Drought Risk in the Mahanadi River Basin: A Multidimensional Approach for Integrated Urban-Rural Drought Management Strategies

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Abstract

Droughts are one of the most spatially complex geohazards, having a significant impact on the economic status of any region. To mitigate drought risks, a comprehensive drought management plan is required, and the first step toward that goal is to assess the various aspects of drought risks in the preparation of a drought risk map. To produce an integrated drought risk map for the Mahanadi River basin, India, the current study combines geospatial methodologies with the Analytical Hierarchy Process (AHP) technique to assess various dimensions, viz., hydrological, meteorological, agricultural, and socio-economic drought risk in the region in view of integrated rural-urban management strategies. A total of 17 criteria from different aspects were taken into consideration in different groups. Each parameter was given its own spatial layer, which was then normalized by the AHP eigenvector. The weighting of each factor was measured by constructing pair-wise comparison matrices using AHP. For validation, we used a receiver operating characteristic (ROC) curve, which indicates both methods are very useful in drought risk assessment. The five drought risk classes were finally categorised across the Mahanadi River basin, using the weighted overlay approach to create multi-dimensional and integrated drought risk maps. The results showed that the districts like Raipur, Bilaspur, Durg, and Ragnandgaon faced extreme drought conditions. The combining assessments of agriculture, water resources, socioeconomic factors, and weather patterns reveal varying levels of risk across the region. According to the findings, 22.01% of the region is vulnerable to extreme drought, and 31.64% of the area is suffering from severe drought. Furthermore, statistical criteria such as the area under the Receiver Operating Characteristics curves were utilized to validate the method, which indicates about 72.4% accuracy of the model output. The results indicate that the technique used for identifying the region's susceptibility to drought is effective, which will help planners develop strategies for mitigating drought.

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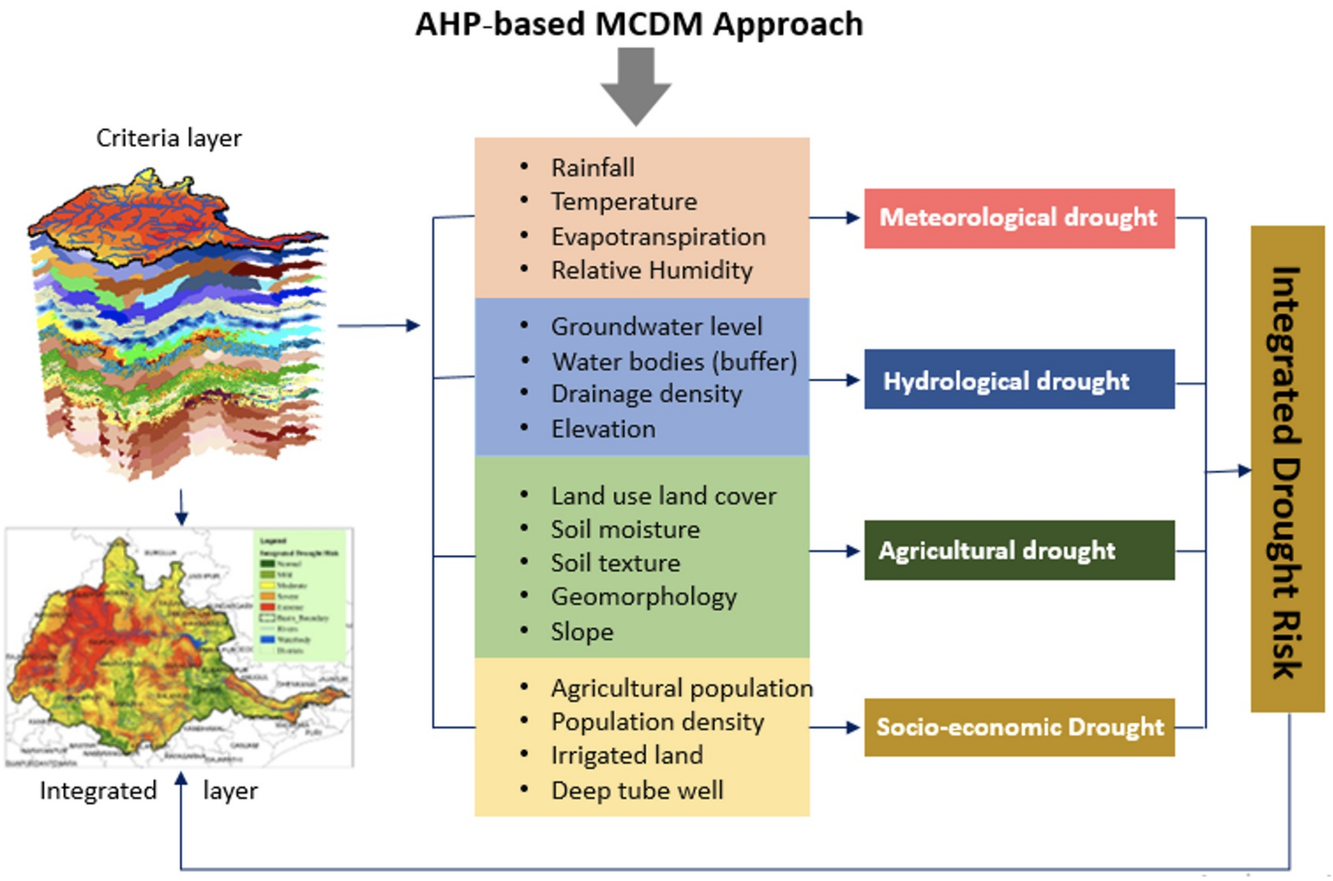
Keywords: Analytical Hierarchy Process; disaster mitigation; drought risk; drought types; Mahanadi basin.

Graphical abstract



Highlights

- Generated spatial risk maps for assessing integrated urban-rural drought risk.
- Analysed drought risk across meteorological, hydrological, agricultural, and socio-economic factors.
- Provided insights for effective drought management strategies through specific risk factors.

- Identified gaps in managing drought risk for the future.
- The varied risk levels across the basin call for tailored intervention measures.

1. Introduction

Drought, a complex disaster, exerts multidimensional repercussions, impacting agriculture, biodiversity, the economy, and the social fabric across diverse climatic regions (Upadhyay and Sherly, 2023). Within the realm of extreme climatic hazards, drought stands out as a pivotal occurrence with significant global repercussions, impacting a substantial number of people worldwide (Steinbruner et al., 2013). Considered the least understood and the most dynamically evolving of all environmental disasters, drought affects more individuals than any other hazard (Pulwarty and Sivakumar, 2014). Every year, it has a detrimental impact on millions of people, affecting societies, economies, and the environment on a global (Marengo et al., 2017; Naumann et al., 2018; Vicente-Serrano et al., 2020; Zhou et al., 2023).

Over the past 50 years (1970–2019), drought has proven to be the most lethal meteorological disaster, leading to 650,000 deaths and causing significantly higher economic losses than other similar events (WMO, 2021). Worldwide, disasters related to drought contribute to an economic loss of approximately 6–8 billion dollars each year (Chen, 2018; Eckstein et al., 2021; Lee et al., 2020). In recent years, many regions across the globe have experienced an intensification of drought occurrences, both in terms of frequency and severity (Brás et al., 2021; Christian et al., 2021; Haile et al., 2020; Kuruva et al., 2021). Recent research suggests that droughts are expected to become more frequent and severe, primarily as a result of the combined impacts of climate change and human interventions (Afshar et al., 2020; AghaKouchak et al., 2021; Hao et al., 2022; Tripathy et al., 2023; Zhao et al., 2022).

In India, more than 50% of the territory is identified as susceptible to drought, and the prevailing susceptibility to drought may undergo changes due to the influence of climate change (Pramanik et al., 2018; 2021; Rawat et al., 2022). As per projections from the Community Response to Extreme Drought (2016), nearly 1.3 billion individuals in India have been affected by drought conditions spanning from 1900 to 2016 (Saha et al., 2023a). Moreover, on an annual basis, approximately 55 million people experience the impacts of drought hazards (Masroor et al., 2022; Saha et al., 2023b). The anticipated escalation in both the severity and duration of potential drought events poses a significant risk to the nation's water supply and food safety.

By integrating prevention, mitigation, and preparedness measures, a holistic drought management approach can be implemented to minimize the overall impact of droughts (Bandyopadhyay et al., 2020; Haile et al., 2020; Raikes et al., 2019; Yang and Liu, 2020). Drought management involves a combination of short-term and long-term measures to reduce the adverse impacts of droughts (Haile et al., 2020; Vogt et al., 2018). These measures typically focus on water conservation, efficient water use, and community resilience. Remote sensing and GIS-based spatial information plays a crucial role and provides a powerful tool for understanding the complex and dynamic nature of drought (Belal et al., 2014; Hoque et al., 2020; Murthy et al., 2015; Rahmati et al., 2019). By analyzing spatial patterns and relationships, decision-makers can develop targeted strategies and implement effective measures to minimize drought-related losses and reduce the impacts of drought on communities, agriculture, and ecosystems (Hoque et al., 2019; Murthy et al., 2015; Paramesh et al., 2022; Seyedmohammadi et al., 2019a, 2019b, 2018; Seyedmohammadi and Navidi, 2022; Wu et al., 2017).

Certainly, a substantial number of research studies have been carried out in assessing and mapping drought and environmental vulnerability, employing remote sensing data and spatial analysis techniques (Chaudhary et al., 2021; Kumar et al., 2023a, 2023b). A comprehensive evaluation framework, Multi-Criteria Based Decision-Making Method (MCDM) based on the Analytical Hierarchical Process (AHP) (Alharbi et al., 2022; Sivakumar et al., 2021; Topcu, 2022), fuzzy-AHP (Hoque et al., 2020; Saha et al., 2021), composite drought (Balaganesh et al., 2020; Murthy et al., 2017), composite index (Bravo et al., 2021; Srinivasareddy et al., 2019), standardized precipitation evapotranspiration index (SPEI) (Liu et al., 2021; Sein et al., 2021; Tirivarombo et al., 2018; Zhao et al., 2021), standardized precipitation index (SPI) (Lakshmi et al., 2020; Masoudi and Elhaeesahar, 2019; Tsesmelis et al., 2022), multispectral image-based vegetation indices and surface temperature condition indices (Alamdarloo et al., 2018; Deiveegan et al., 2016; Melese et al., 2018; Tran et al., 2017) have been applied, involving integrating multiple factors and employing reasoning to provide a more nuanced understanding of drought-prone regions.

The precision and reliability of risk information are predominantly contingent on the careful selection of criteria that influence drought, encompassing various types of droughts, namely, hydrological, meteorological, agricultural, and socio-economic. Equally critical is the implementation of a weighting scheme that effectively integrates these factors. Droughts, being intricate phenomena, exhibit interconnections among the four types. Thus, opting for an adequate set of criteria representing each drought category and amalgamating them can furnish comprehensive and reliable information on drought risk. Nevertheless, a comprehensive approach to drought risk mapping that seamlessly integrates all types of droughts with a sufficient array of criteria is infrequently found in existing literature.

Predominantly, studies have concentrated on particular drought risk mapping types or amalgamated various types with a restricted set of criteria. A critical challenge in risk assessment involves selecting an appropriate weighting scheme to rank and assign weights to criteria under various drought types and their combinations (Kumar et al., 2023a). The majority of current studies have employed equal weighting procedures; however, in reality, the contribution of each criterion to drought risk is not uniform. The Analytic Hierarchy Process (AHP) stands out as a widely employed multi-criteria weighting scheme. Nonetheless, only a handful of studies have incorporated AHP into drought risk assessments, despite its common use in risk analyses for other natural hazards. An essential requirement is the development of an integrated assessment and spatial mapping approach for drought risk. This approach, grounded in multiple criteria and employing a judicious weighting scheme, is pivotal for producing intricate risk information necessary for devising effective strategies to mitigate the impact of drought. This approach aims to combine all drought categories utilizing the Analytic Hierarchy Process (AHP) and geospatial techniques. The specific objectives of this current study encompass (1) hydrological, meteorological, agricultural, and socio-economic drought risk categories for developing integrated spatial drought risk mapping, (2) evaluating the efficacy of the developed approach in assessing the spatial drought risk in the Mahanadi River Basin, and (3) model reliability assessment and validation of results obtained through the spatial risk assessment approach.

2. Study area

The Mahanadi basin is among the major river basins that drain to the east coast of India in the Bay of Bengal. The basin originates in the state of Chhattisgarh and has a drainage area in the states of Odisha and Maharashtra. The basin lies between 85° 30′ and 86°52′ E longitude and 19° 40′ and 20° 45′ N latitude. The Mahanadi River, along with its tributaries, drains a significant portion of central and eastern India before discharging into the Bay of Bengal. The main Mahanadi distributary, Seonath, the Jonk, the Hasdeo, the Mand, the ib, the Ong, and the Tel. **(Fig. 1).** There are two tributaries of the Kuakhai River: Kushabhadra and Bhargabi. Makara and Rajua are part of two branches of the River Daya. With the exception of Daya and Bhargavi, which discharge into Chilika Lake, all rivers empty into the Bay of Bengal. In the delta region, four large doabs are formed by the rivers' orientation. The delta covers an area of around 9,0632 km^2. The basin's climate is characteristic of a tropical environment, with moderate to heavy precipitation, high relative humidity, high mean temperatures, and short, mild winters (Sahu et al. 2020). The annual average rainfall ranges from 1080-1830 mm, with most of it falling between June and September. Various climatic disasters, such as floods, droughts, and cyclones, are very frequent every year, with varied degrees of intensity (Sahu et al. 2020; Panday et al. 2022).

According to the 2011 Indian Census, the Mahanadi River basin includes 28 districts, 17 of which are in Odisha (Baleshwar, Dhenkanal, Baudh, Cuttack, Bhadrak, Debagarh, Gajapati, Jagatsinghapur, Jajapur, Jharsuguda, Kandhamal, Kendujhar, Malkangiri, Mayurbhanj, Nabarangapur, Rayagada, and Sundargarh) and 11 in Chhattisgarh (Bastar, Dakshin Bastar, Uttar Bastar Kanker, Bilaspur, Dantewada, Durg, Janjgir – Champa, Kabirdham, Koriya, Mahasamund, Rajnandgaon, Surguja), with about 40.1 million people (3.33% of the country). The inhabitants of the Mahanadi River basin are accustomed to the occurrence of drought. Every year, with varying degrees of severity and extent, there have been droughts in several locations in Odisha and Chhattisgarh. Since 1866, there have been 17 moderate-to-severe drought occurrences in this region, after the first severe drought. All of this suggests that in Odisha, moderate-to-severe droughts happen around every eight years (1866, 1919, 1965, and 2000-2001). The state was hit by very severe droughts in 1866, 1919, 1965, and 2000–2001, with the latest one being the worst. The western and south-central portions of the basin have previously experienced drought. Therefore, a drought risk assessment of this region is essential for strategic planning and management.

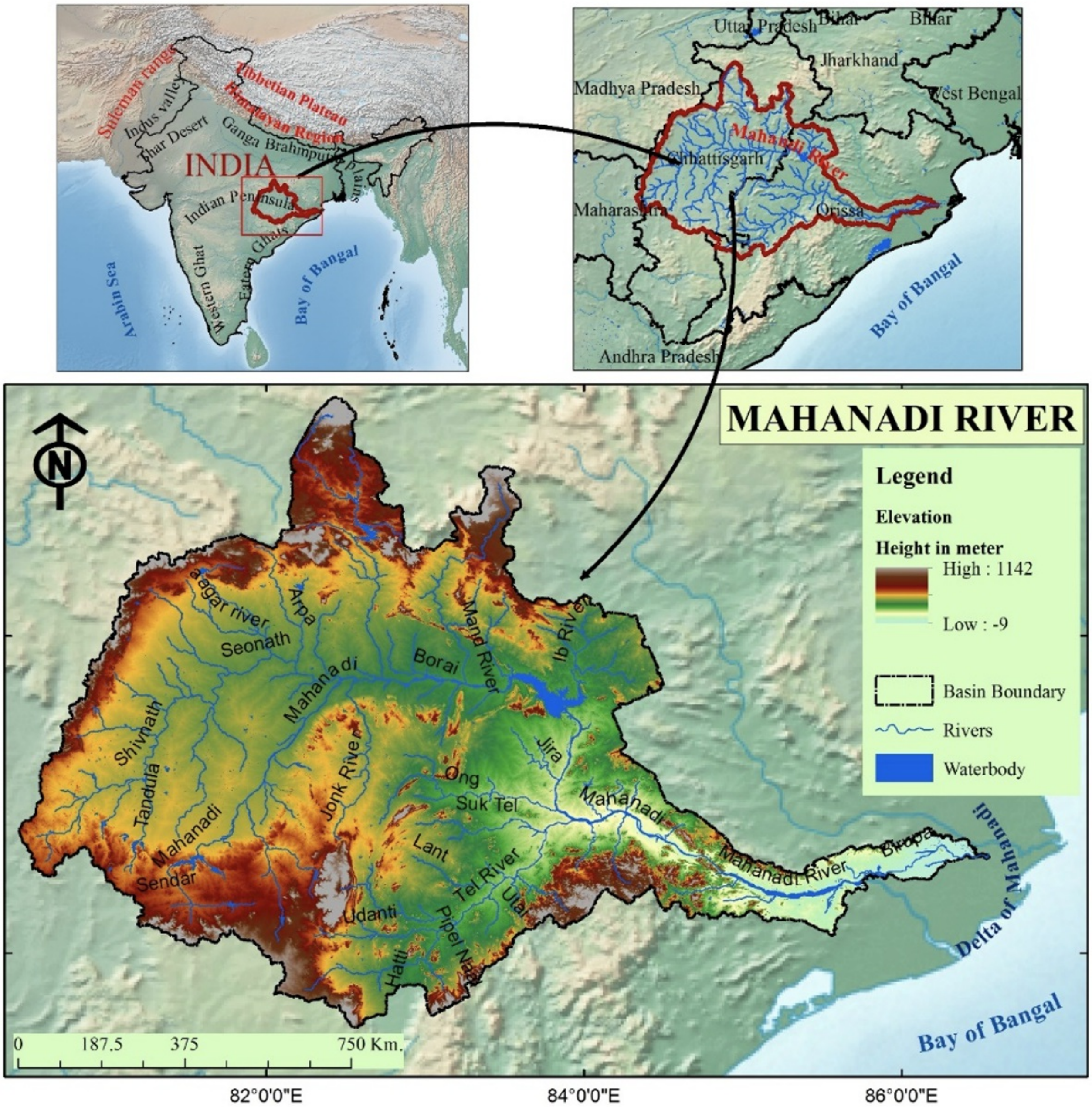


Figure 1. Showing location, geographical extent and topographic characteristics of the Mahanadi River Basin, India

3. Materials and methods

In this present assessment, we examined and adopted multi-criteria decision-making (MCDM) methods for drought risk mapping that integrates different drought categories using AHP and GIS techniques. An efficient method for determining overall drought risk is to combine geospatial approaches with AHP (Ahmad et al., 2016; Hoque et al., 2020). Using geospatial technologies, we identified 17 criteria related to meteorological, agricultural, hydrological, and socioeconomic droughts gathered from various data sources. A comprehensive drought risk map was produced by rating and weighing the criteria and evaluating how they were incorporated. The developed and evaluated methodologies used in this investigation are discussed in more detail and systematically in the sections that follow and are seen in **Fig. 2.** By integrating multi-criteria decision-making methods and GIS analysis, a comprehensive and informed understanding of drought conditions, risk, and potential mitigation strategies can be achieved in the Mahanadi River Basin.

Figure 2. Showing methodological steps of the study

Table 1. List of datasets used for study

Details of the satellite data and ancillary map				
Data	**Descriptions**	**Duration**	**Agency**	**Resolution**
Elevation	SRTM DEM	-	USGS	90m
Surface slope	Prepared from SRTM DEM	-	″	90m
Drainage	Prepared from SRTM DEM	-	″	90m
Landform	Digital layer	-	https://bhukosh.gsi.gov.in/	1:50000
Land cover	Landsat 8	April-2019	GLCF	23 Meters
Soil texture	Global Hydrologic Soil Groups	2020	https://daac.ornl.gov/SOILS	250m
Annual Precipitation		1970-2018	Indian Meteorological Department (IMD)	0.25°
Annual Mean Temperature		1970-2018	IMD	-
Annual Evapotranspiration	-	1970-2018	IMD	
Soil Moisture	-	1970-2018	IMD	-
Population Density	-	2011	Census of India, 2011	-
Agricultural dependency	-	2011	Census of India, 2011	-
Irrigated agricultural land	-	2015	Agricultural Census, 2015	-
Number of Tube wells	-	2019-20	Chhattisgarh & Orissa water resource boards	-

3.1. Data used and sources

We employed a variety of parameters to map integrated drought risk assessment in this study. Using remote geospatial techniques, data was collected from a variety of sources to create criteria layers. The majority of the geographical data came from the Indian Meteorological Department and the census of India. Only satellite images of the Landsat were gathered from the Earth Explorer platform of the United States Geological Survey (USGS). The data that was utilised to validate the study's outputs came from relevant peer-reviewed scientific journals. Table 1 lists the specific features (such as layer of data set, description about data, agency from where data is obtained, and duration of data) of the datasets used in this investigation.

3.2. Risk evaluation criteria, alternatives, and mapping

The selection of criteria and alternatives for drought risk assessment involves a systematic and comprehensive approach. In this present study, we went through a literature review, regional study on drought evaluations, expert opinions, alongside exploring the accessibility and reliability of geo-spatial data and their relevance to drought risk assessment (see details in Table 2). To do this, the authors contacted 20 experts using a systematic questionnaire that included the influencing factors and sub-parameters utilised in drought risk across all dimensions addressed in the study. For the consultation, the experts evaluated stakeholders who had experience with drought in the Mahanadi River region for more than 10-30 years. They came from hydrological, geography, climate, and environmental fields, and included government officials, drought champions, and local residents. The response for further analysis using the accuracy criterion was appropriate for 15 of the 20 experts selected for the report by preparing a questionnaire that identifies relevant parameters considered for the study.

All the thematic spatial layers of all criteria with several alternatives were prepared with a standard spatial resolution of 90m and reclassified into certain classes using Environmental Systems Research Institute (ESRI) ArcGIS version 10.5. For the classification of parameter layers, the natural break statistical method was employed in the software system (Baeza Nieves; Amorim, Samuel, 2016; Tehrany Biswajeet; Jebur, Mustafa Neamah, 2014). This approach employs a mathematical procedure that minimizes discrepancies between data values belonging to the same class while enhancing disparities between classes, as demonstrated by previous studies such as Nasrollahi Hassan et al. (2018), Mallick et al. (2021), and Mondal et al. (2017). The spatial pattern of the drought at the research site was effectively shown using this technique. ArcGIS 10.4 was used to prepare and process the spatial criterion layers. The next sections explain the justification, significance, and criteria for preparing an assessment of risk under each category of drought.

3.2.1. Criteria for meteorological drought

Meteorological drought is typically defined as a prolonged period of abnormally dry weather conditions characterized by a significant deviation from the long-term average of precipitation in a particular region (Wilhite Michael H., 1985). While there are variations in the precise definition, the concept generally revolves around the lack of adequate precipitation. Four pertinent factors were chosen for meteorological drought mapping in the current study: average rainfall (mm), average temperature (°C), average evapotranspiration (mm), and average humidity (%) as shown in Fig. 3.

Vapour pressure deficit is an important factor in controlling drought processes; therefore, it might be regarded as a viable metric for the evaluation of meteorological drought, according to research by (Will et al. 2013; Ding et al. 2018). To measure the intensity of the drought and track its evolution, several meteorological indices are used. The Palmer Drought Severity Index (PDSI), Standardized Precipitation Evapotranspiration Index (SPEI), and Standardized Precipitation Index (SPI) are examples of common indices. These indices combine precipitation, evapotranspiration, and temperature data to assess the departure from normal conditions and identify drought periods. According to Ahin et al. (2013) and Ficklin and Novick (2017), calculating the vapour pressure deficit is relatively difficult and necessitates the use of many datasets. The primary variables that influence meteorological drought are rainfall, temperature, and humidity. In comparison to regions that experience high levels of rainfall and humidity, low-precipitation areas are more vulnerable to drought (Pandey et al., 2012). In addition, regions with high temperatures are particularly prone to drought than regions with low temperatures.

The maps of annual precipitation (Fig. 3a), temperature (Fig. 3b), and average humidity (Fig. 3c) were made using the climate data obtained for 48 years (1970-2018). First, using station datasets covering the area of the basin located in the districts of Chhattisgarh and Orrisa, we prepared maps of yearly precipitation, temperature, and average humidity. The study region was then extracted from these maps. The datasets were interpolated using the Inverse Distance Weighted (IDW) method. Meteorological drought and evaporation are closely related. Due to the increasing amount of water evaporation, regions with excessive evaporation rates are more susceptible to meteorological drought (Palchaudhuri and Biswas, 2016).

3.2.2. Criteria for agricultural drought

Geospatial agricultural drought assessment in the Mahanadi River Basin can involve various criteria, depending on the specific goals and objectives of the assessment. However, some common criteria that can be considered are soil texture, soil moisture (%), surface slope (°), land use/land cover, and geomorphological features, as shown in Fig. 4 & 5.

a. **Soil Texture**: Soil characteristics, such as texture, depth, and water-holding capacity, play a crucial role in determining the level of agricultural drought. Soils with high water-holding capacity can retain moisture for longer periods, which can help crops withstand drought conditions. In contrast, soils with low water-holding capacity may lead to an increased risk of agricultural drought.

Table 2. An alternate ranking system that takes the drought risk into account.

Component	Criteria	Unit	Very low (1)	Low (2)	Moderate (3)	High (4)	Very high (5)
Meteorological drought	Average Rainfall	Mm	1550–1830	1440–1540	1350–1430	1270–1340	1000–1250
	Average Temperature	°C	23.9–24.9	25.0–25.4	25.5–25.7	25.8–26.1	26.2–26.9
	Average Evapotranspiration	mm	1370–1480	1490–1540	1550–1600	1610–1690	1700–1880
	Average relative Humidity (%)	%	68.4–76.4	63.9–68.3	61.3–63.8	58.7–61.2	56.2–58.6
Hydrological drought	Average Groundwater level (m)	m	2.33- 3.52	3.53-3.85	3.86-4.26	4.27-4.76	4.77-5.44
	Surface water bodies (buffer)	buffer	Rivers (500m)	Reservoirs (250m)	Wetlands (100m)	other waterbodies (50m)	Others
	Drainage density	km/km2	2.0–3.2	1.6–1.9	1.1–1.5	0.51–1.0	0–0.5
	Elevation	m	4.84–12.88	12.88–15.87	15.87–23.91	23.91–45.53	N45.53
Agricultural drought	Land cover	raster	Water bodies/ wetlands	Evergreen/deciduous vegetation	Settlements	Bare areas/shrubs and other	Irrigated/ Unirrigated Cropland
	Soil moisture	%	20.0-23.7	18.4-19.9	17.1-18.3	17.0-15.5	12.3-15.4
	Soil texture	Type	C	D	C/D	D/D	-
	Geomorphology	class	Fluvial origin	Structural origin	Alluvial deposits	Deltaic deposits	Other water bodies
	Slope	degree	0-2.75	2.76–7.56	7.57–14.0	14.1–22.4	22.5-58.4
Socio-economic Drought	Agriculture dependent population	%	9.28–21.8	21.9–29.8	29.9–36.8	36.9–41.1	42.2–49.8
	Population density	sq. km	64–200	201–300	301–400	401–500	501–1290
	Irrigated land	%	0.48–6.49	6.5–19.8	19.9–35.5	35.6–54.9	55.0–85.6
	Deep bore well	Count	0–21	22–52	53–87	88–230	240–490

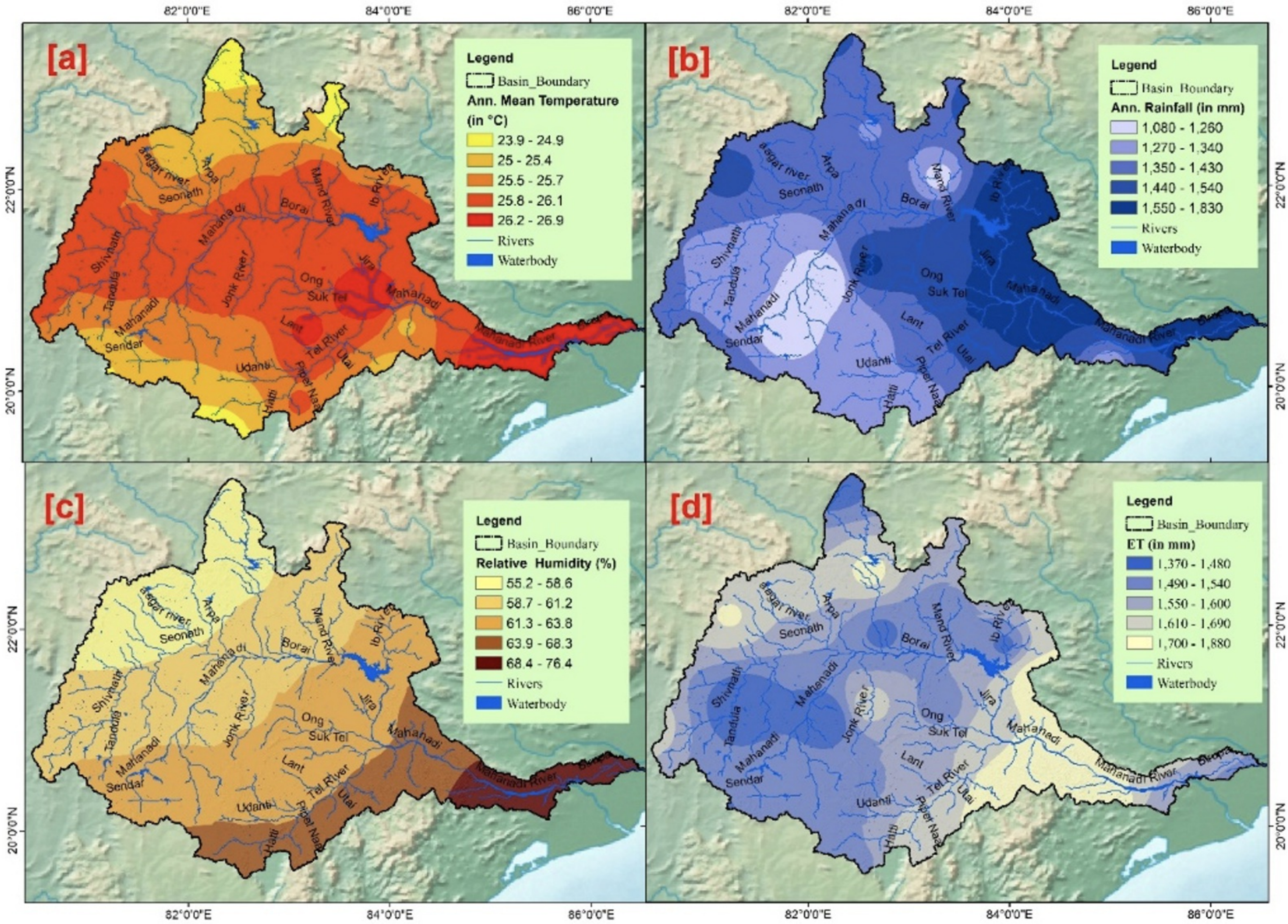


Figure 3. Showing climatological drought criteria [a] annual mean surface temperature, [b] annual rainfall distribution, [c] relative humidity, and [d] evapotranspiration (ET) pattern.

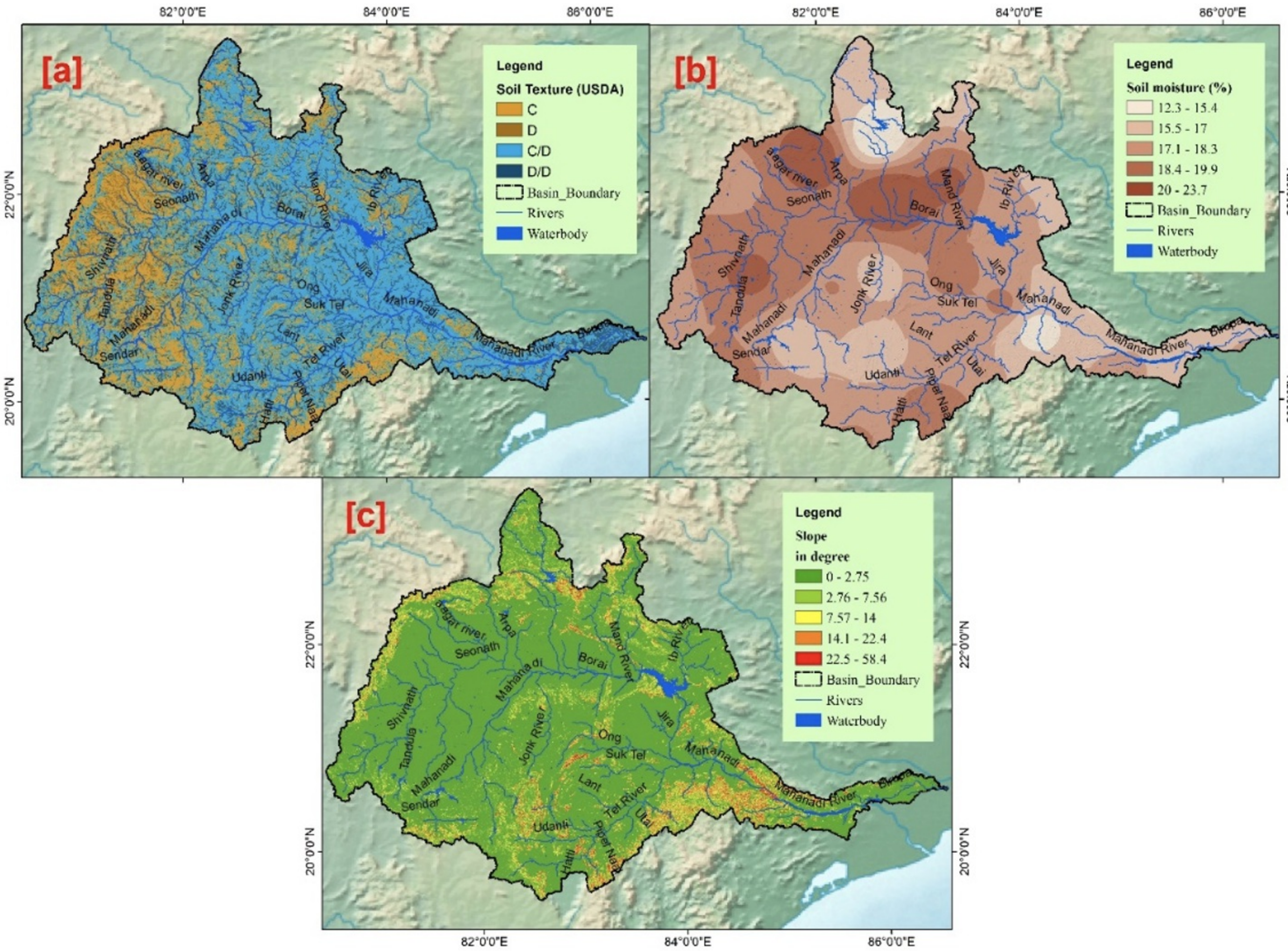


Figure 4. Showing agricultural drought criteria [a] soil texture, [b] soil moisture, and [c] land surface slope maps.

b. **Soil moisture:** Soil moisture is an essential factor for plant growth and development, and drought conditions can cause soil moisture deficit, which can affect crop yields. The assessment considers the level of soil moisture deficit in different regions of the basin using remote sensing data.

c. **Land Surface Slope:** Land surface slope plays a crucial role in agricultural drought assessment. Steeper slopes can lead to faster runoff, reducing water retention for crops. Higher slope gradients may intensify soil erosion, exacerbating drought impacts. Slope-related water drainage patterns influence soil moisture distribution. Understanding slope characteristics is essential for effective agricultural drought mitigation strategies.

d. **Land use and land cover (LULC):** LULC affects the amount of vegetation cover, which is a critical factor in agricultural drought assessment. For example, areas under forest cover may have a higher water retention capacity than areas under agricultural land use. Similarly, urban areas may have low vegetation cover and high impervious surfaces, leading to increased runoff and reduced soil moisture retention capacity (Pramanik, 2017). Therefore, LULC and soil characteristics have a significant impact on agricultural drought. The assessment uses a satellite-based LULC classification technique to assess vegetation health and land use patterns in different parts of the basin.

e. **Geomorphological features:** These landforms can have a significant impact on agricultural drought assessment in the Mahanadi River Basin. The basin is characterized by a diverse range of geomorphological features, including hills, plateaus, valleys, and coastal plains. The northern and western parts of the basin are characterized by the Chota Nagpur Plateau, which is a hilly area with an average elevation of 600 meters above sea level. The plateau is composed of hard rock formations and is dotted with several rivers and their tributaries. The plateau is also rich in minerals and is an important mining area (Pramanik et al., 2016). Mountainous and hilly areas may have higher precipitation rates due to orographic lifting, which can help reduce the risk of agricultural drought. However, these areas may also have steep slopes and poor soil moisture retention capacity, which can lead to increased runoff and reduced soil moisture, increasing the risk of agricultural drought. Plateaus may have a moderate to high precipitation rate and a relatively flat terrain, which can help maintain soil moisture levels and reduce the risk of agricultural drought. However, the risk of soil erosion due to wind and water can be higher in these areas, which can affect soil moisture retention capacity and increase the risk of agricultural drought.

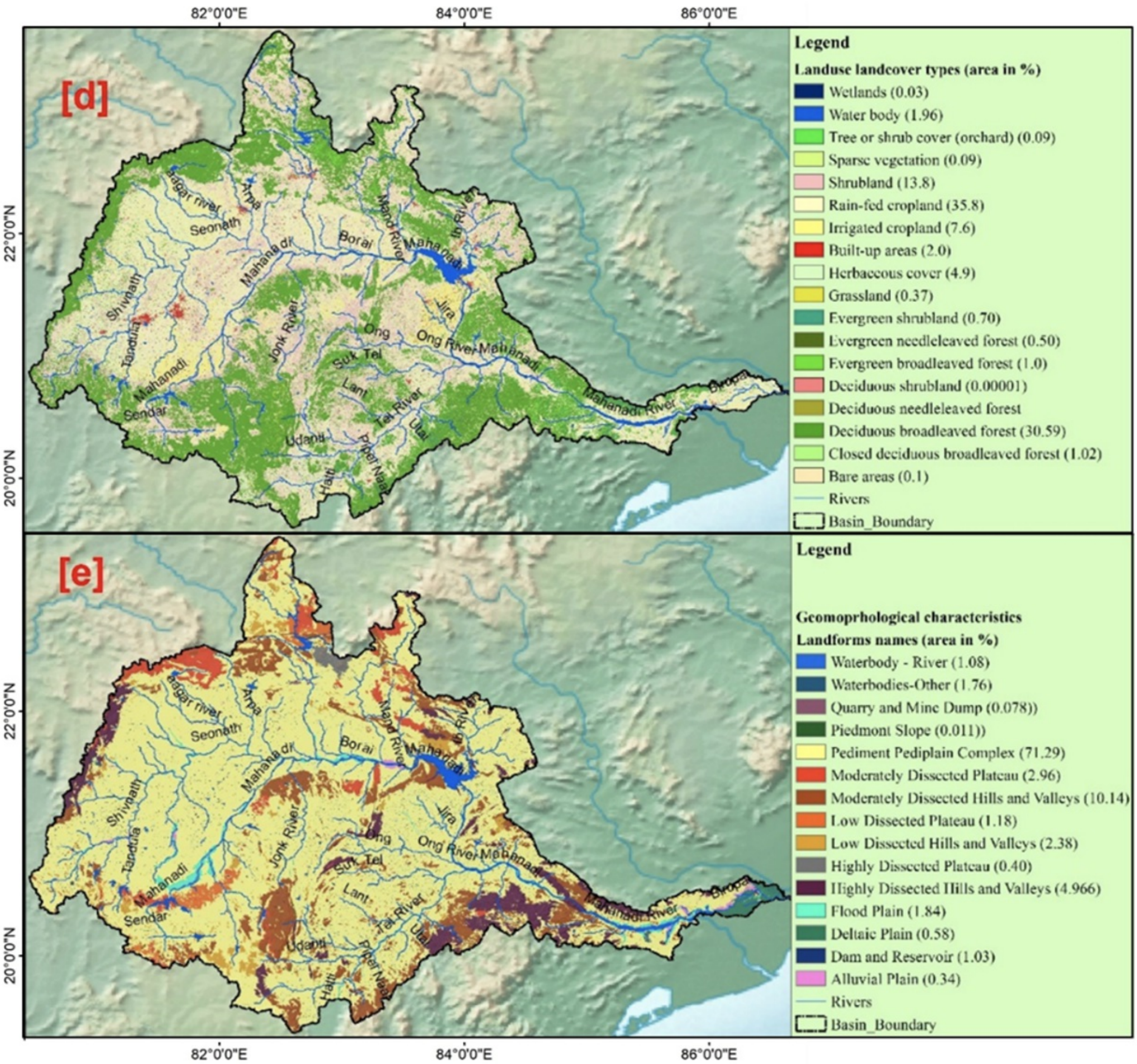


Figure 5. Showing agricultural drought criteria [d] land use and land cover map and [e] geomorphological map indicating various landform features

In the central and southern parts of the basin, valleys and coastal areas, relatively flat terrain is dominated by alluvial plains and received moderate to high precipitation (Pal et al., 2016). The Mahanadi River and its tributaries have formed several deltas in this region, which are susceptible to cyclones and floods that affect crop growth and increase the risk of agricultural drought. These areas also have better soil moisture retention capacity due to the flat terrain and deeper soils, which are important areas for rice cultivation. However, these areas also have higher evapotranspiration rates due to higher temperatures and solar radiation, which can reduce soil moisture and increase the risk of agricultural drought.

Overall, the geomorphological setup of the Mahanadi River Basin is characterized by a diverse range of features that have a significant impact on the ecology, economy, and livelihoods of the people living in the region. Understanding these features is important for managing the resources of the basin and mitigating the impacts of natural disasters such as floods and droughts. By integrating these criteria, a comprehensive geospatial agricultural drought assessment can be conducted for the Mahanadi River Basin, which can help identify areas that are more prone to drought and inform drought management and mitigation strategies.

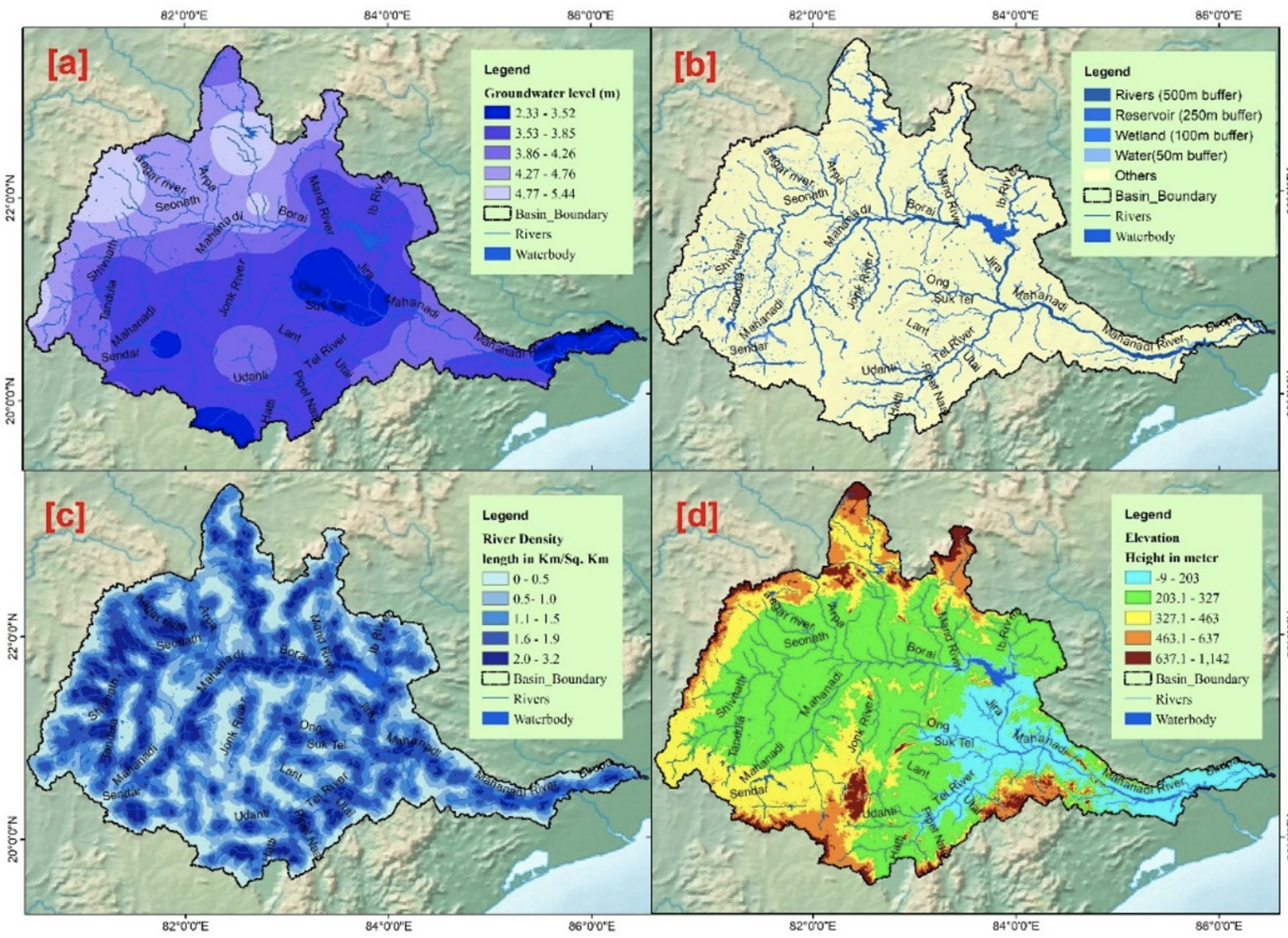


Figure 6. Showing hydrological drought factors [a] Annual Average groundwater level; [b] Surface waterbodies; [c] drainage density; and [d] elevation zones.

3.2.3. Criteria for hydrological drought

Hydrological parameters play a crucial role in droughts in the Mahanadi River Basin. Groundwater, surface waterbodies, drainage density, and elevation zones are the hydrological parameters that impact droughts; the special distribution of these features is as shown in Fig. 6:

a. **Groundwater:** Groundwater is a crucial component of the hydrological cycle in the Mahanadi River Basin, and it plays a significant role in drought conditions in the region. Groundwater recharge is the process by which water infiltrates into the ground and replenishes groundwater reserves. During periods of drought, when surface water sources are depleted, groundwater can become a critical source of water for agriculture and other uses (Kumar et al., 2023b; Reddy et al., 2022). Groundwater levels can be significantly impacted by drought conditions; when there is a lack of rainfall, recharge rates decrease, which can cause groundwater levels to drop. This can have significant impacts on the availability of water for agriculture, drinking water, and other uses. Groundwater-dependent ecosystems, such as wetlands and riparian habitats, can be significantly impacted by drought conditions (Pramanik, 2016). Reduced groundwater levels can lead to the loss of habitat, changes in species composition, and other ecological impacts. Effective management of groundwater resources, including water conservation, recharge, and monitoring, is essential for ensuring the sustainable use of this resource during times of drought.
b. **Surface waterbodies:** During droughts, streamflow becomes reduced or even ceases, which can have significant impacts on aquatic ecosystems, water supplies, and other uses. It is home to several major water bodies, including the Mahanadi River and its tributaries, as well as lakes and ponds, i.e., Tandula Reservoir, Ravishankar Dam, Hirakud Reservoir, Chilika Lake, Ansupa Lake, Jonk Reservoir, and several other waterbodies, and they play a crucial role in the region's ecology, economy, and culture. These water bodies are important sources of water for agriculture, drinking water, and other uses. During times of drought, when groundwater levels are depleted and precipitation is low, surface water bodies become critical sources of water. The proper management of these water resources is essential for mitigating the impacts of drought on communities and ecosystems. Strategies such as water conservation, water allocation, and ecosystem restoration can help to ensure the sustainable use of these resources during times of drought. Overall, hydrological parameters are closely linked to droughts in the Mahanadi River Basin. Monitoring and managing these parameters can help to mitigate the impacts of droughts and ensure the sustainable use of water resources in the region.
c. **Drainage density:** Drainage density is an important factor that can impact hydrological drought conditions in the Mahanadi River Basin region. Drainage density refers to the amount of channel length per unit area of the basin and is influenced by various factors such as topography, soil, and vegetation cover (Kumar et al., 2022; Kumar et al., 2024). High drainage density implies that there are more channels and streams in a given area. This can increase the surface runoff during rainfall events, reducing the infiltration and recharge of groundwater. During drought conditions, this can lead to a lower availability of water resources in the basin. Areas with high drainage density are likely to have higher soil moisture levels due to the increased runoff and infiltration. During drought conditions, areas with high drainage density may have a greater resilience to drought conditions due to higher soil moisture levels. Higher drainage density can lead to higher streamflow volumes during rainfall events, which can have a significant impact on water availability

during drought conditions.

d. **Elevation zones:** Elevation and hydrology are closely associated, and they both have significant impacts on drought conditions in an area. Surface elevation plays a crucial role in regional drought conditions in the Mahanadi Basin. It affects precipitation, runoff, streamflow, groundwater availability, soil moisture, and evaporation rates. Understanding these elevation-related factors is important for drought management, water resource planning, and the implementation of appropriate adaptation strategies in different elevation zones of the basin. Higher elevations tend to receive more precipitation due to orographic effects; hence, higher streamflow, maintaining water availability in rivers and streams during dry periods (S. Kumar et al., 2022).

3.2.4. Criteria for socio-economic drought

Socio-economic drought assessment is an approach that evaluates the impact of drought on the socio-economic aspects of a region or community. It goes beyond the physical and hydrological aspects of drought and focuses on understanding the risk and resilience of human systems to drought events (Parven et al., 2022; M. K. Pramanik et al., 2021). The goal of socio-economic drought assessment is to identify and quantify the potential impacts of drought on various socio-economic sectors, such as agricultural systems, water supply, crop and livestock production, irrigation practices, livelihoods, and to inform decision-making processes for drought mitigation and adaptation (Szabo et al., 2021b, 2021a). By considering criteria such as population density, proportion of agricultural population, percentage of irrigated land, and number of deep tubewells existing in agricultural systems, socio-economic drought assessment provides a comprehensive understanding of the potential impacts of drought on human systems, as shown in Fig. 7. This information can then be used to develop targeted strategies and policies to reduce risk, enhance resilience, and effectively manage drought risks.

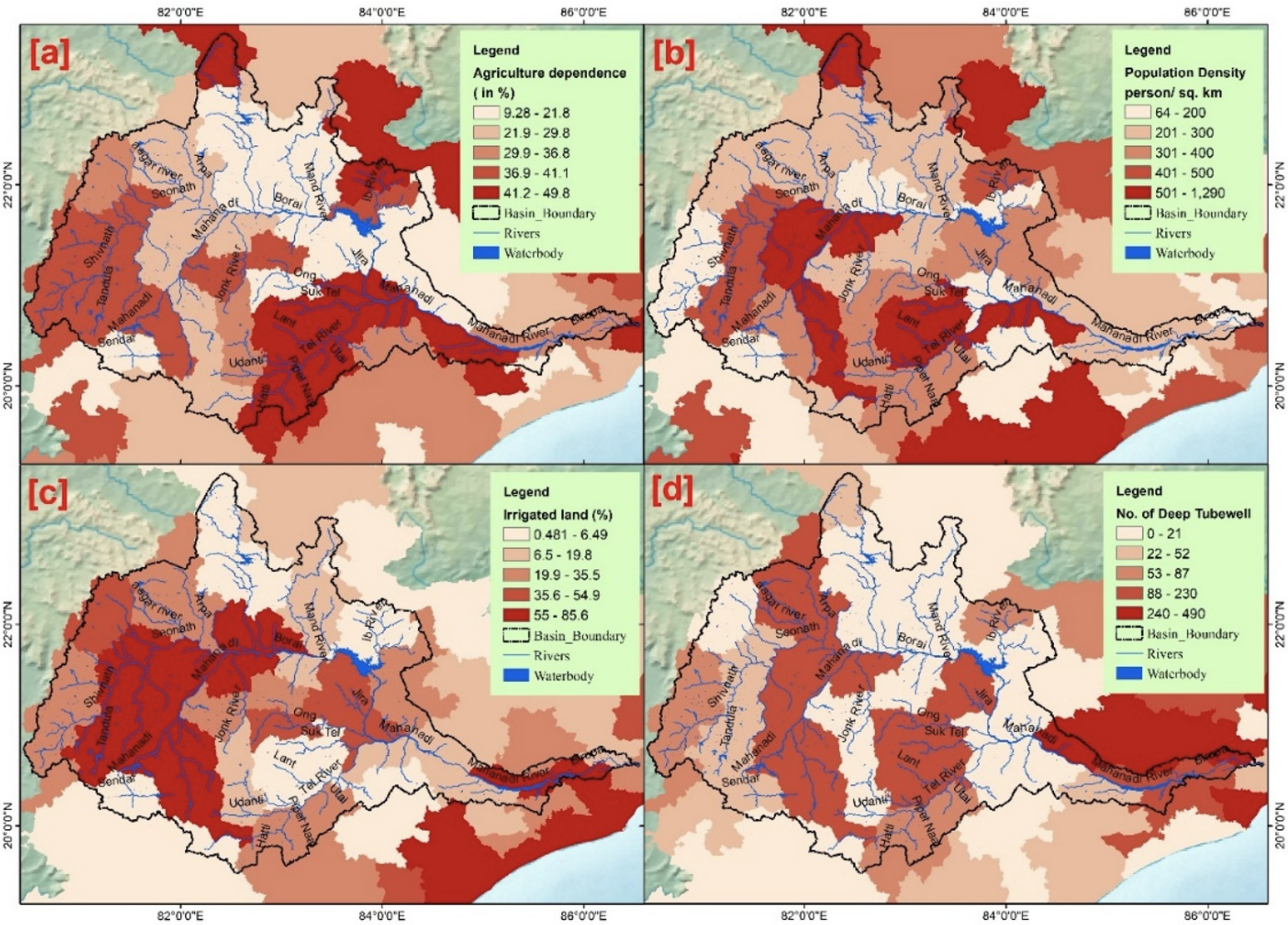


Figure 7. Showing socio-economic drought factors (a) agricultural dependence, (b) population density, (c) irrigated land, and (d) availability of the deep tube wells in the districts of the Chhattisgarh and Odisha states confined in the Mahanadi basin

3.3. Alternative ranking and standardization criteria layer

Each alternative was ranked according to a different specific criterion using a numerical ranking system from 1 to 5. According to each alternative's contribution to drought risk and AHP methods, the value of each rank was provided (Table 2). The alternative of the provided criterion is less vulnerable if the rank value is 1; however, the rank value of 5 indicates that the alternative is extremely vulnerable to drought. To implement an AHP-based spatial multi-criteria decision, the relevant ranking values for the alternatives in the spatial criterion layers were standardized in a range of 0 to 1. This involves transforming the raw data of each criterion into a standardized form using the standardized z-score method according to equation 1.

$$p = \frac{x - \min}{\max - \min}$$

Where, x denotes the value of the cell, min and max denote the minimum and maximum values of each dataset, respectively, and p indicates the standardised score

3.4. Evaluation of drought risk mapping accuracy

It is vital to verify the outcomes of modelling and mapping drought risk to see if the predictions accurately reflect the anticipated outcomes. The efficacy of model results hinges fundamentally on their accuracy, and the significance of models lies in their validation (Chaudhary et al., 2021; Pramanik et al., 2018). Diverse approaches are utilized to validate the results of suitability modeling, and typical procedures involve creating a Receiver Operating Characteristics (ROC) curve to assess the vulnerability model for drought. This process entails computing the Area under the Curve (AUC), a frequently employed metric. The ROC curve serves as a visual representation, mapping false positive values on the Y-axis against false negative values on the X-axis across the entire spectrum of threshold values (Pourghasemi et al., 2013; Pramanik et al., 2020a). In this analysis, the AUC serves as a measure of prediction accuracy, elucidating the system's ability to anticipate the absence or presence of predefined "events". According to (Pramanik et al., 2020b), AUC values range between 0 and 1.0. A value of 0 suggests that the model's results were no better than random, while a value of 1.0 signifies absolute discrimination. Furthermore, the ultimate map depicting predicted drought risk suitability underwent validation through diverse methods. This validation process included leveraging data collected from various sources pertaining to drought conditions in the region.

The occurrence of previous drought catastrophes across the dryland ecosystem is a prerequisite for validating the overall susceptibility to drought (Naumann et al. 2014; Wu et al. 2017). The frequency of previous drought catastrophes provides insight into the overall number of years experiencing drought between 1970 and 2018. Based on standards established by the India Meteorological Department (IMD), the number of droughts has been determined. A drought is defined as an epoch in which the deficit of precipitation exceeds 25% of the corresponding mean. Furthermore, the number of pixels allotted to every class (normal, mild, moderate, severe, and extreme) has been used to establish the drought susceptibility status for each district. Then, using the product of the number of pixels and the drought-susceptible area of the Mahanadi River Basin (aggregate area/total number of pixels of drought-susceptible classes), the area of each drought class in each district has been determined. The calculation of each class's drought-prone area involves taking the rank of the region within the same class and dividing the result by the Mahanadi River Basin total area. Lastly, the district's overall drought risk, suitably associated with the historical drought, is verified by adding together all of its drought classifications.

4. Results

4.1. Climatological drought risk factor

Although the consistency ratio of these weights is roughly 7%, the climatological drought map was created by properly merging the indicators (rainfall, temperature, evapotranspiration) according to their weights. This confirms the use of these meteorological variables for assessing drought sensitivity in the Mahanadi Basin.

The research region is almost 94% susceptible to moderate to intense drought, whereas only 6% is in normal to mild drought, according to the meteorological drought sensitivity map (Fig. **8**). The regions that are most susceptible to drought are often found in the northern region of Orissa, the middle to northern region of Chhattisgarh, and a few isolated locations in eastern Maharashtra. The majority of these regions are in the northern regions of Orissa and Chhattisgarh, and they are characterized by high temperatures, high evapotranspiration, and little rainfall. Panda and Singh (2016) claim that the rainfall distribution in the Mahanadi River Basin is asymmetric and lasts for three to four months. The whole catchment region of the Mahanadi River is expected to be impacted by changes in the Mahanadi River Basin mean monthly, seasonal, and yearly precipitation. Due to heavy rainfall, cold temperatures, and low evapotranspiration rates, the south and southeast are the regions most vulnerable to a moderate to mild drought.

4.2. Agricultural drought risk factor

In addition, as with the Climatological and hydrological drought maps, the final agricultural drought map was created by precisely combining the available water holding capacity indicators, such as soil, land use, and slope maps, in accordance with their respective weights (Table **2.**). This confirms the dependability of the three indicators that were chosen for the agricultural drought assessment. The developed map of agricultural drought (Fig. **8**) clearly shows that, due to the high available water holding capacity of the soils and the greater presence of wastelands, waterbodies, and slope areas, the middle and eastern parts, and only small pockets of the western and north-eastern parts of the Mahanadi River basin, fall under normal (2%) to mild (24%) agricultural drought. However, due to the low accessible water holding capacity of soils and the greater area covered by populated regions and agricultural practices, the majority of dryland ecosystem areas have been dominated by moderate (29%) to severe (19%) and extreme (26%) agricultural drought susceptibility. The Land Use Land Cover Change (LULC) of the Mahanadi River basin since 1985 was examined by Behera et al. (2018). The analysis indicates that 55% of the total rainfed area is made up of agricultural land. Since 1985, there have been reported instances of direct forest to agricultural land conversion as well as scrub land conversion to waste and cropland.

4.3. Hydrological drought risk factor

Moreover, the final hydrological drought map was created by precisely combining the four hydrological indicators (average groundwater level, elevation, drainage density, and surface water bodies) in accordance with their weights, just like the meteorological drought map (Roy et al., 2023; Topçu, 2024). This was made possible by the consistency ratio of these weights, which is around 7% (Table 2), and which validated the choice of the aforementioned five hydrological indicators for the assessment of hydrological drought.

According to the hydrological drought sensitivity map (Fig. 8), 46% of the dryland ecosystem's area is susceptible to severe to extreme drought in the northern, north-central, western, and minor pockets in the southern regions. Metamorphic rocks, higher altitudes, lower groundwater levels, excessive groundwater use, and a dearth of surface waterbodies have all been associated with these places. Most of the northern, south-eastern, and north-eastern regions are under normal (3%), slight (18%) to moderate (36%), and prone to hydrological drought. These regions are made up of sedimentary deposits, lower ground elevations, inadequate groundwater levels, safe groundwater development, and an abundance of surface waterbodies.

4.4. Socio-economic drought risk factor

Last but not least, the final socio-economic drought susceptibility map was created, similar to the other maps for meteorological factors, hydrological factors, and agricultural factors. This was achieved by combining data on population density, the female to male ratio, the % of population that is dependent on agriculture, % of irrigated land to total land, and the % share of deep bore wells to the total count of bore wells. The accuracy of these maps is ensured by the weights assigned to them, which consistently correlate to a ratio of about 7% (Table 2), providing evidence of the reliability of the five indicators chosen for agricultural drought assessments.

Based on the established socio-economic susceptibility map (Fig. 8), roughly 38% of the region is prone to normal drought, followed by mild drought (15%), moderate drought (11%), severe drought (33%), and extreme drought (3%). The majority of the eastern regions, such as Anugul, Balangir, Baragarh, Cuttack, Jajapur, Khordha, Dhenkanal, Raipur, Bilaspur, and Dhamtari, are extremely to severely drought-prone due to factors such as high population density, a high proportion of women to men, irrigated land, and deep tube wells. These findings corroborate those of Danbanli (2018), Singh et al. (2019), and Nghia et al., (2022), who observed that a region's socioeconomic drought rises with population density, a high female to male ratio, a higher proportion of the population dependent on agriculture, irrigated land, and deep tube wells.

4.5. Overall drought risk

The Mahanadi River basin area's general state of drought risk is depicted in Fig. 9. Fig. 10 indicates that just 2% of the state is susceptible to normal drought, whereas the majority of the state (32%) and 31% of the state (32%) are susceptible to severe and moderate droughts, respectively.

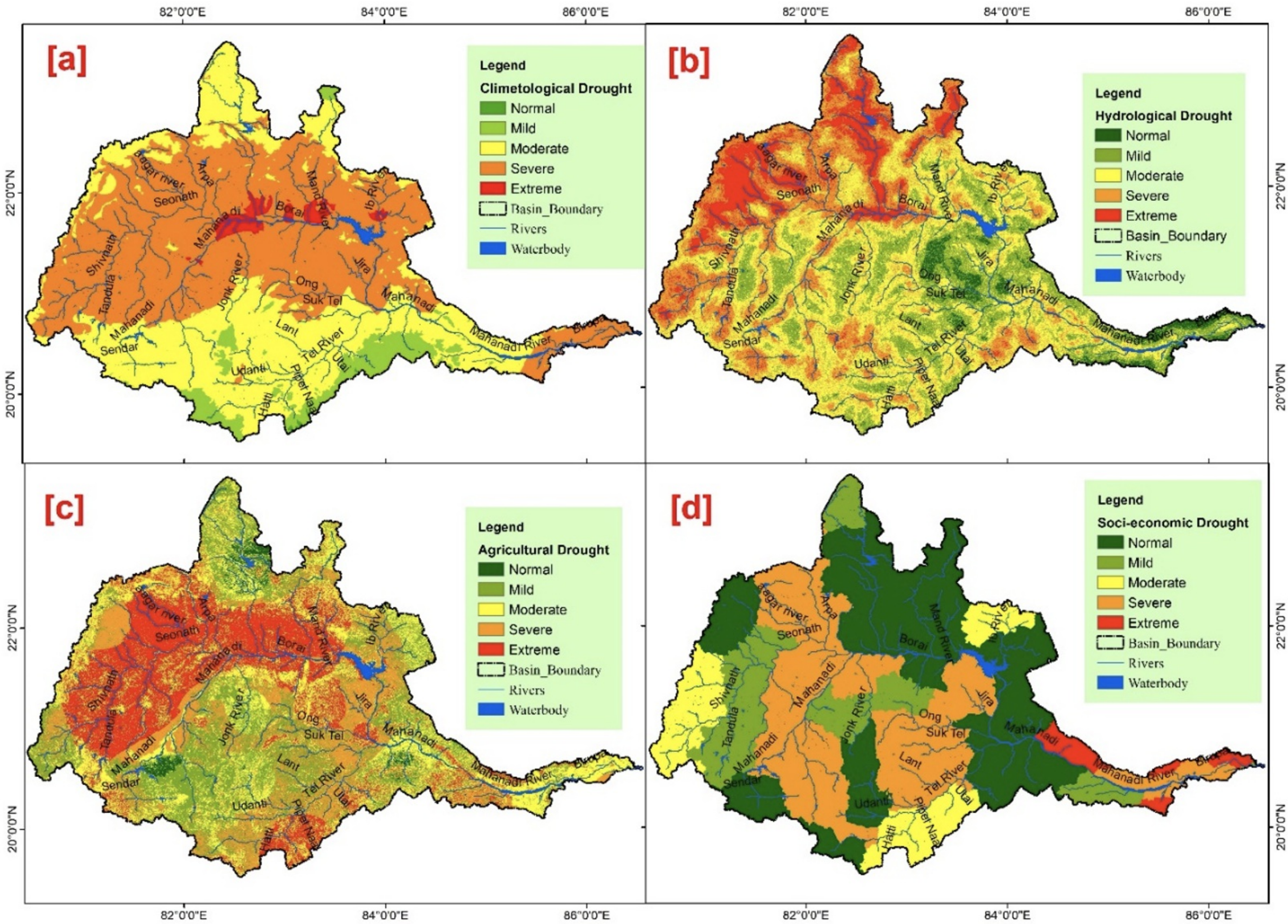


Figure 8. Showing [a] climatological drought risk; [b] hydrological drought; [c] agricultural drought risk; and [d] socio-economic drought risk

The majority of these drought-prone areas are found in the northern, eastern, central, southern, and northeastern regions. Similarly, 54% of the region is susceptible to severe to extreme drought, which has more severe drought-related effects than other regions. Over the dryland ecosystem, the eastern, western, central, northern, and little pockets of the southeast are the region's most at risk from drought (severe to extreme). Across the Mahanadi River basin, districts like Raipur, Bilaspur, Durg, and Rajnandgaon faced extreme drought conditions (see figure 11 – district-wise drought risk). The overall drought risk map, combining assessments of agriculture, water resources, socioeconomic factors, and weather patterns, reveals varying levels of risk across the region. The catchment area of the Mahanadi River basin is heavily inhabited and mostly made up of agricultural and forest areas (Behera et al., 2018). In Chhattisgarh, agriculture is mostly focused on the Central Plains (e.g., Durg, Dhamtari, Raipur, Mahasamund, as well as Janjgir-Champa) and the Western region. The upland regions (e.g., Kawardha, Rajnandgaon, and Bilaspur) (Dsouza et al., 2017, Samuel et al., 2017). Farmers' agricultural livelihood is mostly impacted by the Mahanadi River's decreased water flow (Ratha, 2019).

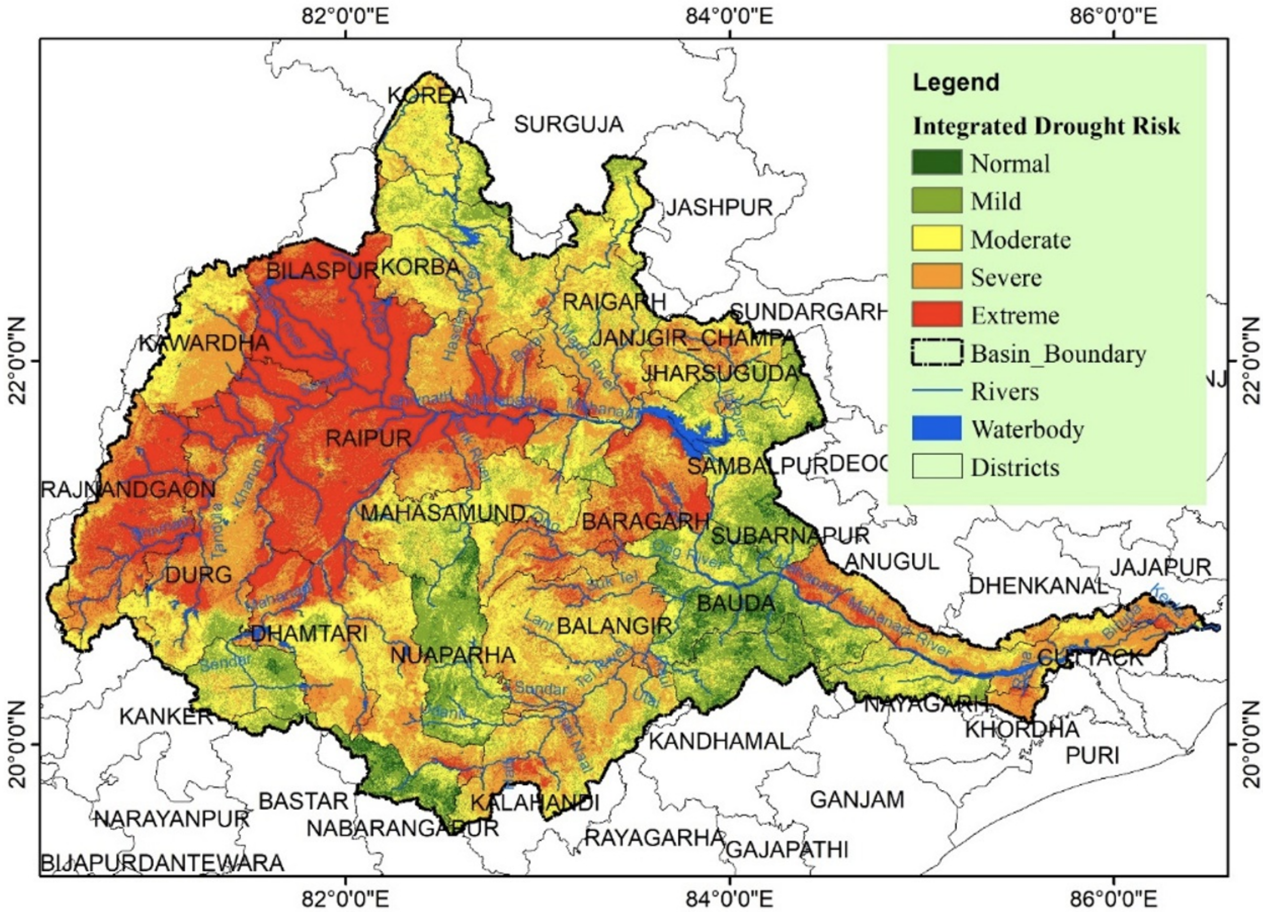


Figure 9. Showing integrated drought risk in different parts of the Mahanadi River basin region

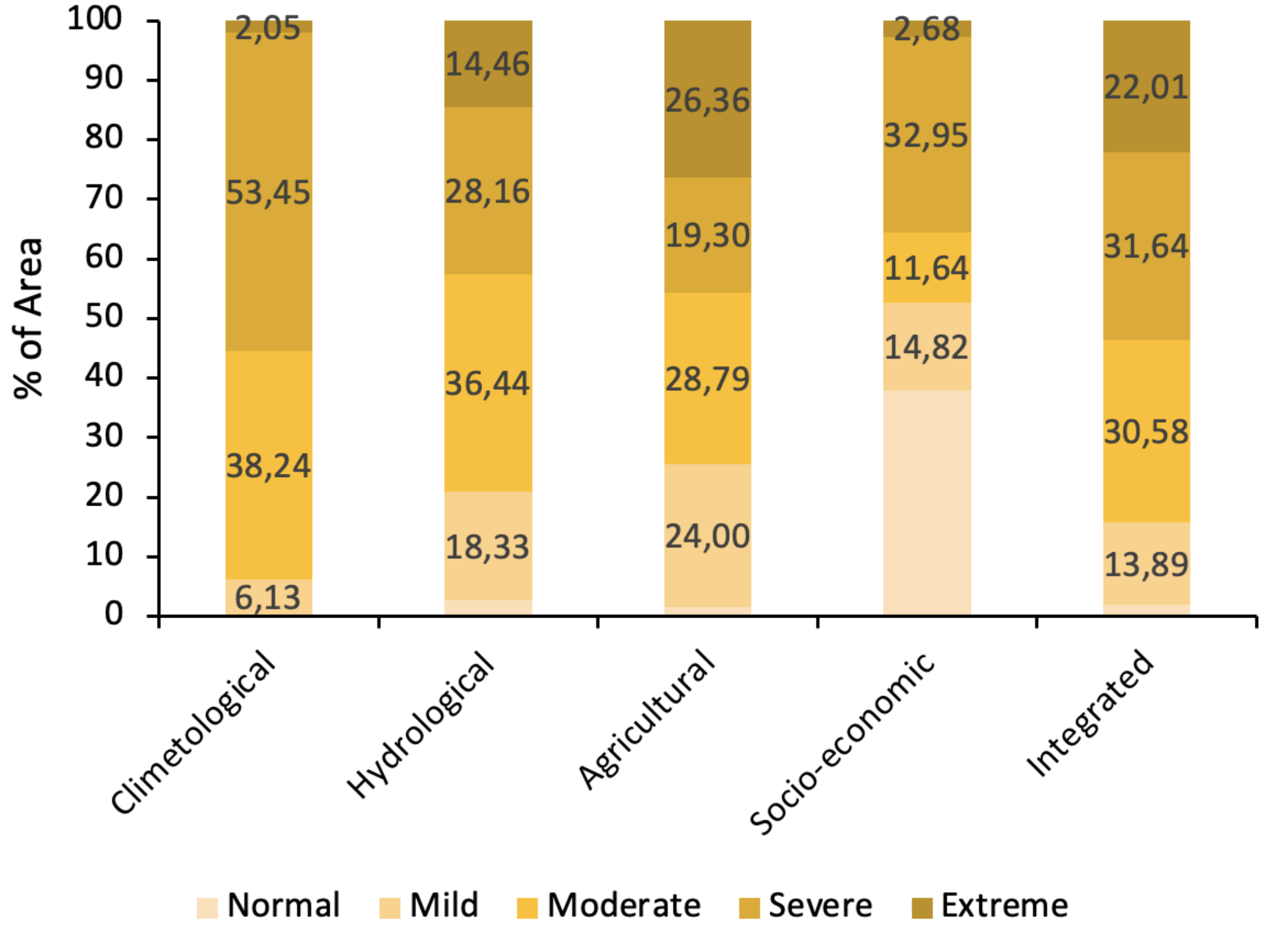


Figure 10. Graphical representation of drought in different aspects and areal coverage in associated drought risk classes

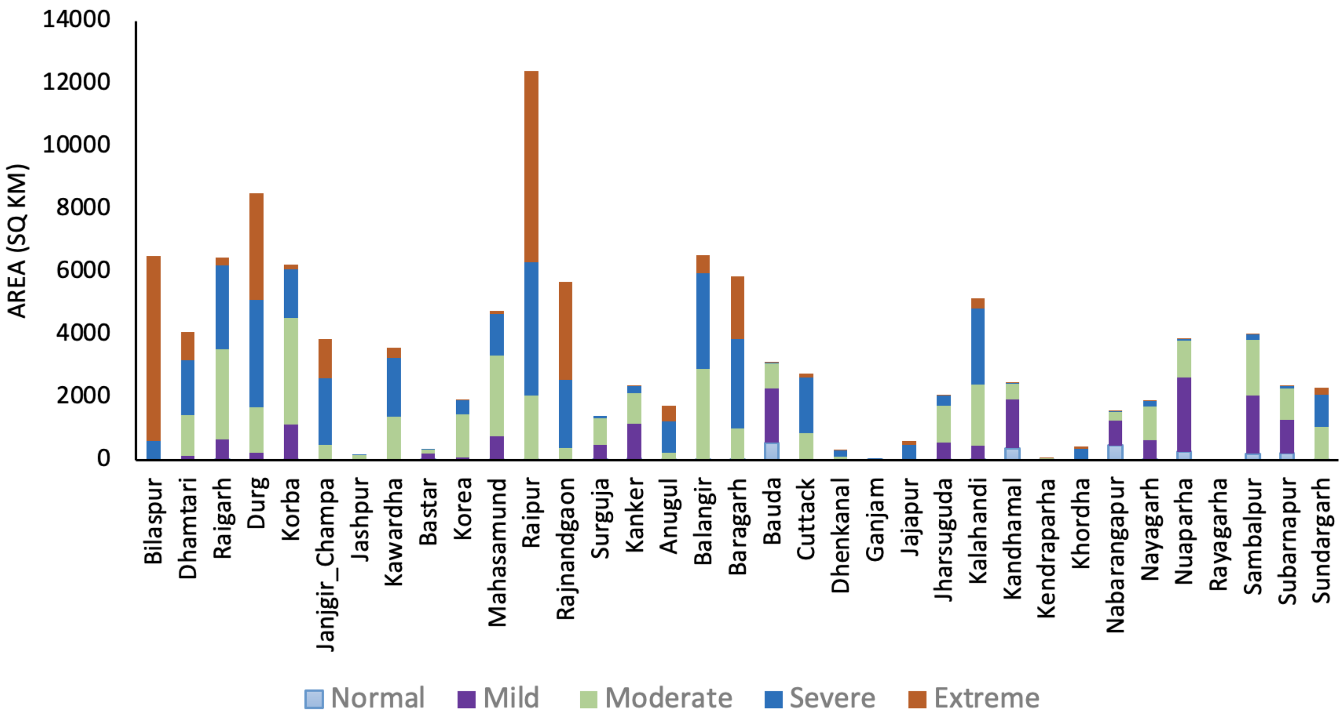


Figure 11. Showed the district-wise areas under drought risk in the Mahanadi River basin considering drought risk classes

4.6. Validation of drought risk assessment

In our study, the validation of our model results was conducted through the construction of a ROC curve for identifying suitable drought risk sites and estimating the AUC, among other metrics. To assess the drought risk site suitability using the AHP model (Regmi et al., 2014), existing sites facing drought conditions were juxtaposed with predicted sites. In ROC curve analysis, the models demonstrated a moderate capacity to distinguish between actual and predicted sites based on the AHP model. The ROC curves, along with the AUC, are visually represented in Fig. 12.

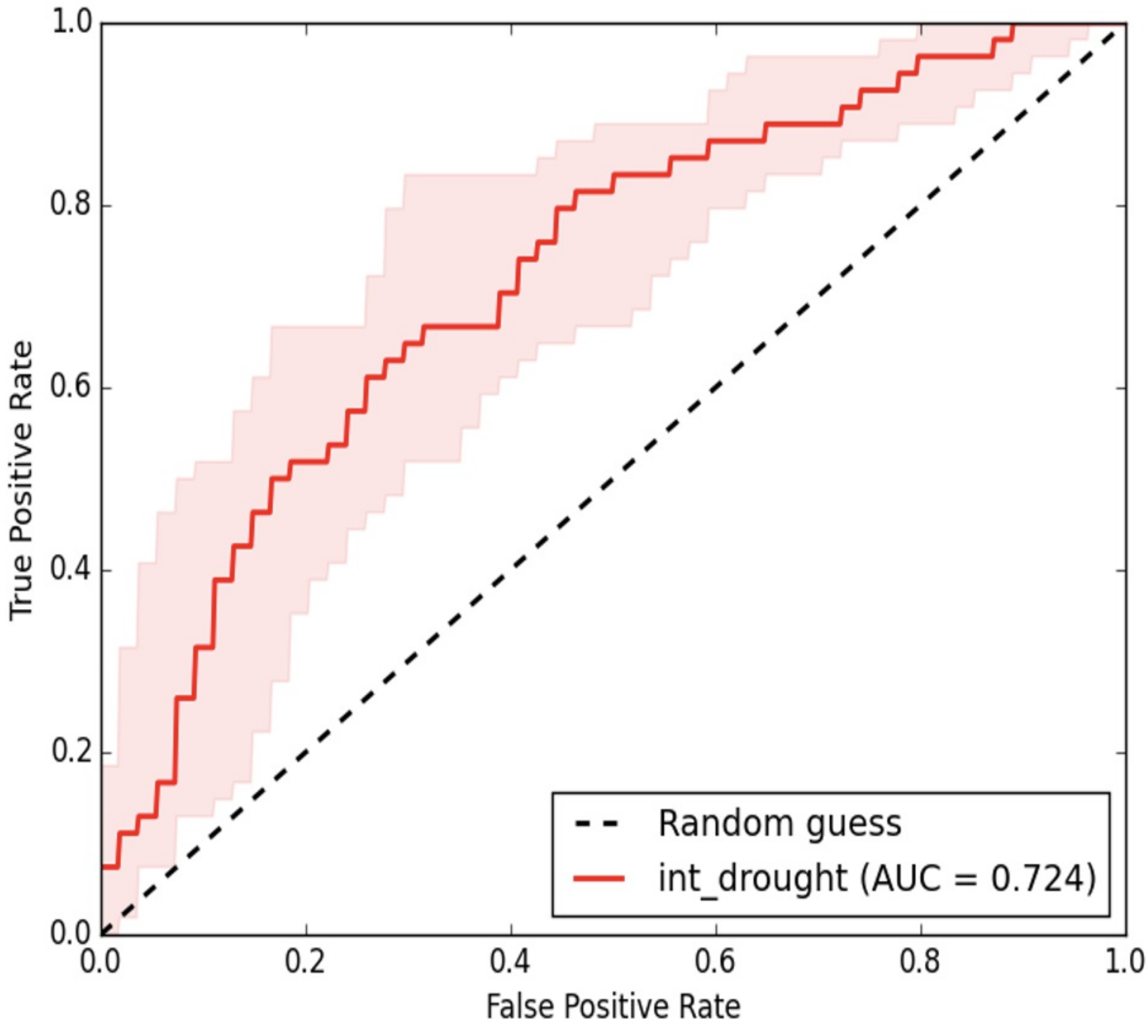


Figure 12. Showing validation and accuracy of the model used in the study using AUC curve analysis for integrated drought prediction

The AUC value for the AHP method was found to be 72.4%, indicating that the potentiality maps were predicted quite well, attesting to a moderate level of accuracy. As a result, the model utilized in this study can be reasonably considered accurate in forecasting drought risk sites within the Mahanadi River Basin. Moreover, the findings uncovered a congruence between the maps depicting drought risk suitability and the actual sites experiencing drought conditions in the region. This alignment emphasizes the dependability of the predictive process, confirming the precision of the model in delineating areas susceptible to drought within the river basin.

5. Discussion

Urbanization also plays a significant role in highlighting the drought risk. There are several urban centers spread out throughout the whole stretch of the Mahanadi River and its tributaries in Chhattisgarh. Durg, Korba, Bilaspur, and Raipur are a few major cities. This river provides water, either directly or indirectly, to rapidly growing metropolitan areas. In the upcoming decades, urbanization, deforestation, and agriculture expansion are expected to be significant and likely to persist in the Mahanadi River Basin, according to Das et al. (2018). The Mahanadi River Basin's changing land use and cover can be attributed to a number of socioeconomic variables, including human habitation and proximity zones around habitats (Behera et al., 2018). The Mahanadi River in Chhattisgarh is being impacted by industrialization and thermal power plants, as explained by Ratha (2019). Odisha receives 944 MCM of Mahanadi River Basin water, compared to the state's approximate 1130 MCM (Patra and Jena, 2018).

The whole catchment region in Chhattisgarh is now susceptible to climate change due to the six-fold rise in the industrial circulation of river water since 1997 (Panda, 2019). The state's industries—mining, electricity, cement, steel and iron, and others—are growing quickly. The Mahanadi River provides water to 58,000 MW power plants in the state (Ratha, 2019). The amount of water allotted to industry has grown considerably from 364 MCM in 2007 to 1661 MCM presently (Forum, 2017; Dsouza et al., 2017). As a result, there is a greater likelihood that in the next decades the river will be overused and have low flow. Whenever a river is overused, its natural flow is jeopardized, and it will probably become a lesser river. The Mahanadi River Basin is under tremendous ecological strain due to rising pollution levels and the development of new companies in the area. The Mahanadi River's ability to flow freely is hampered by our interference with the natural ecology. The Hasdeo River in Korba was the subject of an investigation by Bhaskar et al. in 2020 about organic and inorganic pollution.

The districts of Chhattisgarh that cover the western, north-western, eastern, southern, and central parts of the dryland ecosystem are Bilaspur, Dhamtari, Durg, Janjgir_Champa, Kawardha, Raipur, and Rajnandgaon, as well as certain areas of Baragarh, Balangir, Kalahandi, Anugul, Cuttack, and Khordha in Orissa. These districts have been found to have the highest overall risk to drought (severe to extreme). The streams and sub-tributaries of the Mahanadi River Basin have been the subject of several research studies (Singh and Singh, 2012, Singh et al., 2011, Singh et al., 2019). Singhet al. (2019) used IRS P6 and 1D, LISS 3 satellite imagery to examine the LULC distribution of the Gej sub-watershed, a tributary of the Hasdeo River that flows through the state of Chhattisgarh. According to the study, between 2000 and 2013, there was a decrease in thick forest, open forest, and barren land, but a rise in LULC types such as agricultural area, scrub land, riverbed, and water resources.

In the districts of Balangir, Baragarh, Cuttack, Jharsuguda, Kalahandi, Nayagarh, and Sundargarh in Orissa, as well as in limited sections of Dhamtari, Raigarh, Durg, Korba, Kawardha, Mahasamund, and Raipur in Chhattisgarh, there have been reports of moderate drought risk. While this is going on, the districts of Bauda, Kandhamal, Nabarangapur, Nuaparha, Sambalpur, and Subarnapur in Orissa, as well as a few pockets of Korba, Bastar, Surguja, and Kanker in Chhattisgarh that are dispersed throughout the eastern and southern regions and a few small patches in the northern and central regions, have mild to normal drought. The 58-year rainfall, temperature, evapotranspiration, and soil moisture data utilised in this analysis are limited to the years 1970–2018 because of the availability of those data sets. Similarly, 90 m resolution of SRTM DEM has been utilized to create slope as well as elevation maps, although higher-resolution DEM might have produced more precise and trustworthy findings. Furthermore, our study will be more accurate if we have more recent socioeconomic data on things like population density, agricultural reliance, irrigated agricultural acreage, and the number of tubewells. Similarly, more accurate information may have been generated if high-resolution data on variables such as hydrology, land-use, and surface water bodies had been taken into account. Furthermore, the temporal variation of drought susceptibility has been totally disregarded in favor of just accounting for spatial variation. Additionally, there is a chance to enhance the study's general approach by adding more contributing indicators and assigning the indicators more exact weights. Moreover, the overall drought risk map has been effectively evaluated and validated utilizing data sets from secondary sources rather than primary data, such as the NDVI and the incidence of previous drought records. Despite all of these negatives, the modelled drought sensitivity map will help managers of water resources, farmers in particular, and decision-makers create efficient mitigation plans to lessen drought risk across the dryland habitat of the Mahanadi River Basin in India.

Several studies indicate that the spatial drought risk and extent are continuously increasing over the Mahanadi River basin and that exposure to a high meteorological drought hazard (Adnan and Ullah, 2020; Sharma and Mujumdar, 2017) is also contributing to an increased likelihood of drought occurrence, whereby meteorological droughts may have a significant impact in this region for relying heavily on rainfed agriculture and related livelihoods in the districts of Odisha and Chhattisgarh (Adnan and Ullah, 2020). Rice, lentils, oilseeds, jute, coconut, and turmeric are among Odisha's primary crops (Welfare, 2016). With agricultural production impacting 38% of its land covered by irrigation, the districts of Odisha have seen 19 years of drought over the past 50 years, occurring once every five years on average (Upadhyay and Sherly, 2023). Many studies have revealed that the districts in the basins of the Mahanadi River have a significant degree of sensitivity to hydrological drought (Upadhyay and Sherly, 2023).

Effective strategies for water management are necessary given the current imbalance in the availability of water resources throughout the region (Upadhyay and Sherly, 2023). The districts of Odisha and Chhattisgarh exhibit considerable sensitivity to socio-economic drought risk, whereas Odisha and Madhya Pradesh have seen very high rates of poverty exceeding 30% (Mehta and Shah, 2001). Districts with a high marginalised population are more vulnerable to droughts due to disparities in access to water and sanitation facilities (Schewe et al., 2014). Scheduled Caste families in low-income districts of Madhya Pradesh and Odisha face severe drinking water scarcity and rank among the lowest performing states in terms of total rural habitations completely serviced by drinking and urban water supplies (Ezbakhe et al., 2019). There were no initiatives, insurance plans, or assistance programmes to directly lessen the socioeconomic effects in any urban areas. This is not like the rural areas where these kinds of actions are common. The majority of actions made to reduce demand are short-term (tactical or emergency), whereas large-scale infrastructure initiatives are typically used to enhance supply (strategic). The majority of cities spread messages on water conservation through the media. Few communities worldwide place a strong emphasis on strategically reducing demand, such as by modifying water pricing and reusing water. For both supply expansion and demand reduction, a variety of tactical strategies are available, such as voluntary water consumption targets, groundwater extraction, water transfers, and regulates on drought. Because of their potential lower per capita consumption, the urban areas in the study region may have fewer opportunities for demand reduction than industrialised ones.

Even though the Mahanadi River Basin's drought risk areas have been better understood through this study, there are still some important gaps that need to be addressed in order to make changes in the future. Real-time accuracy and thorough evaluations may not be maintained by the usage of datasets with a resolution of 90 meters and the dependence on previous data up to 2018. Future research should use higher-resolution datasets and more recent data to improve the study's precision. The robustness of the model could further be increased by investigating temporal fluctuations in drought and adding other indicators with precise weights. A more accurate and trustworthy estimate of the region's susceptibility to drought would involve ongoing efforts to reevaluate and modify the weights given to various variables. Our understanding of the dynamics of drought in the Mahanadi River Basin would surely improve if these constraints are addressed and these suggestions are put into practice in future studies. This will provide important insights for proactive drought management methods and efficient decision-making.

6. Conclusion

The current study tries to fill the knowledge gaps related to drought risk in the Mahanadi River Basin by providing a thorough, integrated, and multi-dimensional assessment that clarifies the factors and locations of drought risk. The methodological approach used in the study is notable and rigorous for its careful incorporation of a wide range of parameters, including expert opinions, into the AHP model that covers agricultural, hydrological, socioeconomic, and meteorological aspects. Detailed spatial risk maps have been produced by integrating cutting-edge methods like the Analytic Hierarchy Process, GIS approaches, and multi-criteria decision-making. The study presents a comprehensive understanding of the complex relationship between drought risk in the basin by methodologically taking into account the interdependence of these elements. Droughts are frequently a catalyst for new strategic measures that address water stress in the long run in the cities in the selected study areas. However, many urban areas approach drought management reactively, meaning that these measures are haphazard and do not help reduce the long-term water shortage risk due to drought. In another context, while their attitude may be reactive, the likelihood of a drought-related water scarcity will be mitigated when they rely on proactive solutions. Long-term risk is also impacted by the strategic, tactical, and emergency measures; tactical and emergency (temporary) actions further mitigate the effects of extreme drought occurrences. Consequently, cities must create or evaluate their own strategies for managing drought risk, and decision analysts must provide recommendations on how to improve proactive risk management and the combination of actions that provides a strong strategy for managing drought risk.

The comprehensive characterization of distinct risk factors pertaining to agricultural, hydrological, socioeconomic, and meteorological understanding enhances our understanding of the complex dynamics of drought susceptibility in the Mahanadi River Basin. Through identification and comprehension of these distinct risk factors, decision-makers and stakeholders can develop focused and efficient strategies for mitigating the drought risk analyzed in each dimension. The study conclusions drawn from it provide a solid basis for improving the region's drought resistance, assisting in decision-making, and encouraging sustainable agricultural practices in the face of shifting weather patterns. The extensive map of drought risk shown here emphasizes the various degrees of susceptibility dispersed throughout the Mahanadi River Basin, highlighting the necessity of focused and situation-specific intervention efforts. Adding up-to-date, high-resolution data can improve drought assessments' precision and currency. The study will also help in essential forward-looking approaches for developing resilient strategies and ensuring sustainable management of drought risk in the region.

Data availability statement

Data will be made available on reasonable request.

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