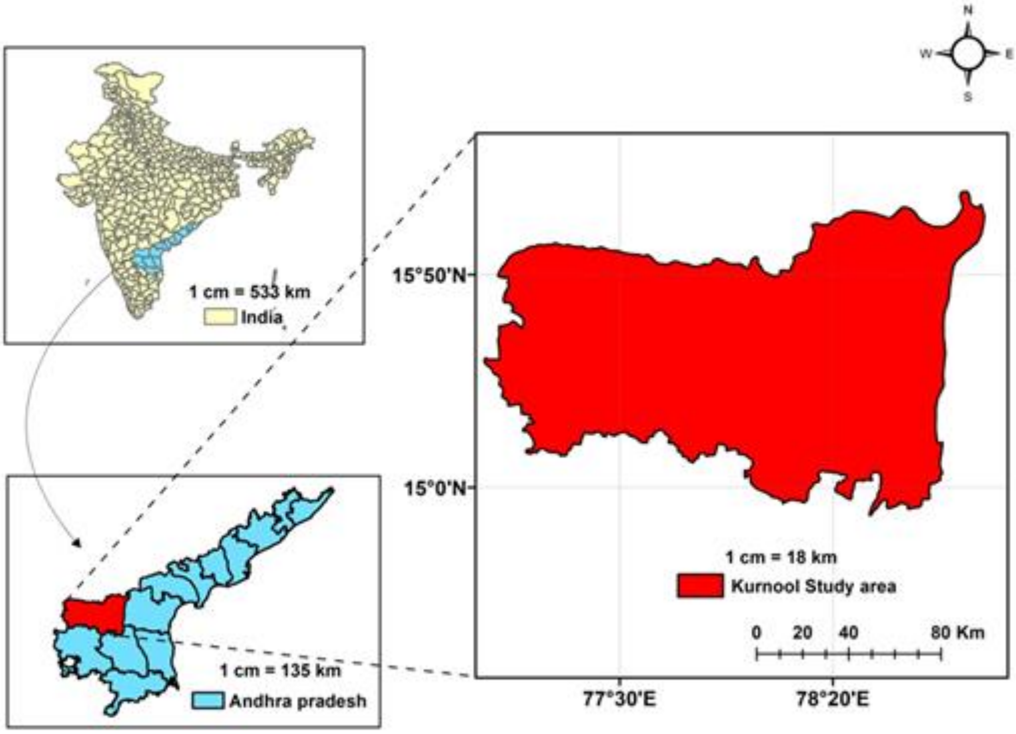

Fig. 1. Location map of the study area.

Elevation

Elevation can be used to determine the severity of a drought. Water always flows from higher elevations to lower elevations. Lower elevations can store more water (N. D. Zagade and Umrikar, 2021). It is pertinent to note that altitude and temperature are inversely related. It tells us that lower elevations experience higher temperatures than higher elevations, and also, there is a direct relationship between the rate of evaporation and the temperature (Belal et al., 2014). This way, evaporation will occur more at lower elevations due to the higher temperatures. In addition, the surface area directly affects water drainage. The elevation map of the study area is divided into five classes ranging from < 15 to > 66m, shown in Fig. 3. According to this study, flat zones have a larger surface area than highly elevated ones. Drought is caused by an increase in temperature and evaporation combined with a decrease in altitude.

Aspect

Different aspects begin receiving varying levels of solar radiation. Hydrological processes influence this parameter. The study area’s aspect map was divided into several classes (Khampeera et al., 2018). A value was established for every class based on the influence of heating rate, Infiltration, soil evaporation, humidity and runoff. Using relevant literature and regional specialist knowledge, vulnerability classes of various aspect ranges have been ascertained (Mohammad Ekrami et al., 2016). In accordance with this study, the aspect map is divided into five classes, as shown in Fig. 3.

Soil texture

The pace at which water permeates the soil surface is influenced by the texture of the soil. The size and arrangement of the mineral particles that make up the soil determine its texture. The soil’s permeability and infiltration rate decrease with decreasing particle size. One of the most permeable soils that allows for quick infiltration is sand and sandy loams. The least permeable soils, on the other hand, are clay and clay loam soils, which also have lower infiltration rates. In comparison to pure sand and pure clay, sandy clay soils offer a medium level of permeability. Sandy soils’ high porosity and permeability can promote more water penetration. As indicated in Figure 3, the soil in the research region was divided into three types: clay, loam, and clay loam. Based on each soil type’s water permeability and porosity, weights were allocated to them. The clay soil type was given the lowest rank and most weight since it has the highest risk of drought. On the other hand, soils with a finer texture can hold onto moisture for an extended amount of time.

Lithology

This component, particularly regarding permeability, seems to have a storage capacity that varies depending on the kind of rock (Penki et al., 2022a). Rainfall water penetration has been lowered whenever the rock seems impermeable, allowing water to runoff and resulting in no groundwater recharge, paving towards a dry surface and resulting in drought. The Lithology map of the study area depicts the Undivided Pre-Cambrian rocks (pc) depicted in Fig. 4.

LULC

The land use type is essential in determining the hydrological configuration of almost any river basin/watershed. Land use/land cover is critical in determining drought severity (Ramu et al., 2022). Land use influences the rate of Infiltration. Water infiltration is aided by forests and plants, for example. Storm runoff is exacerbated in urban areas, predominantly made up of impermeable surfaces and barren land. Fig. 4 depicts the LULC classes of water, vegetation, built-up area, and barren terrain.

Drainage Density

The drainage density, demonstrated in kilometres per square kilometre, signifies the total length of streams per unit of area. It is a significant criterion that, in many ways, connects the basin's landform characteristics with the processes that happen along the stream course. Drought conditions may get worse if water infiltration causes deep groundwater tables to become unavailable to plants. This is due to the fact that water that permeates deeper into the soil is unavailable to support plant growth and development, increasing water stress and decreasing yield. Conversely, if the soil has a high rate of infiltration, the extra water will drain to the surface and lessen the likelihood of drought. When assessing the likelihood of drought in a certain area, it is crucial to take soil texture and water penetration rates into account (Penki et al., 2022a; Ramu et al., 2022; Ravinder et al., 2020; Sivakumar et al., 2021). A low drainage density indicates that the vast majority of stormwater infiltrates the subsoil and, as a result, few channels have been formed to transport the produced surface runoff. The relationship between the erosional power of overland flow and also the resistance of surface soils and rocks is reflected in drainage density. Because soil and rocks with a high infiltration rate minimise overland flow, drainage density is low in that region. Higher drainage density causes more surface water flow in that area, making it more prone to drought conditions. This study classified drainage density into five classes, as shown in Fig. 4, ranging from 0.5 to > 2 km/km2. Because of the low soil-water interaction and poor infiltration, the areas with the highest drainage density have been assigned low ranks and high weights.

Distance from water bodies

A surface water depression is created by heavy rains or artificially by humans. These small depressions can serve many different purposes, from washing clothes to farming to drinking water. Due to the high temperatures, these can dry up and form again when it rains. Additionally, they are only capable of serving the residents around them. So, in this study, these were given minor importance, and ranges are taken from 0.5 Km to >2 Km, as shown in Fig. 5. As a result of the limited supply of surface water in areas >2km, these areas received the lowest rankings and the highest weights, followed by those areas nearby the surface water with the highest rankings and lowest weights.

Groundwater level fluctuation

The weathered/fractured zone is underlain by hard massive basalts that form the phreatic aquifer's base rock, restricting its downward extent. Seasonal replenishment of the groundwater in these shallow aquifers causes water levels and fluctuations to be important in drought assessments. Groundwater levels in dug wells drop due to various factors, including rainfall variability, groundwater extraction during the rainy period (prolonged dry spell) for irrigating rain-fed crops, increased demand, and hydraulic connection with the restricted aquifers. Groundwater levels are directly associated with drought severity. The groundwater level fluctuations for the study area range between 0.09 to 22.8 m, shown in Fig. 5. High fluctuation (>17) and the maximum area is situated in moderate to high fluctuations where lowest ranks and high ranks were allocated to the highly fluctuated regions and followed by low ranks. These high fluctuations may mostly be due to the unprecedented withdrawal for crop irrigation and domestic use.

Normalised difference vegetation index (NDVI)

This research is concerned with calculating vegetation cover based on NDVI, a method developed to measure the density and intensity of vegetation cover. NDVI can be used to assess drought indirectly. It measures the amount of vegetation cover and is used to assess drought. The NDVI ranges from -0.24 to -0.58 shown in fig 5. NDVI values of -0.1 and 0.13 indicate areas with water bodies, rivers, or barren areas with exposed rocks. Crops are identified by values ranging from 0.13 to 0.27. The areas with dense vegetation cover and forest or tree plantations in the northeastern and southeastern parts of the study area are indicated by high NDVI values. The highest NDVI values indicate the highest risk of drought and the lowest rank, while vice versa. From Fig. 5, we can observe that the NE and SE regions cover most of the vegetation where agricultural drought occurs, but not only NE and SE regions; almost 90% of the Kurnool is under moderately to very high vulnerability to drought as per NDVI consideration.

Rainfall

The quantity of rainfall determines the severity of drought, the number of rainy days, the intensity of rainfall, and the length of drought periods. Dry periods between rainfalls are critical in retaining moisture in soil zones and providing water to various crops, thus making them an essential component of drought analysis. Reservoirs, rain-fed agriculture, and groundwater saturation all increase in areas with an above-average amount of rainfall. As a result, dug wells are often overwhelmed by groundwater. Rainfall is the most important source of recharge in the study area. The most rainfall recorded was 880.65 mm, with the least being 419.2 mm, shown in Fig. 6. The greatest amount of rainfall occurs in the summer months. The low ranks and high weights were allocated to areas with less rainfall due to high drought vulnerability, and the highest ranks and low weights were assigned to the areas with maximum rainfall.

Land Surface Temperature (LST)

The LST provides information about the surface's physical properties and climate by monitoring the earth's energy balance. A lack of rain, which resulted in a lack of moisture and a lower vegetation cover area in lower elevation regions, resulted in a dramatic rise in surface temperature. Because vegetation cover declined due to the increased LST in the SE and SW regions of the study area, it is shown in Fig. 5. This shows the negative repercussions of elevated LST on plant growth and development environments, leading to a decrease in vegetation area (NDVI) in the region. In the NE and SE regions of the study area, the LST was reduced in a few areas, which was subsequently reflected in an increase in vegetation (NDVI). This increased temperature, in turn, results in increased evaporation and dries out the soil and vegetation, leaving little surface water and causing drought. According to this study, the LST is classified into five classes ranging from < 17.6 to 48 °C shown in Fig. 6.

Topographic wetness index (TWI)

The slope of the terrain impacts the amount of water that can be collected there; likewise, a low TWI implies a low amount of water, while a high TWI indicates a higher amount of water. Therefore, areas with lower TWIs are more prone to drought due to the low quantities of water that can be collected there. The map in Fig. 6 shows that a TWI value of (<2.8) is associated with a high probability of drought, whereas a TWI value of (>10) is associated with reduced risk.

Reclassification and integration of the thematic layers

In Table 3, the criteria specified are compared one by one to determine which one is more essential concerning the goal. Similarly, sub-criteria are also compared according to their value in relation to the main criteria. Finally, the ranks of the alternatives were determined using the thirteen parameters shown in Table 5. Each criterion and sub-feature class within each thematic raster layer was ranked for reclassification. Using weighted overlay analysis, the thematic layers have been integrated, resulting in a map that indicates drought levels based on the area under study. The spatial resolution of each raster layer must always be adjusted to 30 mx30 m cell size prior to integrating thematic layers. It must be overlaid using a raster calculator in ArcGIS based on the effective weights of the AHP technique. This offers a comprehensive database that includes drought vulnerability. A map of the research region's drought vulnerability is shown in Fig. 7. The area has been further categorised using the manual edit approach to be divided into very high, high, moderate, and low drought zones and shallow drought zones.

Overall Drought Impact

The zonation map illustrates that 2664.57318 square kilometres of the research region and 5441.58962 square kilometres of that area are both very sensitive to extreme drought conditions having hills, fallow and barren land as important land use, soil texture with poor water holding capacity, steep slopes, high drainage density indicating more surface runoff and moderate to high groundwater level fluctuation occupying. Results reveal that almost 25% of the area faces severe/very high drought. Because of the good rains and cooler temperatures in the NE and SE, there is good NDVI and no drought. However, the remaining part is a rainfall deficit area; hence, very high to moderate droughts were seen, especially in these areas. Because of the severity of the drought, most agricultural lands have not been farmed because there is not enough water or moisture in the soil. It is unnecessary to take additional drought reduction measures in regions with mild to moderate drought conditions. A water shortage concerns sustainable agriculture practices in the Kurnool district and severe drought risk areas. During a dry spell, these regions need to strengthen their water resources infrastructure with access to water supplies. Protecting cultivated land, implementing trans-basin water transfer strategies, and utilising agricultural water-saving technologies will aid in reducing the severity of droughts in the SW and NW regions of Kurnool. Nearly 76% of the area is at risk of drought (very high and high drought combined). Therefore, stress has to be given to these areas while preparing drought management plans. Finally, drought risk zones identified in the study could help manage and mitigate drought in Kurnool. Furthermore, the study's methodology might well be used in several nations. The study could be further investigated using P-GIS (participatory geographic information system), which gathers evidence from various sources, including the general public and data interpreters, and then distributes the processed data to various users, increasing the accuracy of the final map.

Validation

The validation process is carried out by identifying previous drought events in the drought vulnerability assessment map, as shown in Fig. 7. A record number of 14 drought samples over the past decade were gathered from various sources such as newspaper articles and disaster manuals. The validation results strongly correlate previous drought events and mapped zones. Most previous drought events occurred typically in the southwest and northwest of the region with the high and very high vulnerability zones, with only a few drought events occurring in the moderate zone. However, according to the vulnerability map, the zones characterised as very low had not experienced any flood events in the past. Out of 14 total drought events, 1, 6, and 7 drought incidents happened in moderate, high, and very high severity zones.

DISCUSSION

To contain and reduce the debilitating effects of drought and the ultimate achievement of drought-proofing an area, it is necessary to pursue proactive, relentless, but planned long- and short-term measures that combine structural/physical and non-structural measures. The short-term initiatives often manage the in-season drought through emergency preparation and relief provision. They are frequently reactive or relief-focused. Long-term mitigation efforts, such as using sensible crop choices and sustainable agronomic and restoration strategies, aim to restore ecological equilibrium. Most such initiatives have been incorporated on the ground through agriculture practices suitable for rain-fed agriculture, watershed management, soil and water conservation, and forestry programs that combine soil, water, and forestry management in an ecologically sound and sustainable manner. Drought mitigation must regularly be part of the Center and State Governments' development programs. Some of the most prominent recent efforts that could substantially impact drought mitigation are the Government Rainfed Area Development Program, the National Rural Drinking Water Program, the Pradhan Mantri Krishi Sinchayee Yojna, and others. Many of these initiatives can be focused on building an agricultural industry by making use of the flexibility built into the government-supported schemes to mitigate disasters like drought. The Kurnool region will see a range of effects, from rising temperatures to a greater danger of wildfires, changing precipitation patterns, increased frequency and intensity of droughts, and changes in agriculture that might result in lower yields and more crop failures. The region will face severe problems as a result of climate change, necessitating resilience-building adaptive strategies (Aruna Jyothy et al., 2021). Drought risk can be comprehensively assessed using the AHP-RS-GIS integration procedure, but the risk is also impacted by changes in land use, human activity, and infrastructure development. In order to evaluate the effectiveness of the procedure and other variables influencing drought risk, ongoing monitoring and research are required (S. et al., 2014).

CONCLUSIONS

According to drought indices, significant drought was discovered in various regions of the research area. Because of the magnitude of the drought, most agricultural lands have not been farmed because there is insufficient water or moisture in the soil. Additionally, periodic rainwater harvesting for agricultural purposes may help this region gradually adjust to drought. The regional impact, geographic complexity of droughts, and factors that influence them should all be considered while regulating drought policy. To improve decision-making, the national meteorological agency should enhance its network of weather stations in the areas with the highest drought risk. However, like an early warning sign, the findings from the various drought indices can help monitor the beginning of an agricultural drought. Changes to agronomic practices, restoration of agriculture, zero tillage, and sowing and planting timings could all help increase resilience to the effects of drought. The best way to reduce drought damage is to use local farmer expertise, build drought monitoring and prediction systems, and purchase drought insurance. With this training, participants can be better prepared to cohabit with and deal with drought situations before they emerge.

Numerous disciplines can benefit from GIS and remote sensing methodology and analysis. Technology has been employed for various purposes in disaster management at different instances and phases for modelling, analysis, and mapping. The Kurnool District drought vulnerability assessment mapping has been enhanced by applying a Geographic Information System-based spatial multicriteria evaluation framework coupled with the AHP approach.

Using remote sensing data with a GIS tool and AHP to create drought vulnerability maps was very beneficial in creating qualitative to quantitative variables. Crop choices, farming practices, soil characteristics, drainage patterns, and groundwater profiles, to name a few, are just a few of the factors that can cause droughts. Most of all, dry spells, the spatial and temporal distribution of precipitation, and their duration are recognised as the most significant causes of drought. It is particularly suitable for use in places with limited data and information due to its ease of handling, flexibility, and low cost. The AHP approach accomplishes its goal in the preliminary assessment of drought susceptibility.

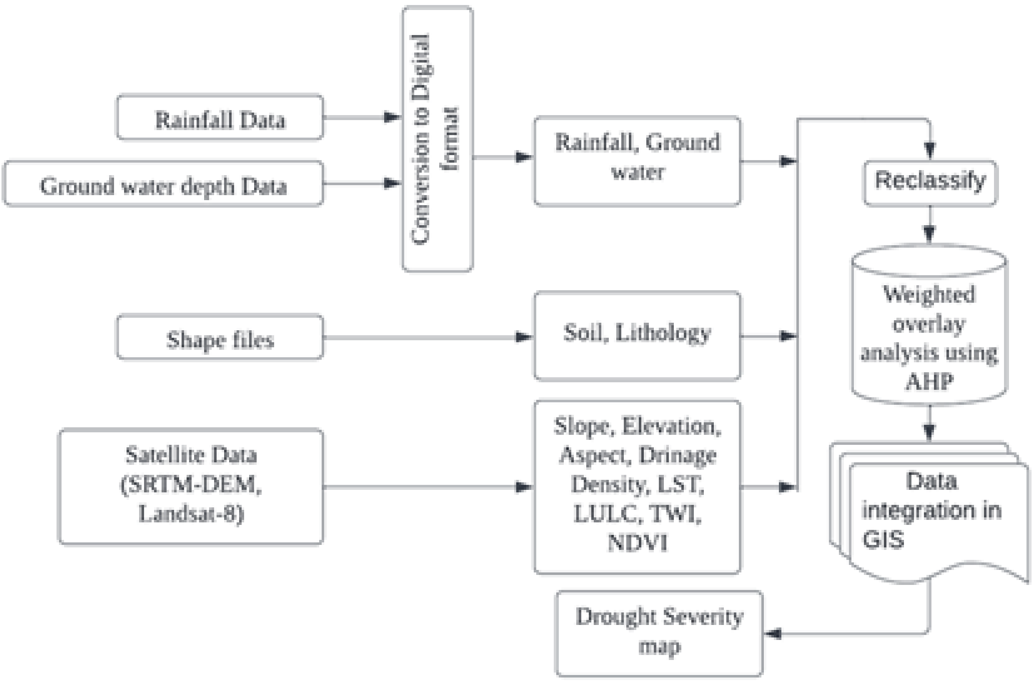

Fig. 2. Methodology flowchart representing the working steps involved in this study.

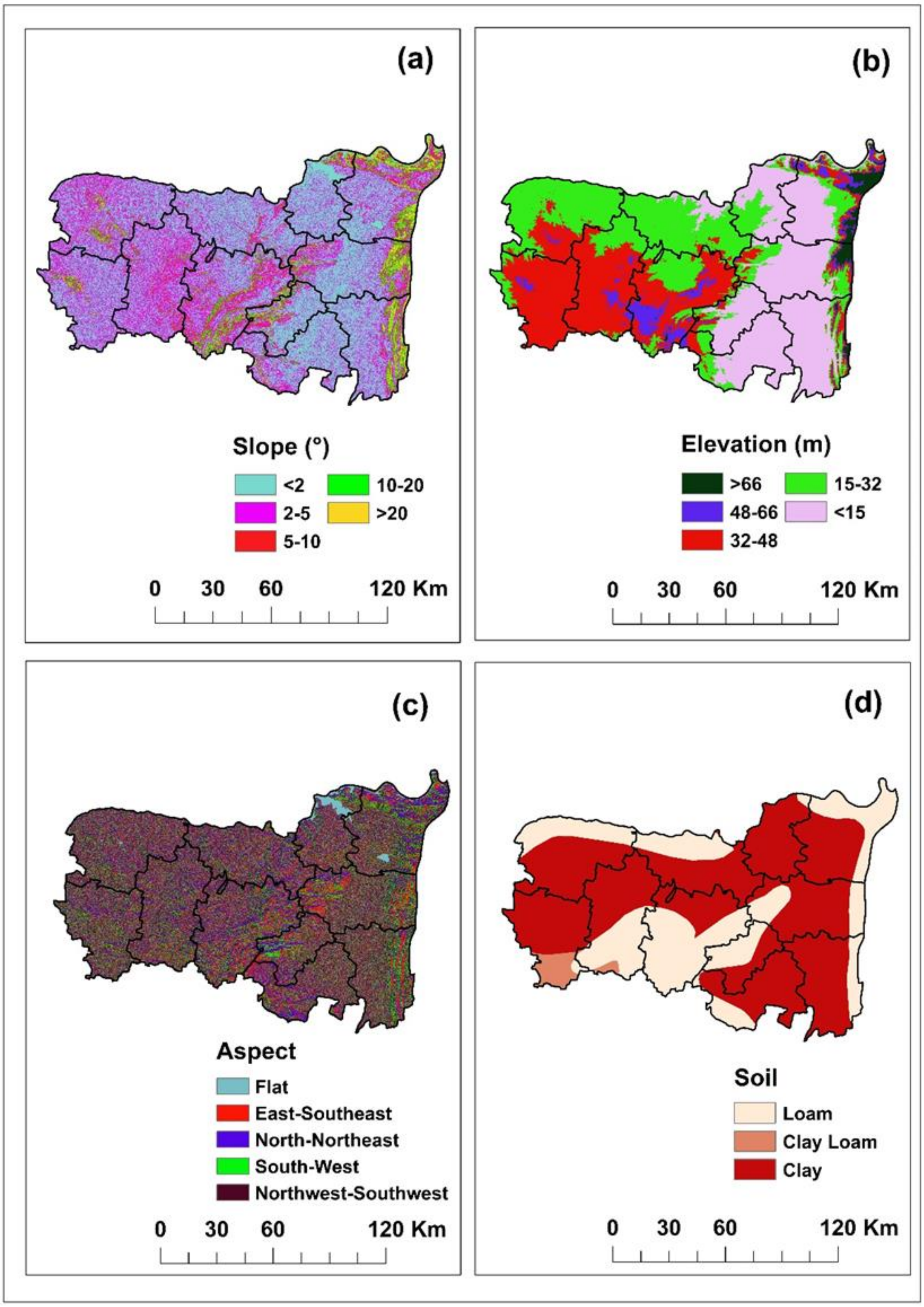

Fig. 3. Parameters used for drought modelling. (a) Slope. (b) Elevation. (c) Aspect. (d) Soil.

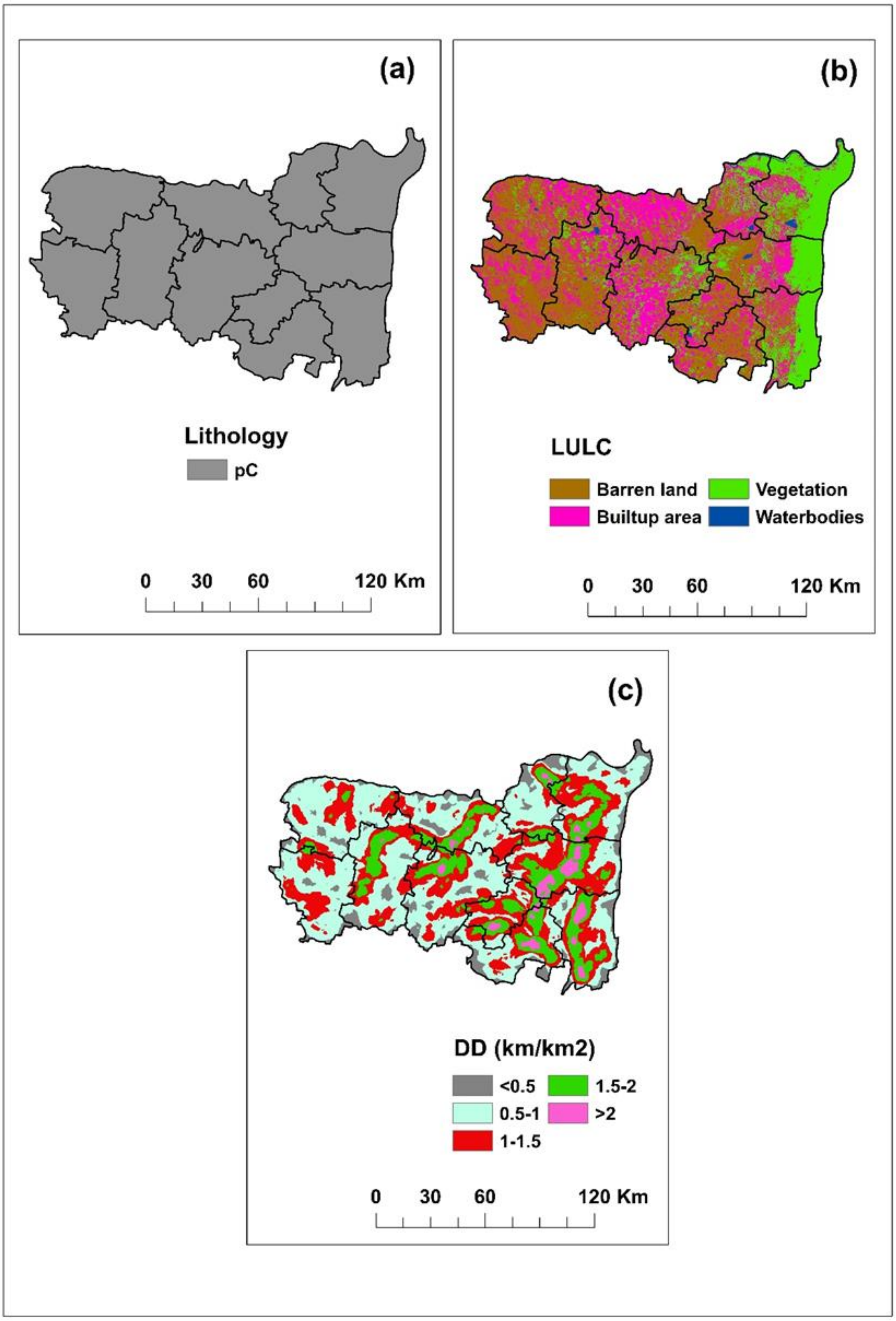

Fig. 4. Parameters used for drought modelling. (a) Lithology. (b) LULC. (c) Drainage density (DD).

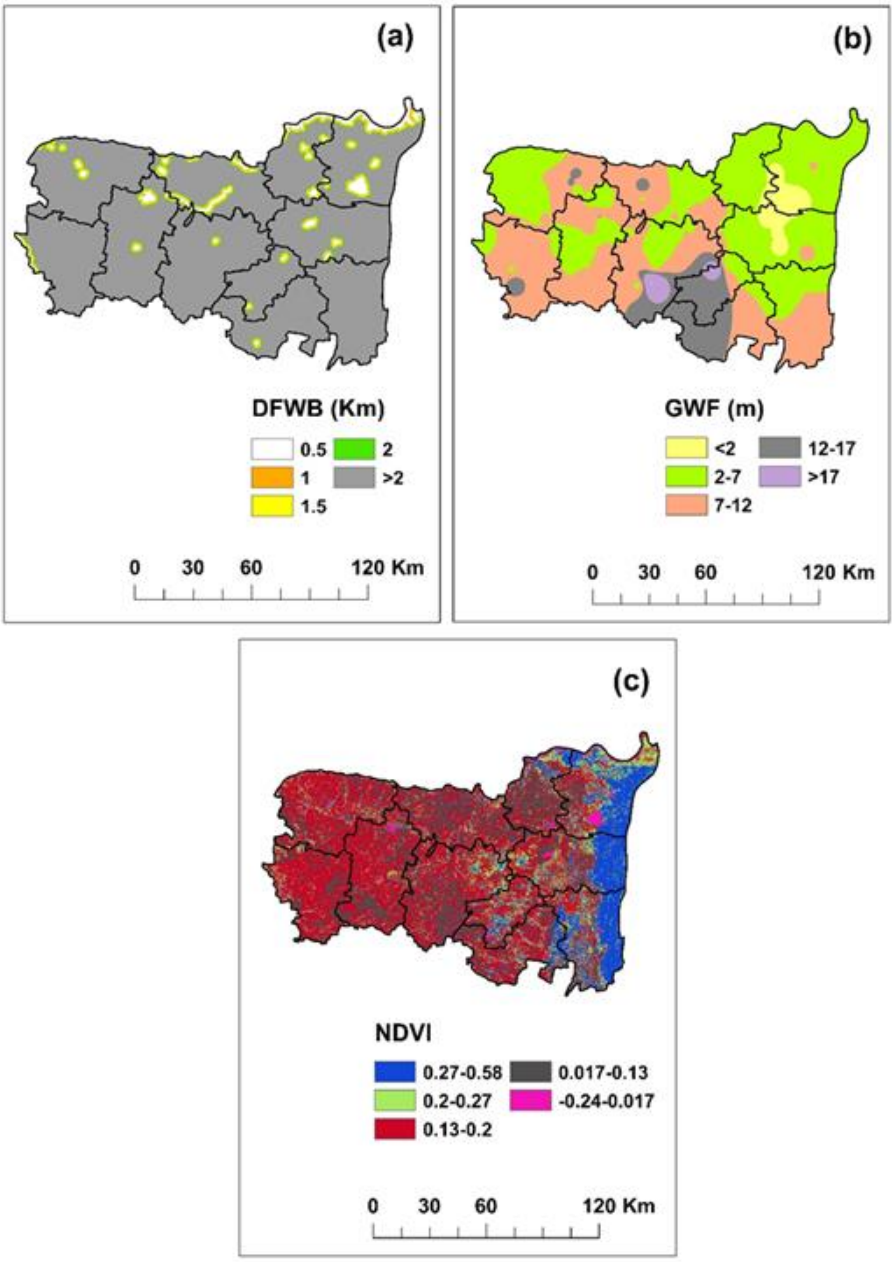

Fig. 5. Parameters used for drought modelling. (a) Distance from water bodies. (b) Groundwater fluctuations (GWF). (c) NDVI.

Tab. 2 Importance scale for AHP

Definition	**Intensity of Importance**
Extremely important	9
Very strongly important	7
Strongly important	5
Moderately important	3
Equally important	1
Intermediate Values between two adjacent scales	2,4,6,8

Tab. 3 Drought Vulnerability via AHP method pairwise comparison matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13
1	1	2	3	4	4	4	6	6	7	8	9	9	9
2	0.5	1	2	3	4	4	5	5	6	6	7	7	7
3	0.3	0.5	1	2	3	3	4	5	5	5	6	6	7
4	0.3	0.3	0.5	1	2	2	3	4	5	5	6	6	6
5	0.3	0.3	0.3	0.5	1	1	2	2	3	4	4	5	5
6	0.3	0.3	0.3	0.5	1	1	2	3	3	4	5	6	5
7	0.2	0.2	0.3	0.3	0.5	0.5	1	2	3	4	5	5	6
8	0.2	0.2	0.2	0.3	0.5	0.3	0.5	1	2	3	4	4	5
9	0.1	0.2	0.2	0.2	0.3	0.3	0.3	0.5	1	2	3	3	4
10	0.1	0.2	0.2	0.2	0.3	0.3	0.3	0.3	0.5	1	2	3	3
11	0.1	0.1	0.2	0.2	0.3	0.2	0.2	0.3	0.3	0.5	1	2	2
12	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.3	0.3	0.3	0.5	1	2
13	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.3	0.3	0.5	0.5	1

Note: 1=Rainfall, 2=NDVI, 3=LST, 4=Soil, 5=Slope, 6=Elevation, 7=Aspect, 8=LULC, =TWI, 10=GWF, 11=DD, 12=Lithology, 13=DFWB

Tab. 4 values for Random index (RI)

N	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.54

Tab. 5 Drought vulnerability mapping parameters and subclasses of different categories based on weights

Parameters	**Sub-Class**	**Rank**	**Parameter weight**	**Sub-Class weight (%)**
	< 2	5		4
	2 - 5	4		5
Slope	5 - 10	3	0.067	12
	10 - 20	2		23
	> 20	1		56
	< 15	1		53
	15 - 32	2		23
Elevation	32 - 48	3	0.072	13
	48 - 66	4		7
	> 66	5		4
	Flat	5		5
	East - Southeast	4		8
Aspect	North - Northeast	3	0.056	19
	Northwest - Southwest	1		44
	South - West	2		24
Soil	Clay	1	0.103	56

	Loam	2		12
	Clay Loam	3		32
Lithology	Undivided Precambrian rocks (PC)	1	0.015	52
	Water bodies			25
Land use & Land cover	Vegetation		0.042	62
	Built area			8
	Bare ground			5
	< 0.5	5		5
	0.5 - 1	4		9
Drainage Density	1 - 1.5	3	0.017	14
	1.5 - 2	2		26
	> 2	1		46
	0.5	5		3
	1	4		5
Distance from waterbodies	1.5	3	0.013	14
	2	2		26
	> 2	1		52
	< 2	5		5
	2 - 7	4		8
Groundwater Fluctuations	7 - 12	3	0.023	12
	12 - 17	2		26
	> 17	1		49
	-0.24 - 0.017	1		46
	0.017 - 0.13	2		30
Normalised difference vegetation index	0.13 - 0.2	3	0.184	13
	0.2 - 0.27	4		8
	0.27 - 0.58	5		3
	> 500	1		44
	500 - 600	2		26
Rainfall	600 - 700	3	0.241	16
	700 - 800	4		9
	> 800	5		5
	< 17.6	5		4
	17.6 - 19.8	4		8
Land Surface Temperature	19.8 - 22	3	0.137	16
	22 - 26	2		24
	26 - 48.1	1		48
Topographic wetness	< 2.8	1	0.03	67

index	2.8 - 5.2	2	17
	5.2 - 7.6	3	8
	7.6 - 10	4	5
	> 10	5	3

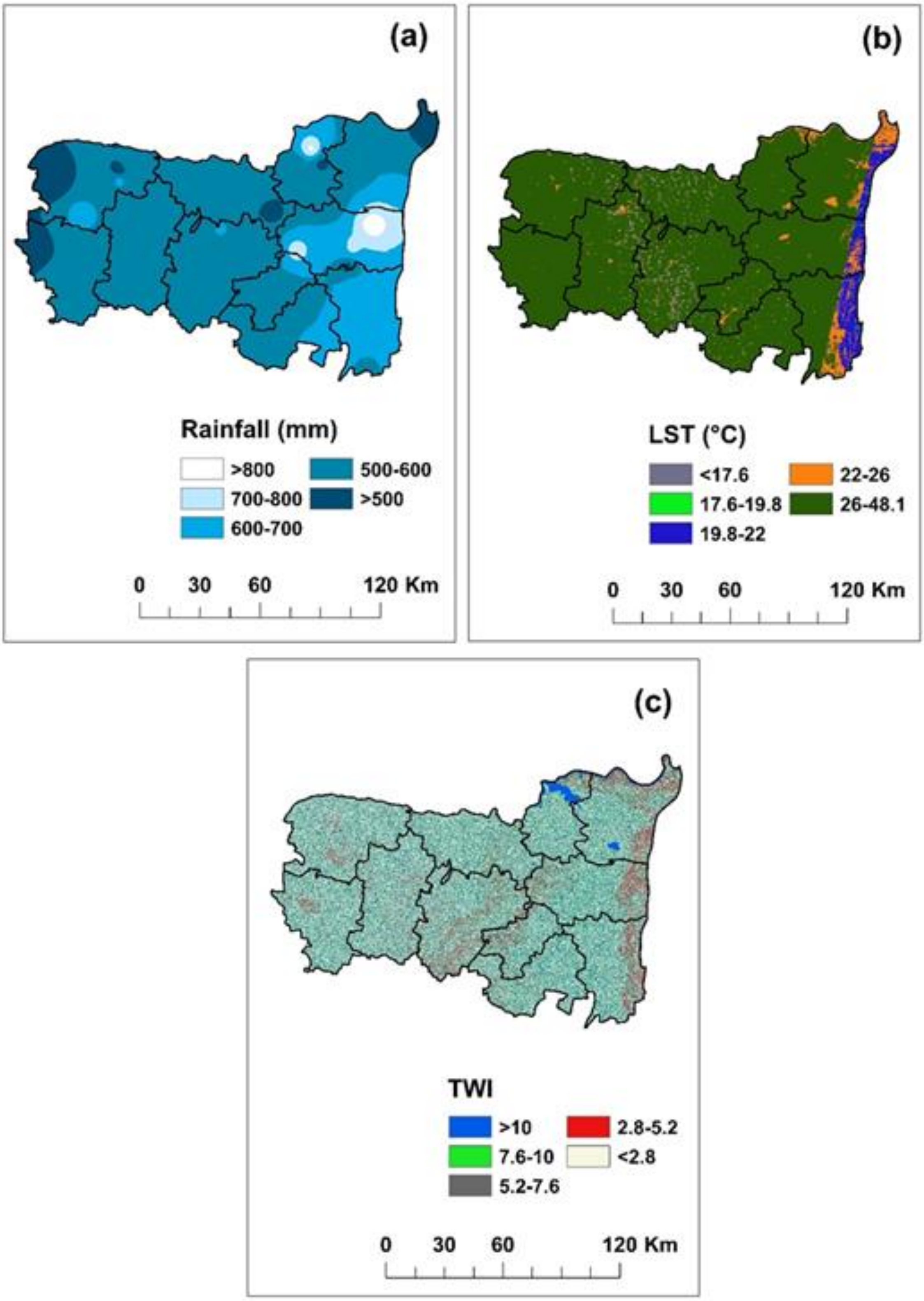

Fig. 6 Parameters used for drought modelling. (a) Rainfall. (b) LST. (c) TWI.

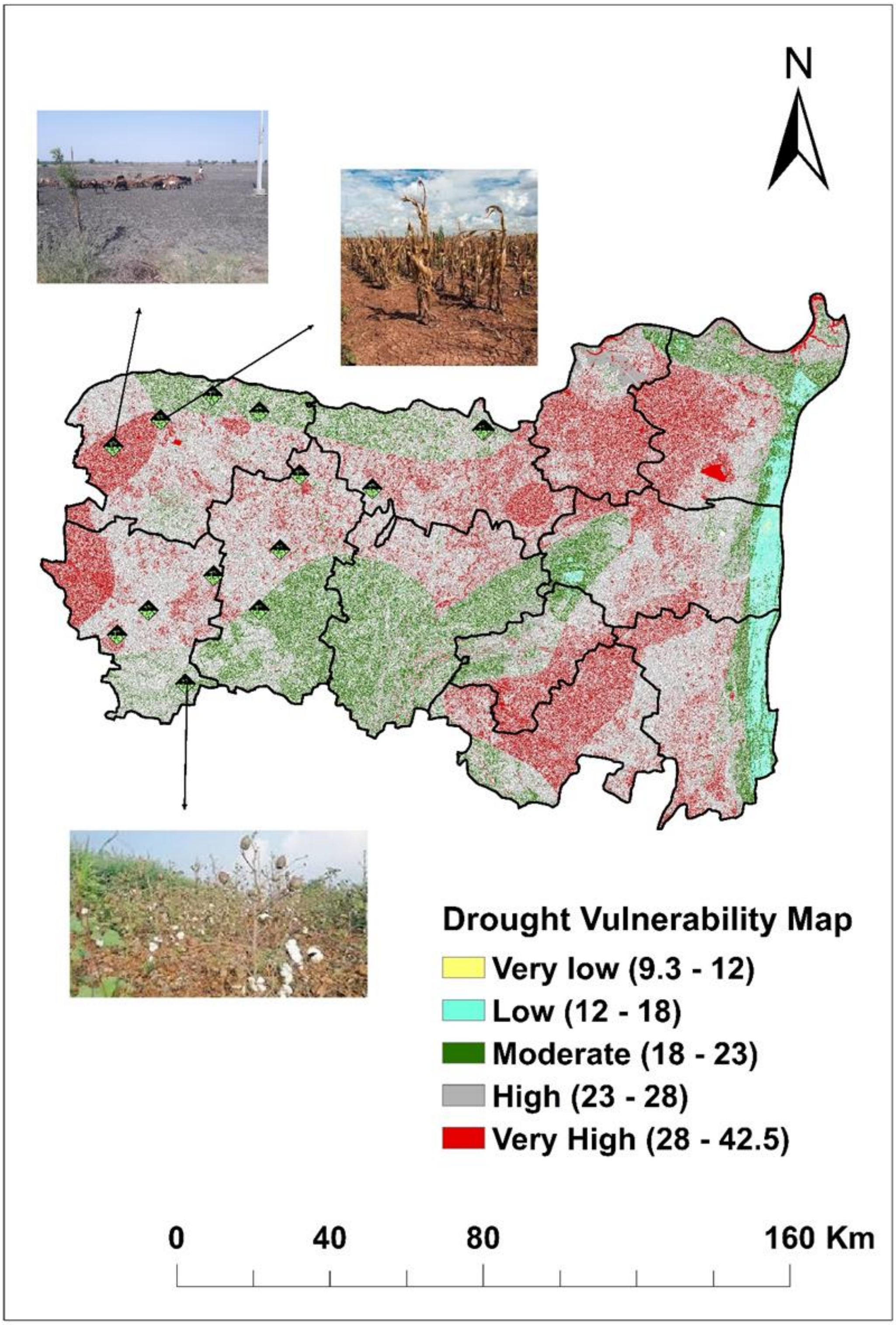

Fig. 7. Drought Vulnerability Assessment mapping of the study area

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