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Impacts of climate change on drought and its consequences on the agricultural crop under worst-case scenario over the Godavari River Basin, India

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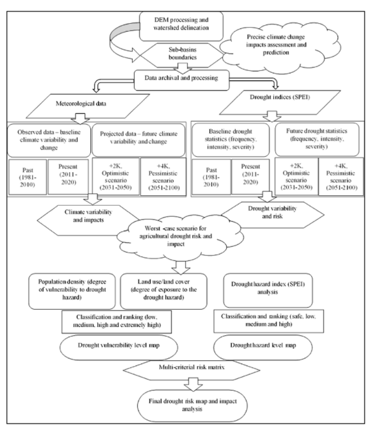
HIGHLIGHTS

- Climate warming is expected to increase future drought severity and frequency.
- Drought severity varies for different sub-basins and through time.
- Rice production can be severely affected in some areas of the GRB.
- Mitigation measures include the use of drought-resilient/less water-intensive crops.

GRAPHICAL ABSTRACT



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ABSTRACT

Extreme dry and hot conditions lead to intense droughts in central India. However, the precise changes in future drought characteristics and their consequences on crop production have not been fully examined in Godavari River Basin. Therefore, this study focuses on the spatiotemporal modelling of climate change impacts on drought

Abbreviations: CWC, Central water commission; DEM, digital elevation model; DOAC, department of agriculture and cooperation; DIAS, data integration and analysis system program; d4PDF, database for policy decision-making for future climate change; DAAC, distributed active archive center; GRB, Godavari River Basin; GHG, greenhouse gas; IMD, Indian meteorological department; ICRISAT, international crops research institute for semi-arid tropics; EM-DAT, international disaster database; JMBSC, Japan meteorological business support center; NDC, national data center; NRSC, national remote sensing centre; ORNL, Oak Ridge national laboratory; OGD, open government data; PD, population density; PET, potential evapotranspiration; SDG, sustainable development goals; SEDAC, socioeconomic data and application center; SPEI, standardized precipitation evapotranspiration index; SPI, standardized precipitation index; SRTM, shuttle radar topography mission; WMO, world meteorological organization.

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SPEI
Crop production risk, Godavari river basin

over the past, present, and future periods using long-term high spatial gridded data. The past and present observed datasets were obtained from Indian Meteorological Department, whereas the future datasets were obtained from d4PDF Scenarios. The standardized precipitation evapotranspiration index (SPEI) was applied to analyse drought statistics to identify the worst-case drought scenario (i.e. year most affected by severe-to-extreme drought with high drought severity), which was used further to access precise drought risk. Because SPEI considers the effect of both rainfall and temperature and therefore it is the widely recommended meteorological drought indices and best suited for climate change impact assessment. Drought severity was analysed using a Multi-criteria assessment risk matrix, and the areas under higher agriculture drought risk were mapped. The frequency of droughts with higher intensity and magnitude increased in the present decade compared to the past three decades. 75% area showed higher vulnerability to drought risks, whereas only 25% showed lower risks and less vulnerability to drought occurrences. Results demonstrate that drought severity varies from one sub-basin to another. More drought episodes were predicted for the central belt, particularly over the sub-basins of Wardha, Wainganga, Pranitha, and part of Indravati and Lower Godavari. 11% of the area covering six districts in the GRB was identified as highly vulnerable, and rice production was drastically reduced, accounting for 41.02% of production loss during the worst-case drought event. The frequency of severe-to-extreme droughts is expected to increase under future scenarios; therefore, effective mitigation strategies are recommended to minimise the agriculture drought risks and economic loss.

Practical implications for stakeholders, water resource managers, and policy makers

Climate change has impacted freshwater resources, putting many places around the world at risk for sustainable development (Bates et al., 2008). Climate warming will lead to more extreme changes in climate systems and increase the associated risk over the GRB in India. Droughts are a frequently occurring and widespread natural hazard that adversely affects many people and economic sectors, among which agriculture is the most affected (Prabnakorn et al., 2019) because of its high dependency on water resources (UNDRR, 2019). It has become a constant visitor and most occurring natural disaster in India, affecting badly the agriculture and water resource sector, especially most in the central part where agriculture is the primary economic activity of >80% of the population. Unevenly distributed and unpredicted rainfall made it difficult in understanding the extreme situation, and its consequences on agricultural production. It is the most significant constraint for crop production in the central part of India. And the Godavari River Basin is one of the main primary water sources for irrigation and other water use purposes in central India. Therefore, addressing this issue is crucial to minimise the crop production risk and the economy of the farming community in the GRB in India. The assessment of rainfall prediction and expected impacts under climate change scenarios and their variability is critical to addressing the water scarcity and water resource management problems. And hence, this study aims to produce a useful background for impact assessment studies and adaptation planning for global warming, and to examine the effect of anthropogenic warming on the estimated drought frequency, and its associated impacts on crops. The results provide a relative statistic that indicates the regional ranking of potential impacts, which can be used to prioritise actions for drought risk management and adaptation plans. The trend analysis of rice production and related drought impacts on production volumes and income outcomes represents an important initial background work that bridges an information gap and can be used by decision-makers when addressing risks and future sustainability. The findings are beneficial in quantifying the absolute impact of drought on rice crops and in comparing the loss incurred with that of other major crops. This could facilitate the selection of the best feasible crop to be cultivated during drought conditions in order to mitigate potential risks and minimize impacts on crop production and economic loss.

As the globe continues to warm, more extreme climate situations and the frequency of severe-to-extreme droughts are expected to increase in the future. The average mean temperature risk in India is predicted to increase by 2.4 to 4 °C by the end of the 21st century, which may surely cause more hydro-meteorological hazards (Krishnan et al., 2020). However, no study has investigated the comprehensive drought risk for crop production suggesting the best feasible location-specific risk mitigation strategies. Most previous research has focused primarily on drought hazards and their impacts, with very few studies considering in-depth drought risk assessment in combination with drought hazards, vulnerability, and exposure risk.

The results do not only help to understand the impacts of drought but also help to adapt the best feasible drought risk mitigation strategies and effective climate-proofing strategies over the most affected region under the worst-case scenarios. The results of future projections help prioritize the risk mitigation strategies and justify utilizing the appropriate resource inventory for implementation. Eventually, this will support government efforts to achieve sustainable agricultural development, alleviate hunger, and move closer to meeting the pledged international targets, including the Sendai Framework and the SDGs.

Introduction

Various studies on climate projections demonstrate that freshwater resources are strongly impacted by climate change worldwide, which can affect the sustainability of ecosystems and human societies (Bates et al., 2008). Water availability and accessibility are the most significant constraints for crop production. Therefore, it is crucial to address them in areas affected by water scarcity to maintain the crop production sustainability. According to the Intergovernmental Panel on Climate Change, most water resources worldwide will be subject to the adverse effects of climate change (Mancosu et al., 2015). Water shortage is a primary global issue, and many regions already experience serious water availability issues, which are expected to become more critical in the future (Bharat and Dkhar, 2018). In India, water demand has increased several manifolds over the years owing to the increasing urbanisation, agriculture expansion, population growth, rapid industrialisation, and economic development (Mall et al., 2006; Bhuvaneswari et al., 2013).

The most critical impacts related to water resources are associated with agricultural systems and food security. Water supplies are often inconsistent, severely dependent on weather patterns, and unequally distributed, both spatially and temporally. In India, the climate is dominated by the monsoons. Monsoonal precipitation is not uniform throughout the country, and it creates erratic events, such as floods and droughts, which affect strategies and policies on water resource management (Saraf and Regulwar, 2018). As the globe continues to warm, an increasing number of water-related issues are expected. Additionally, the estimated increment of urban sprawl, deforestation, intensive industrialisation, and population growth further pressure the water and food security. A significant global warming has occurred in the last five decades (Jarraud and Steiner, 2012; Mancosu et al., 2015). If current greenhouse gas (GHG) emissions rates are maintained, the global average temperature is likely to increase by nearly 5 °C or more by the end of the 21st century (Krishnan et al., 2020). The mean temperature over India by the end of the 21st century is predicted to increase by 2.4–4.4 °C considering a GHG warming scenario (RCP8.5, the high-emission climate change scenario) compared to the average temperature in 1976–2005 (Krishnan et al., 2020).

The temperature rise attributed to global warming is not uniform. Some areas experience greater warming and, thus, present more intense effects, including changes in rainfall patterns and higher temperature extremes. India is expected to witness more extreme climatic conditions in the future. Extreme dry and hot conditions that lead to more intense droughts and floods are likely to occur more frequently under future climate change scenarios. The frequency and spatial extent of droughts have increased significantly from 1951 to 2016 (Krishnan et al., 2020). In particular, areas over central India, southwest coast, southern peninsula, and north-eastern India have experienced on average more than two droughts per decade in that period. The area affected by drought has also increased by 1.3% per decade over the same period. Climate model projections indicate a high likelihood of an increase in the frequency (>2 events per decade), intensity, and area under drought conditions in India by the end of the 21st century under the RCP8.5 scenario because of the high variability in monsoon precipitation (Krishnan et al., 2020).

Given the significance of global warming effects, an increase in future drought risks in India is expected, especially in central areas. Therefore, the frequency and drought conditions in the future need to be investigated and future changes and the potential impacts must be analyzed. In recent, to the best of our knowledge, there have been some studies focused on the water storage anomalies, evaluation of drought identification, and analyzing drought characteristics and their severity over the major river basins including the Godavari River Basin in south India using different datasets, and drought indicators (Kumar et al., 2021a; Sarkar, 2022; Kumar et al., 2020; Kumar et al., 2021b; Sehgal et al., 2017). Over the historical period, the studies by Kumar et al., 2021a, Kumar et al., 2020 and Sarkar, 2022 used GRACE Groundwater Drought Index (GGDI) using GRACE data, Standardized Precipitation Evaporation Index (SPEI) using global gridded SPEI datasets of course resolution of 1° × 1°, respectively, to monitor and characterize the regional drought over Godavari River Basin. Whereas Kumar et al. (2021b) used the SPI drought index to understand the future drought risk, potential changes of drought properties and characteristics over the homogeneous regions of the Godavari basin using the precipitation datasets with a spatial resolution of 1° × 1° from the Indian Meteorological Department (IMD) and Global Climate Model (GCM)—MIROC-ESM-CHEM. However, the potential changes in the frequency and spatiotemporal characteristics of future droughts have not been thoroughly investigated at the sub-basins and districts level over the Godavari River Basin. Due to large-scale climate variation in India, the impacts are also varying from place to place, and hence comprehensive assessment is needed to determine the precise changes. In addition, a gridded analysis at a fine resolution of an entire river basin covering each sub-basin together over GRB is particularly lacking. Therefore, this study investigated long-term high spatial-resolution gridded data of past, present, and future periods based on different warming scenarios from a large ensemble high-resolution database, d4PDF (Database for Policy Decision-making for Future climate change), developed by the Japan Meteorological Business Support Center (JMBSC). The optimistic (+2 K) and pessimistic (+4 K) scenarios consider a 2 °C increase by the mid-21st century and a 4 °C increase by the end of the 21st century, respectively.

The Godavari River Basin (GRB) was selected as the study area because it is the second-largest basin in India and a crucial primary water resource in central India (Kumar et al., 2021b; Sarkar, 2022). In GRB, rainfall is unpredictable and unevenly distributed. This is associated with frequent droughts, which affect agriculture production and socio-economic activities (Garg et al., 2016; Bhuvaneswari et al., 2013). Therefore, considering present drought risks and future challenges for agriculture, this study aims to assess and predict the climate change impacts on drought in this area. The specific objectives are to (1) analyse the standardised drought indices to quantify the drought occurrences using long-term historical and future climate data, (2) identify the areas facing high drought risk, and (3) investigate the respective impacts under the worst-case drought scenario to address potential risks over the GRB. Because, to propose effective mitigation measures, an integrated approach to investigate climate change considering future temperature projections and respective impacts should be developed to clarify the possible spatiotemporal changes in drought occurrences.

Materials and methods

Several recent studies predict that climate change in this century will have a profound effect on rainfall patterns and stream flows in the arid and semi-arid regions of the world. The occurrence of dry spells during the monsoon season, late arrival of monsoon rains, and uneven spatio-temporal distribution of rainfall further exacerbate the situation. The high rainfall variability has a severe impact on the agricultural production and the rural economy of the region. However, most studies are limited to the global or country scale. The translation of these predictions into river basin and sub-basins levels is challenging but important to clarify the risk levels and potential impacts. Because the quantitative knowledge about the impacts of climate change can provide meaningful insights to address its adverse effects.

Therefore, spatiotemporal assessment is crucial to understand the precise impacts of climate change on drought and associated risks in the agriculture sector. And, hence, the location-specific changes (one sub-basin to another within the Godavari River Basin) and the relative statistical change over time have been analyzed in order to perform precise risk assessment, because the intensity and magnitude of impacts of climate change differ from place to place due to the rapid variability in driving factors such as rainfall and temperature. The purpose of analysis over past and present baseline periods was to understand the recent changes and variability over the space (between sub-basin and districts in sub-basins) and time (between past, and future periods), which helps determine the severity of risk over place and time, and useful for planning and implementing effective climate adaptation strategies towards achieving sustainable development goals (SDGs), number 6, 13 and 11.

Study area

This study was carried out in the GRB, located between 73°24′–83°4′E and 16°19′–22°34′N. The GRB occupies nearly 9.5% of the geographical area of India (Fig. 1) and is second longest river in the country (Garg et al., 2016), encompassing an area of 313346 km^2 across the states of Maharashtra, Madhya Pradesh Andhra Pradesh, Orrisa, Chhattisgarh, and a small part of Karnataka.

GRB drains an area of 152598 km^2 (i.e., approximately 49.7% of the total Godavari catchment area) in Maharashtra (CWC and NRSC, 2014), and it is an important primary water resource in Maharashtra and other surrounding states. Agriculture is highly dependent on rainfall, which in turn is influenced by the high inter-annual variability in monsoon rainfall and the occurrence of frequent droughts (Kumar et al., 2021b; Sarkar, 2022). The fairly heavy, irregular, and unevenly distributed rainfall varies temporally and spatially across the basin. All areas of the basin receive the maximum amount of rainfall (84% of the annual rainfall) during the monsoon period from June to September (Mondal et al., 2012, Kumar et al., 2021b).

Datasets

This study used both meteorological and geospatial data collected through primary and secondary data sources for the drought risk

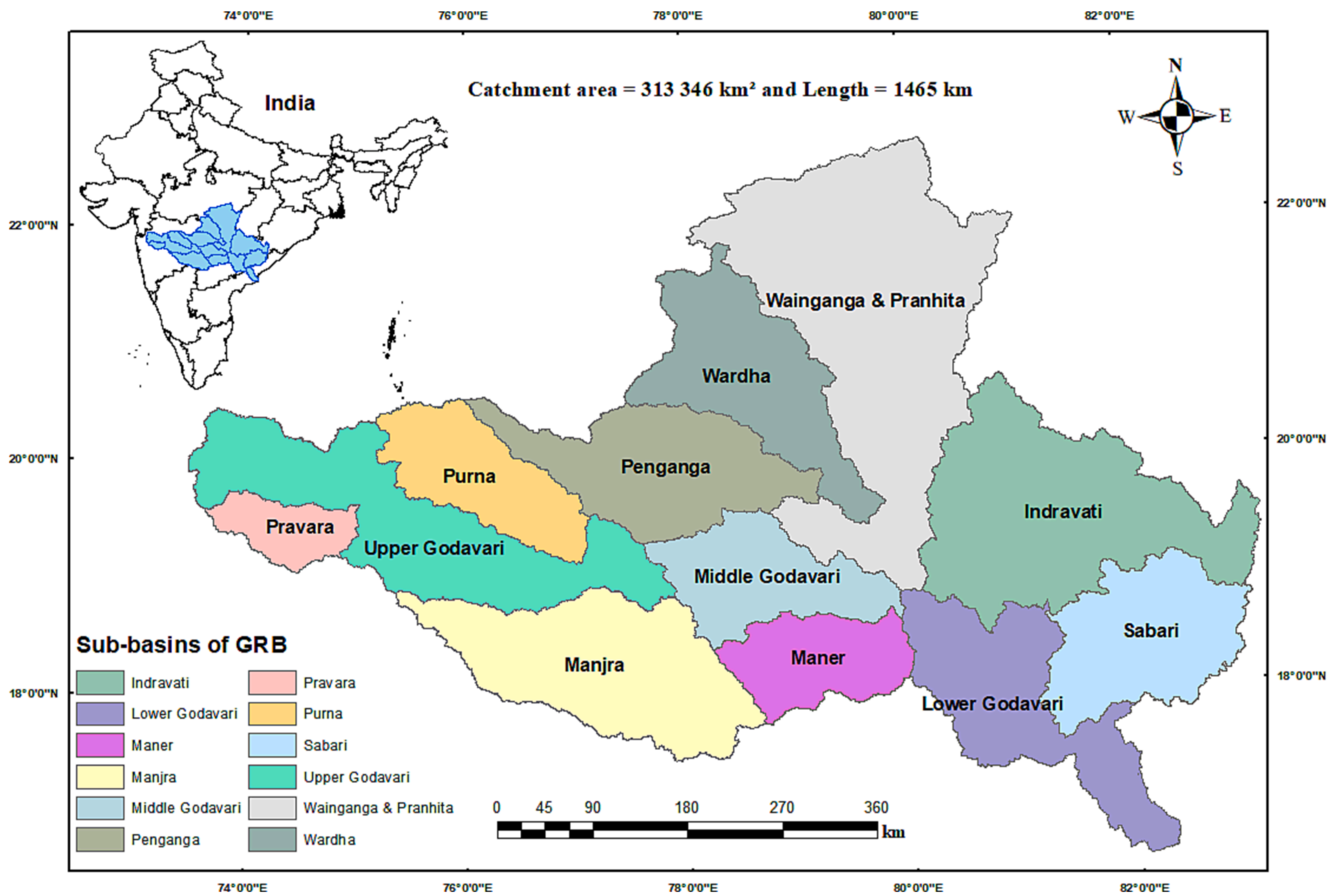


Fig. 1. The study area map of GRB, India.

assessment and impact evaluation. The obtained data were broadly categorised into physiographic and socio-economic datasets. The physiographic dataset included a thematic geospatial layer of land use, land cover, and topographic elevation (DEM), which were obtained from the Oak Ridge National Laboratory (ORNL), Distributed Active Archive Center (DAAC), and Shuttle Radar Topography Mission (SRTM), respectively. The socio-economic dataset included population, crop production, and disaster damage data obtained from the Socioeconomic Data and Application Center (SEDAC), International Crops Research Institute for Semi-Arid Tropics (ICRISAT), Open Government Data (OGD) Platform India, and International Disaster Database (EM-DAT), respectively. Detailed information on data variables and their respective sources is provided in Table 1.

Daily observed meteorological gridded datasets with the best available high spatial-resolution (precipitation: 0.25° longitude × 0.25° latitude; temperature: 1° longitude × 1° latitude) were obtained from the Indian Meteorological Department (IMD). This dataset has been used in drought monitoring as well as climate change research (Kumar et al., 2020; Shah and Mishra, 2015). This dataset captured well the extreme rainfall variability in the foothill of the Himalayas region and Western Ghats (Pai et al., 2014). A future climate projection database called d4PDF (the **d**atabase for **P**olicy **D**ecision-making for **F**uture climate change) was used to examine the effect of anthropogenic warming on the projected changes in the frequency of droughts in GRB. This database consists of outputs from multiple global warming simulations by a global atmospheric model with a horizontal grid spacing of 60 km. We selected d4PDF to estimate the future potential risk, due to its strengths (reducing the uncertainty in prediction) and advances (with the inclusion of the large number of ensemble members varying with different initial boundary conditions and external forces). It is a large ensemble dataset (each set of experiments has 54 to 90 ensemble members each for future 4 °C warming (+4K), and 2 °C warming (+2K), respectively), for which initial conditions and lower boundary conditions are set differently, with varied external forces. This decreases prediction uncertainty and has been widely used in impact assessments and adaptation plans related to global warming (Ishii and Mori, 2020). This data was created particularly for use in impact assessment studies and adaptation planning for global warming and is available over specific periods, such as (+2K -warming scenarios available from 2031 to 2091, and + 4 K warming scenarios available from 2051 onwards). Hence the authors have redefined these both scenarios as optimistic (+2K from the available period 2031–2050, where the warming will like to increase by 2 °C by the mid-21st century and we expect and are optimistic that it will not increase beyond considering the ongoing efforts of climate change adaptations. However, on the other hand side, if the greenhouse gas emission sustained like this, and global warming continues then there is a higher probability that the warming will increase by 3 to 4 °C after the mid-21st century to the end of the 21st century, as similar as the IPCC scenarios (RCP8.5). Considering this, the author has redefined this situation as a pessimistic scenario and used 4 K warming scenarios data over the available period from 2051 onwards to analyze the potential impacts of this pessimistic situation. Additionally, the d4PDF data were evaluated over Indian regions and found to be in good agreement (with spatial correlation coefficients of 0.99 and 0.76 in temperature and precipitation, respectively) with some of the highly resolved operational observed datasets of APHRODITE (Nayak and Takemi, 2022).

Socio-economic datasets are important indicators for the evaluation of impacts. In this study, land use/land cover data (100 × 100 m spatial resolution) focusing on agriculture land and population density (resolution of 1 km) were used as an indicator to analyse the impacts of

Table 1
Data type and sources.

Data type	Variables	Data range	Source
Meteorological	• Rainfall Maximum temperatureMinimum temperature	1980–2019 (daily)	- National Data Center (NDC) - Indian Meteorological Department (IMD)
Climate projection scenarios (d4PDF)	• Rainfall Maximum temperatureMinimum temperature	2031–2050 (+2 K)	- Data Integration and Analysis System Program (DIAS)
	• Rainfall Maximum temperatureMinimum temperature	2051–2100 (+4 K)	- Japan Meteorological Business Support Center (JMBSC)
Physiographic datasets	Land use/land cover (LULC)	Recently available	- Oak Ridge National Laboratory (ORNL) - Distributed Active Archive Center (DAAC)
	DEM	30 m	- Shuttle Radar Topography Mission (SRTM)
Socio-economic datasets	**Crop production statistics** Rice production Harvested areaCrop price	Annual	- International Crops Research Institute for Semi-Arid Tropics (ICRISAT)
		Seasonal	- Open Government Data (OGD) Platform India
	Population	Density (people/km^2)	- Socioeconomic Data and Application Center (SEDAC)
	Drought damage statistics Occurrence Crop damage Economic lossAffected population	Recently available	- EM-DAT The International Disaster Database

drought hazards (Meiyappan et al., 2017). The data file obtained in the GeoTIFF format (.tiff) was processed using ArcGIS 10.6 to prepare a map on a district-level scale for the analysis of district-level impacts of drought on crop production. The district-level statistical data (crop production and prices) were obtained from reputable and trustworthy data repositories (ICRISAT data portal and the Indian Governmental Data Portal, respectively), including annual crop production for 1981–2015 and seasonal (Rabbi and Kharif) crop production for 1997–2014 based on the period of data availability.

Methodology

In this research, we used a comprehensive approach to assess the climate change impacts on drought, and a comprehensive drought risk assessment to analyse the respective risks to the agriculture sector. This approach allowed for a deeper understanding of the characteristics of climate change and its perception on the occurrences of drought over spatial and temporal scales using a baseline (past and present references) and future (21st century) timeframe analyses. This analysis was used to identify the locations and crops at higher risks, which can be used as background to define mitigation measures to minimise potential risks and maintain socio-economic sustainability towards achieving SDGs, as illustrated in Fig. 2.

Post data processing

To clarify the impacts of climate change, we considered two future climate change scenarios (optimistic and pessimistic) obtained from the d4PDF data simulations. The raw data (observed meteorological data and future climate change projections) were in different formats and resolutions, so bilinear regridding was applied to match the datasets at similar locations considering the performance and suggestions from previous studies using similar data structure (Kumar et al., 2020; Mistry, 2019). The processed data were used for drought vulnerability and risk assessments and to predict the potential risks to crop production. The sub-basins boundaries were delineated via watershed delineation using DEM data (SRTM-30 m) in the Arc-hydrology tool of ArcGIS 10.6. The delineated watershed boundaries were further merged into 12 major sub-basins based on the location of meteorological stations currently used by the IMD to disseminate basin-level information over GRB. These 12 sub-basins have been used as regional units for climate change impact assessments using the spatiotemporal modelling approach. A spatiotemporal analysis was conducted to determine the pattern and magnitude of change using Sen's slope estimator of Mann–Kendall test (Kundu et al., 2015; Panda and Sahu, 2019). Several researchers have used the Mann–Kendall statistical test to quantify the significance of trends for time-series hydro-meteorological variables (Jhajharia et al., 2014; Kumar et al., 2020; Yaduvanshi et al., 2021), and Sen's slope estimator has been widely used to analyse the hydro-meteorological time series data (Kundu et al., 2015; Panda and Sahu, 2019).

Datasets of high-resolution daily gridded precipitation and temperature data from 01 January 1980 to 31 December 2019 were used to determine drought indices, namely the standardised precipitation index (SPI) and standardised precipitation evapotranspiration index (SPEI), over the historical baseline period. The baseline period was subdivided into two sub-timeframes, past and present. The past dataset included the first three decades (1981–2010), and the present timeframe dataset included the most recently available data (2011–2019). The purpose of this division was to clarify recent changes and variability on space (sub-basin and districts) over time (past and present periods). This analysis was used to determine the severity of risk over space and time on the GRB for the past 40 y. This was also be used to test the extent of the research hypothesis ("dry becomes drier and wet becomes wetter") over different successive time frames. Moreover, a large ensemble of high-resolution gridded data (d4PDF) was used to investigate the impacts of climate change on future drought occurrences during the 21st century in the GRB under optimistic and pessimistic warming scenarios, under the influence of the worst-case climate change scenario (RCP8.5). The drought indices were used to estimate the level of drought risk by analysing drought hazard, vulnerability, and exposure. The results were used to identify the most vulnerable drought risk zones and evaluate the risks associated with crop production and the economy of farming communities. The potential impacts on crop production and economy on the most vulnerable regions were then determined, and they can be used to develop and implement effective risk mitigation strategies.

Climate change impact assessment using drought analysis

SPI and SPEI are used as monitoring tools and to investigate the occurrences of drought events. They can be calculated at any timescale but are usually calculated over 1, 3, 6, 12, and 24 months, and can be applied to meteorological, hydrological, and agricultural drought phenomena (Kumar et al., 2021b). Drought calculated using 6- and 12-month timescales are the most useful to investigate agriculture droughts and hydrological droughts, respectively (Beguería et al., 2010; Musei et al., 2021; Niranjan Kumar et al., 2013; Ripin et al., 1989; Vicente-Serrano et al., 2010b). Many researchers have analysed the drought conditions at 12-month timescale in India (Gupta et al., 2020; Kumar et al., 2021a). Because, In India, a major portion of annual

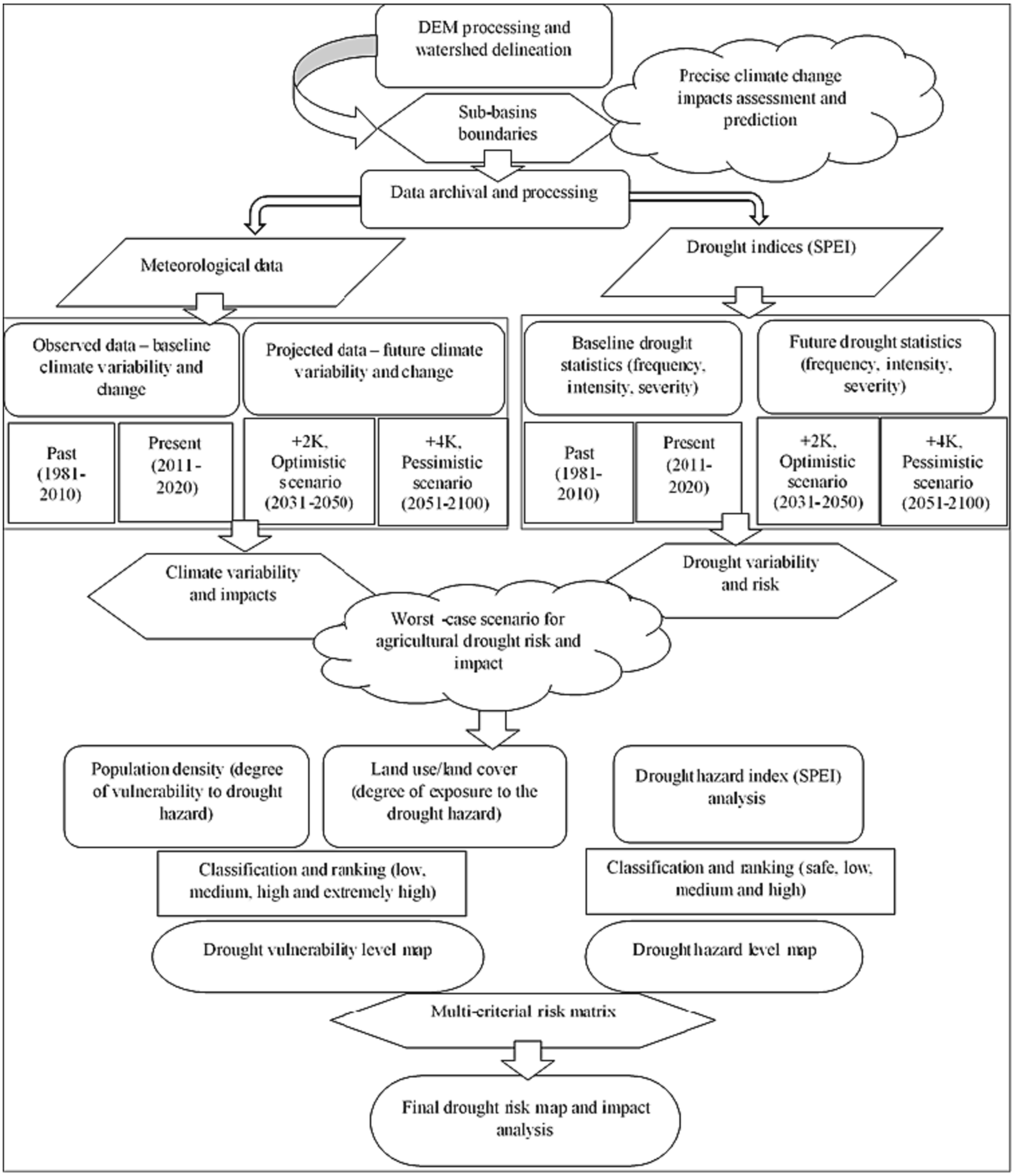


Fig. 2. Schematics of research methodology for climate variability and drought risk assessment.

rainfall is received during the monsoon season (4 months) and is followed by almost 8 months of the dry period. So, the hydrologic regime can be represented well by a 12-month scale over India. Moreover, the 12-month SPI and SPEI reflect the annual trend of the precipitation pattern, so they are well suited for the estimation of annual water conditions and to investigate seasonal variations and their respective impacts on crop production. Therefore, we calculated the values of SPI and SPEI using a 12-month timescale, considering the significance of drought impacts on the agriculture and water resource sectors. The calculated SPI and SPEI values were used to evaluate the climate change impact on drought occurrences. That is, monthly values of SPI and SPEI at 12-month timescales were used to identify intra-annual variability, and the corresponding impacts of extremely-to-severely dry episodes (drought events) on rice production were categorised based on the criteria provided in Table 2. We focused on the impacts to agriculture because the study area is an important agricultural area, and most residents depend on agriculture for their socio-economic welfare. The indices were calculated using observed meteorological data and future climate projections. The SPI and SPEI monthly values represent the average of the last 12 months, whereas the annual value is the summation (or average) of each year. For example, the SPI and SPEI of January 1981 were calculated using the previous 12 months of climate data, from January 1980 to December 1980. A similar concept was applied for the analysis of drought indices using future climate

Table 2
Intensity scale for drought categorisation based on SPEI range (Beguería et al., 2010; Musei et al., 2021; Ripin et al., 1989; Vicente-Serrano et al., 2010a).

Class	SPEI value	Drought category
1	2.0 or greater	Extremely wet
2	1.50 to 1.99	Severely wet
3	1.00 to 1.49	Moderately wet
4	0.99 to −0.99	Near normal
5	−1.00 to −1.49	Moderately dry
6	−1.50 to −1.99	Severely dry
7	−2.00 or less	Extremely dry

projection datasets.

Drought indices. The calculation of SPI and SPEI is based on long-term data, preferably at least 20–30 y of data, and larger periods are recommended. The probability estimates of wet and dry extremes are weak if the data sample size is small. SPI was developed to measure the rainfall deficit over multiple timescales, and to represents the impact of droughts on the availability of various water resources, thereby providing a useful background for decision makers. In 2009, the world meteorological organization (WMO) recommended SPI as the key primary meteorological drought index for countries to use in monitoring drought conditions (WMO, 2012). In over 70 countries, SPI is used to monitor the drought in operational modes. Many drought planners appreciate the versatility of this index. SPI is also used by a number of universities, research institutions, and National Meteorological and Hydrological Services worldwide for drought monitoring, early warnings, and assessment of drought severity. As SPI can be calculated at various timescales, multiple events that affect agriculture and water resources can be investigated. SPI can also be calculated on gridded precipitation datasets, allowing for a broader range of users than those who only work with station-based data. (WMO, 2012). However, SPI is not the most suitable index for climate change analysis because temperature is not an input parameter. As precipitation is the only input, SPI does not account for the temperature component, which affects the overall water balance and water use of a region. This drawback can hinder the comparison of events of similar SPI values but different temperature scenarios. This issue can be overcome by using a newly developed index (SPEI), which addresses the Potential Evapotranspiration (PET) issues by including temperature data in the calculation. Therefore, SPEI was selected as the preferred index in this study for further assessment of drought identification and agricultural drought risk assessment, because it considers the effect of both rainfall and temperature.

Calculation of SPEI. The SPEI drought index was proposed by Vicente-Serrano et al. (2010a), and it is based on the water balance principle. Similar to SPI, long-term time-series data for precipitation and temperature for the desired period are required to calculate SPEI values. At least 30 y of complete data set are desired. SPEI uses the difference among precipitation and the reference crop evapotranspiration as the input datasets to evaluate dry and wet episodes at a given location.

The climate-water balance (water surplus or deficit) was calculated using:

$$D_i = P_i - ETo_i \tag{1}$$

where D_i and Pi are the moisture deficit (mm) and precipitation (mm) in month i, respectively; and ETo_i is the reference crop evapotranspiration, generally calculated using a simple climatic water balance, and it is expressed as:

$$ETo = 16K\left(\frac{10T}{I}\right)^m \tag{2}$$

where the ETo is the reference crop evapotranspiration, K is a constant, T is the monthly temperature, I is the heat index, and m is a coefficient dependent on I.

The values of Di can be aggregated for a given period by considering the accumulation of the water balance during that period.

$$D_i^k = \sum_{j=0}^{k-1} D_{i-j} \tag{3}$$

where, k is the aggregation (accumulation) period, and i is the observed month.

SPEI can be calculated as the standardised value of the log-logistic probability distribution function of the D series.

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x-y}{\alpha}\right)^{\beta}\left(1+\left(\frac{x-y}{\alpha}\right)^{\beta}\right)^{-2} \tag{4}$$

where α, β and y are the scale, shape, and origin parameters for D values in the range ($y > D < \infty$). Therefore, the log-logistic distribution function adopted for the standardized D series for all time scales is provided by:

$$F(x) = \left[\left\{1+\left(\frac{\alpha}{x-y}\right)^{\beta}\right\}\right]^{-1} \tag{5}$$

where F(x) value transforms to a normal variable through the following approximation:

$$SPEI = W - \frac{C_0 + C_1 + w + C_2 w^2}{1 + d_1 + d_2 w^2 + d_3 w^3} \tag{6}$$

$$W = \sqrt{-2\ln(P)}\mathrm{P} \leq 0.5(7)$$

where P is the probability of exceeding determined by the D value as P = 1–F(x). If P > 0.5, then P is replaced by 1–P and the sign for SPEI is reversed. Moreover, C_0, C_1, C_2, d_1, d_2, and d_3 are constants determined to be the following: $C_0 = 2.515517$, $C_1 = 0.802853$, $C_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, and $d_3 = 0.001308$.

The average SPEI value is 0 and the standard deviation is 1. Since SPEI is a standardized variable, SPEI values for different time and spaces can be compared to each other (Vicente-Serrano et al., 2010a). An SPEI of 0 indicates 50% of the cumulative probability of D. As SPEI is a standardised value, it can be categorised by the dryness/wetness grade shown in Table 2.

Based on this SPEI intensity scale, drought events are categorized as near normal, moderate, severe, and extreme droughts. Similarly, wet events are categorised into moderately, severely, and extremely wet for the respective positive values. That is, SPEI represents the severity of the dry and wet periods. A time-series analysis was performed to identify the occurrences of these dry (droughts) and wet (flood) events. Major droughts and floods-like episodes over the selected time frame in the GRB area were identified, and the respective impacts of droughts on crop production were then investigated.

Drought risk assessment

To appropriately define the drought risk, it is essential to identify the drought hazard extent, drought exposure, and drought vulnerability. Therefore, we characterised the spatial variations in drought hazard (degree of severity analysed through assessment of probability and drought intensity), drought exposure, and drought vulnerability to identify the total drought risk for crop production. A flowchart (Fig. 2) for agriculture drought risk assessment was developed by referring to methods and processes adopted by previous researchers (Prabnakorn et al., 2019; Sun et al., 2020).

Analysis of agricultural drought risk elements. Both climate and socio-economic data were considered for the agricultural drought risk analysis. Climate data included daily precipitation, and maximum and minimum temperatures. The drought hazard was analysed using the SPEI computed based on a long-term historical period (1980–2019). To identify the worst-case scenarios for drought hazards (i.e., year with highest number of sever-to-extreme droughts), each statistical indicator of drought characteristics was analysed using the theory of runs.

Drought characteristics based on theory of runs. The 12-month SPEI drought indices were utilised to assess the spatial and temporal changes in drought characteristics, with threshold values of −1 and 1 for dry and wet episodes, respectively. The statistical indicators were computed based on the definitions provided in Table 3.

Fig. 3 shows the diagrammatic representation of drought characteristics. The positive and negative values of SPEI are considered drought and non-drought events, respectively. A drought event is defined as a period with SPEI values below the threshold. Therefore, to measure the drought duration and drought severity, a threshold value was defined. The drought duration is the period through which SPEI is continuously negative, that is, it starts when SPEI = −1 and ends when SPEI > 0. The drought severity is the cumulated SPEI value within the drought duration, and it is defined by the equation provided in Table 3. The drought intensity is the ratio of drought severity to its duration, and it represents the magnitude of the drought event. The drought characteristics were estimated using the 12-month SPEI over the entire baseline reference period (1981–2019). Based on the time-series analysis of drought statistics (drought frequency, occurrence number, severity, magnitude, intensity), a year was identified for the worst-case drought scenario (i.e., the year mostly affected by severe-to-extreme droughts with higher drought severity). The worst-case scenario was considered to assess and map the drought hazards risk. The severity of drought hazard was analysed based on the criteria provided in Table 4, and the areas under higher agriculture drought hazard risk over GRB were mapped using GIS. A multi-criteria classification table was prepared to assess the total drought risk over the GRB (Table 4).

For values above zero, SPEI was categorised as no (safe), low, medium, high, and very high (extreme) risks in terms of drought hazard. Similarly, the vulnerability to drought hazard was analysed using land use as exposure risk, and population density as sensitivity risk. Exposure was cross tabulated with sensitivity to identify the vulnerability of agriculture to droughts. Ranking values were assigned, and the final risk map was illustrated considering the risk intensity (low, medium, high, and very high) of agriculture to droughts.

Estimation of agricultural drought risk. The final agricultural drought risk was analysed by assessing the drought hazard and drought vulnerability risk maps.

$$DR = DH \times DV\ (DE \times DS), \tag{8}$$

where DR, DH, DV, DE, and DS are the drought risk, hazard, vulnerability, exposure, and severity, respectively. The two-dimensional table (Table 5) was applied to the classified hazard map and the classified vulnerability map to produce the risk map.

The overall risk score was derived by multiplying the likelihood by potential impact of the risk. Risks were classified as safe (no risk = 0), low priority (4–6), medium priority (8–9), high priority (10–12), and very high-risk priority (15–25). A risk matrix was prepared to assign a risk level to each pixel. The final drought risk mapping was obtained by overlaying the hazard risk map and the vulnerability risk map using multi-criteria evaluation techniques in GIS based on the rank and assigned scores under the worst-case scenario.

Table 3
Equations for the calculation of drought parameters for spatiotemporal drought analysis.

Drought parameter	Equation	Symbol and units
Duration	$D = \frac{\sum_{i=1}^{n} di}{n}$	D = drought duration (months) di = duration of ith drought event n = total number of drought events
Frequency	$F = \frac{nm}{Nm} \times 100$	F = drought frequency (%) nm = number of drought months Nm = total number of months
Intensity	$I = \lvert \frac{1}{n}\sum_{i=1}^{n} \mathrm{SPEIi} \rvert$	I = drought intensity (−) n = number of drought occurrences in months with SPEI < − 1 SPEIi = SPEI value below the threshold (−1)

Risk evaluation and impact analysis

Droughts reduce crop yield by creating unfavourable conditions for crop development. They are occurred not only in arid regions but also in areas with relatively abundant precipitation. Therefore, understanding the extent of hazard, exposure, vulnerability, and the risk of droughts to agriculture is critical for the developing appropriate water management and mitigation measures to reduce adverse impacts and increase crop yield. Therefore, the developed agriculture drought risk analysis was used to identify the most affected and vulnerable areas (sub-basins and districts) over GRB. The identified districts were used to evaluate the drought impact, and agricultural statistical data (crop production and prices) were obtained for the districts identified. Statistical estimation was performed to analyse the drought impact according to the loss or gain in crop yield and economy during a drought year compared to the previous production year.

Results and discussion

Climate variability

Temporal variability in rainfall and temperature

The intra-annual variability and trends of climatic variables (rainfall and temperature) were analysed for the baseline reference period (1981–2019) over the GRB, as shown in Fig. 4. The slope of the trendline represents the increasing, decreasing, and non-significant nature of climate variability during that particular timeframe.

A slightly decreasing trend (−0.6338 mm) was observed for annual rainfall, whereas a significant increasing trend (0.0191 °C) was observed for annual maximum temperature from 1981 to 2019. These results indicated increased warming over GRB. Rainfall in India is primarily driven by the monsoons (Krishnan et al., 2020; Kumar et al., 2013; Yaduvanshi et al., 2021). The amount of rainfall in the year depends mostly on the amount of rain received during the monsoonal months (June–September). Therefore, we analysed the monthly climatology and relevant contribution from seasonal monsoonal rainfall (Fig. 4) to estimate the contribution and understand the potential changes under the impacts of climate change over the 21st century in the GRB. The contributions were estimated using time-series data over the past four decades, and the results showed that the monsoonal contribution in a year varied between 80 and 90% in the GRB area.

A significant decrease in annual rainfall, which was 90% attributed to the contribution of monsoonal rainfall, was observed during the second half (2015–2019) of the present decade compared to the annual rainfall received during the past reference period (1981–2010). This might partially explain the recently experienced frequent intense precipitation and floods in addition to drought events in the GRB area, which have damaged the water resource infrastructures and caused water scarcity problems during non-monsoonal months, thereby increasing the difficulty in fulfilling local water demands. Therefore, the non-monsoonal months (∼8 months) of a year were associated with negligible rainfall, and the management of external water sources are crucial to help meet the demands. The long-term impact of climate change was determined using the relative statistics of percentage change for the present, future optimistic, and future pessimistic scenarios compared to the past reference period. An average annual mean precipitation of 1032.50 mm was recorded for the past reference period,

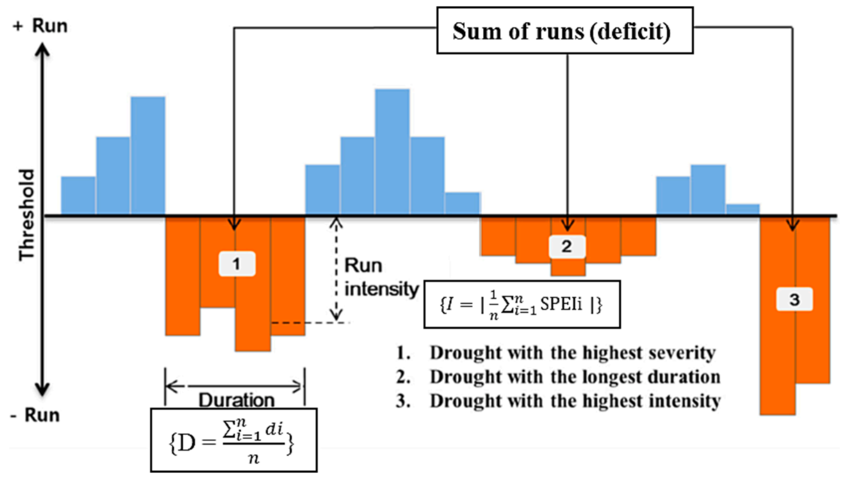


Fig. 3. Drought characteristics using theory of runs for a given threshold level (modified after Lee et al., 2017).

Table 4
Multi-criterial classification table for agriculture drought risk elements.

Drought risk category	Rank	Drought hazard classification	Drought vulnerability classification (drought exposure × sensitivity)
No risk (safe)	0	Beginning of wet episode (SPEI ≥ 0)	PD < 25 percentile and non-agriculture land
Low risk	2	Near normal drought (−0.99 ≥ SPEI < 0)	PD < 25 percentile and agriculture land
Medium risk	3	Moderate drought (−1.49 ≥ SPEI < −1.00)	PD (25–50) percentile and agriculture land
High risk	4	Severe drought (−1.99 ≥ SPEI ≤ −1.50)	PD (50–75) percentile and agriculture land
Very high risk	5	Extreme drought (SPEI ≤ −2.00)	PD > 75 percentile and agriculture land

*PD: Population Density (people/km^2).

Table 5
Risk rank and classification.

	Drought hazard	Drought vulnerability				
		Potential impacts				
		0 (safe)	2	3	4	5
Likelihood	0 (safe)	0	0	0	0	0
	2	0	4	6	8	10
	3	0	6	9	12	15
	4	0	8	12	16	20
	5	0	10	15	20	25

which was slightly reduced to 1012.36 mm for the present reference period. The average annual mean rainfall is expected to increase by 46% and 56% under the optimistic and pessimistic scenarios, respectively (Fig. 5). That is, the average annual mean, maximum, and minimum rainfall values gradually increased in the present, future optimistic, and future pessimistic scenarios.

The years with lower or higher rainfall values than normal may experience severe drought or floods, respectively, depending on the magnitude of those values. The risk from such a drought or flood episode depends on the severity of that episode, and the respective impact depends on the intensity of that episode and the location-specific response. Therefore, to understand the location-specific risks, we analysed the spatial variability and changes using baseline reference, future optimistic, and future pessimistic climate scenario data.

Spatial variability and change in rainfall and temperature

Location-specific changes (one sub-basin to another within the GRB) were analysed separately based on spatial variability trends for annual rainfall and annual mean temperature, and the results over the baseline reference period are shown in Fig. 6 and Fig. 7, respectively. The areas with increasing or decreasing trends are less or more vulnerable, respectively, to water availability risks.

The spatial variation of rainfall over the GRB showed that some sub-basins (Middle Godavari, Maner, Manjra, Lower Godavari, Upper Godavari, Purna, Penganga, and sub-basin of Wainganga and Pranhita) presented a decreasing precipitation trend and higher vulnerability to water availability risk from 1981 to 2019. The remaining sub-basins (Sabari, Indravati, Wardha, and South-Western part of Pravara) showed a positive (increasing) trend for precipitation during this period and, therefore, lower risk for water availability (Fig. 6). Approximately 67% of the GRB area (8 of 12 sub-basins) showed a decreasing rainfall trend, whereas 33% of the area (4 of 12 sub-basins) showed an increasing rainfall trend and less vulnerability to drought occurrence. This is because of increasing temperatures caused by climate change and global warming which will make existing dry areas drier and wet areas wetter. Due to large-scale climate variation in India, the impacts are also varying from place to place, and therefore, some locations show increasing precipitation, and hence there will be a high probability that such locations will experience less intense and lower drought risk. In dry locations, this means that as temperatures rise, water evaporates more quickly, and thus increases the risk of drought or extending drought periods.

Similar to the precipitation analysis, we examined the spatiotemporal changes in temperature to investigate its impacts. Annual mean temperature was used to analyse the spatial variation of temperature over the same timeframe of baseline reference period (1981–2019). Overall, there was a significant positive trend in all sub-basins, with a slight variation in magnitude. No single sub-basins showed a negative trend (Fig. 7). This demonstrates that temperature showed an increasing trend throughout the past four decadal timespans, which indicates an increasing warming over the GRB area.

Rainfall showed higher spatial variability than temperature, with a greater change in magnitude during the baseline reference period. We did not observe any significant reduction in temperature across all sub-basins of the GRB. All sub-basins showed an increasing temperature trend throughout the past four decades (1980–2019), so we assumed a significant increasing temperature scenario in the future for the GRB.

Because of the irregular distribution of rainfall over space and time and the prominent issue of water scarcity, we analysed the spatiotemporal modelling of drought. Moreover, to investigate the climate change impacts on drought occurrences, we estimated the spatiotemporal

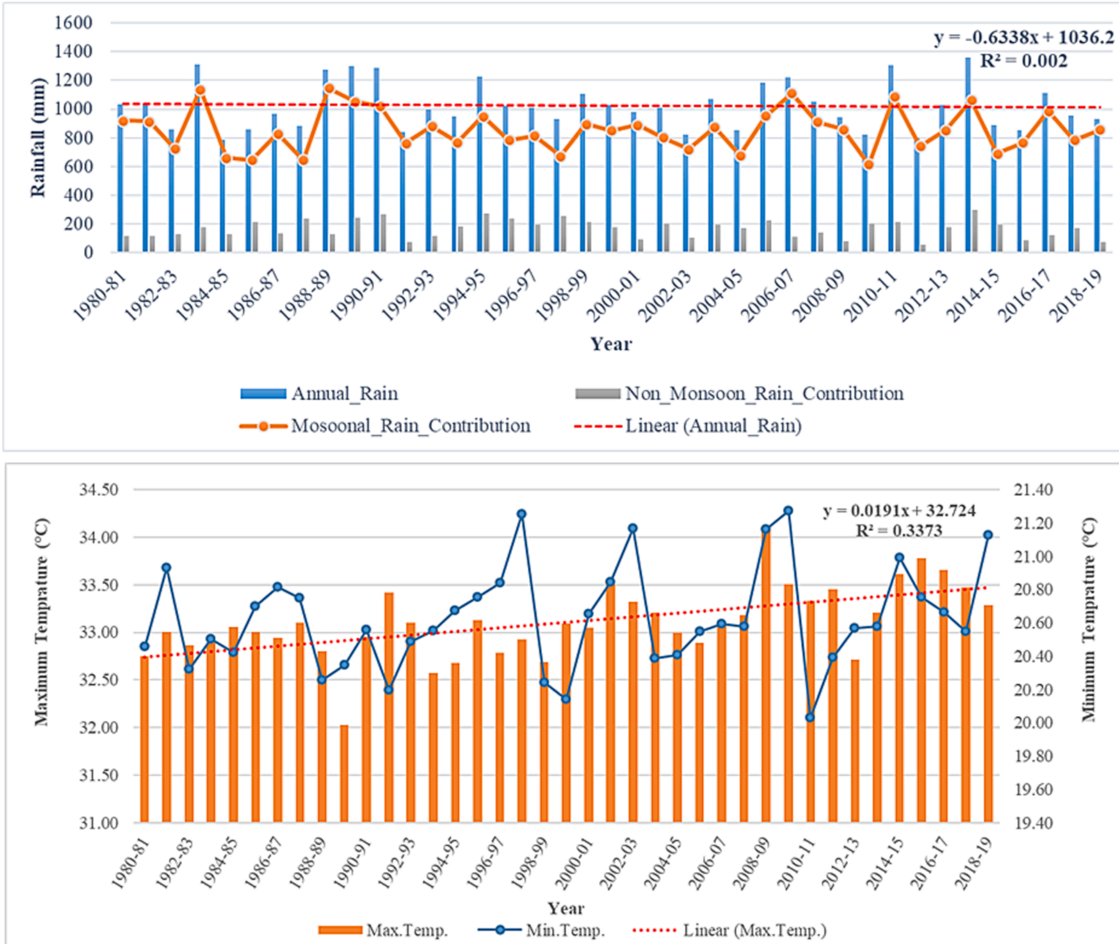


Fig. 4. Intra-annual climate variability and trend over the baseline reference period (1981–2019).

pattern of drought occurrences and severity over different timeframes (past, present, future optimistic, and future pessimistic) using 12-month SPEI drought indices.

Drought analysis

Temporal variation of drought occurrences

To investigate the occurrence of drought events and the fluctuation rate of dry and wet episodes, the annual average values of the time-series SPEI were plotted over the baseline period (Fig. 8). The SPEI showed a significant decreasing trend continuously over the baseline reference period. This indicated an increase in the magnitude of the intensity of droughts throughout the investigated timeframe.

The SPEI values represent the degree of severity of the dry and wet periods over each grid cell for the time scale considered during the analysis. As mentioned in Section 2.3, positive and negative index values denote the occurrence of wet and dry events, respectively, and prolonged dry occurrences can lead to serious drought events that may severely impact crops and livelihoods.

Identification of drought occurrences and statistics

Fig. 9 shows the time-series pattern of temporal variation of dry and wet episodes based on the threshold values. They were used to identify major droughts and floods (Table 6). The most severely-to-extremely dry year from the list of detected major drought events was considered the worst-case drought scenario and used to further analyse the drought impacts.

Spatial variation in drought occurrences

The results of the Mann-Kendal-Sen's slope estimator were used to investigate the magnitude of the changes in the extent of drought occurrences over each sub-basin in the GRB using the 12-month SPEI, as illustrated in Fig. 10.

The negative results (lower values) showed a decreasing trend as the drought intensity increased, and such locations were at higher drought risk. Conversely, positive results (higher values) showed an increasing trend as drought intensity decreased, i.e. areas less vulnerable to droughts. The results showed that nine sub-basins out of twelve (around 75% of GRB area) observed decreasing (negative-SPEI) trend which indicated that such locations (sub-basins) represent the areas for higher vulnerability and increased drought risk during the past four decadal periods. Only three sub-basins (Sabari, Pravara, and Indravati) showed an increased (positive-SPEI) trend. This indicated that only 3 subbasins (around 25% of the areas) presented a lower drought risk and were less vulnerable to drought occurrences compared to other sub-basins. These results also correlate with the finding of increasing drought severity over the Pranhita, Manjra, Wardha, and Lower Gobadavri subbasins in the study conducted by Sarkar, 2022. To validate the results, we compared the spatial pattern trend of the time series of climate data with reputable national disaster databases (EM-DAT), which comprise essential core disaster data on the occurrence and impacts of over 22,000 major disasters worldwide from 1900 to the present. This database was compiled using numerous sources, including research institutes, UN agencies, non-governmental organisations, insurance companies, and press agencies. Although 2009 was one of India's worst drought years, no damage was recorded in this national-level database. This demonstrates

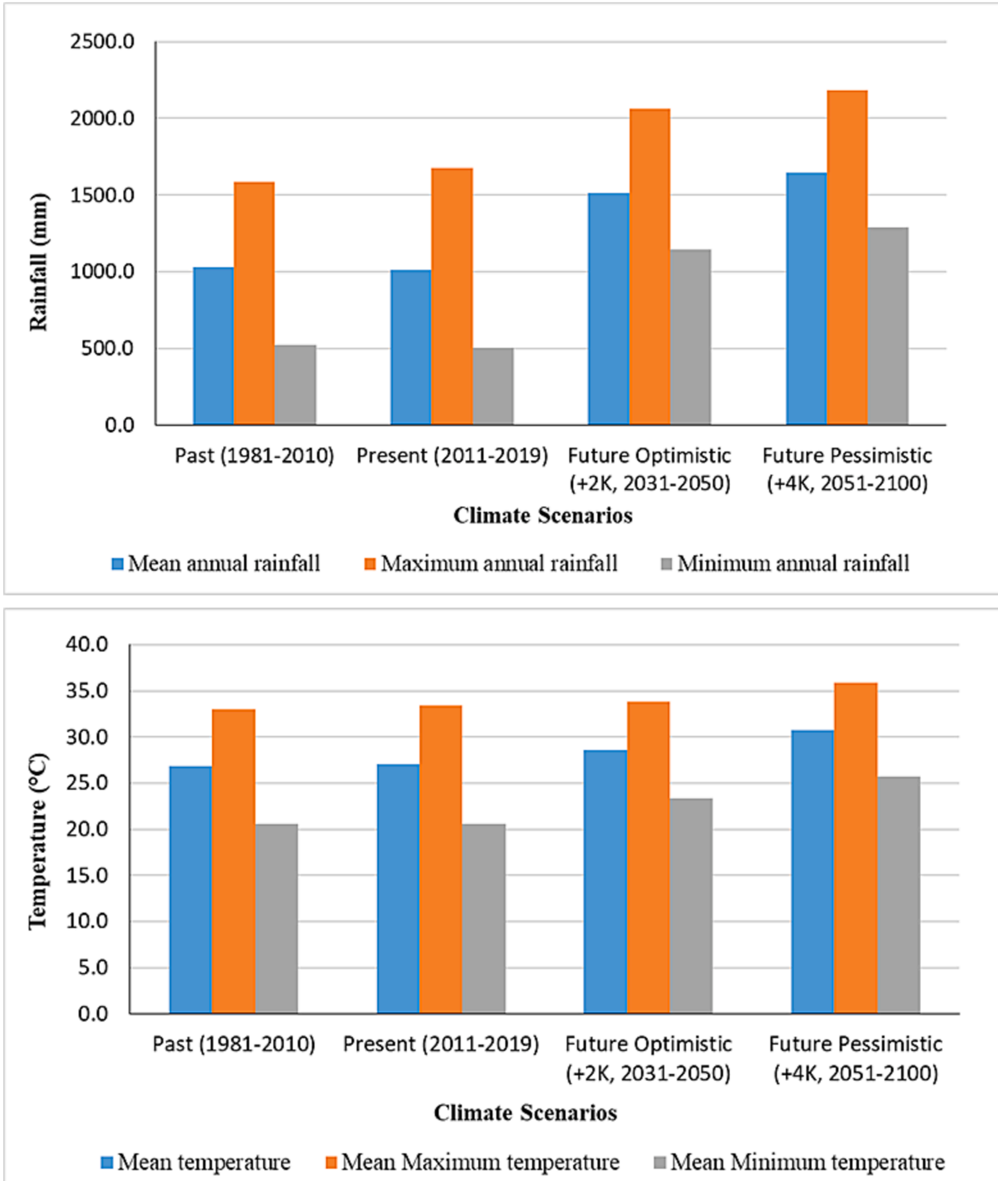


Fig. 5. Influence of climate change on annual average rainfall and temperature using past, present, future optimistic and pessimistic scenarios over GRB.

that it is crucial to conduct regional level drought analysis and impact assessments. To further understand the nature of droughts, we estimated decadal variations in dry and wet episodes in each sub-basin in terms of occurrence number, duration, frequency, and magnitude of severity and intensity of droughts over each sub-basin of GRB.

Drought characteristics – Variability and change using theory of runs

The 12-month SPEI drought indices were used to assess the spatial and temporal changes in drought characteristics. To understand in detail the variations over time and space, we analysed the drought characteristics using past and present reference timeframes (Fig. 11).

The results of drought persistent and nature showed that, on average, the number of drought occurrences increased during the present decade (2011–2019) compared to the past three decades (1981–2010). Therefore, the estimated probability of decadal drought occurrence increased from 10% to 17% from the past to the current decade. Drought severity also increased in the present reference time, which indicated that the drought intensity increased over the GRB (i.e. a more disastrous nature of drought was observed, which is expected to increase in future years). Similar results of the probability of increased drought severity in the future over the GRB have been reported by Kumar et. al., 2021a. However, the changes in the frequency and characteristics of droughts in the future had not been fully investigated at the sub-basins and districts level over the Godavari River Basin. Therefore, we used the future warming scenarios of d4PDF data to study the outlook of future drought perception and potential socio-economic impacts. We also investigated the effects of anthropogenic warming on the projected changes in the frequency of droughts over the sub-basins of GRB (Fig. 12).

Future drought frequency showed an overall increase under both scenarios compared to the past reference period. Among the drought categories, the frequency of severe-to-extreme droughts is expected to increase continuously under both warming scenarios over the near future (2031–50) and far future (2051–2100), whereas total droughts (including moderate, severe, and extremes droughts) is expected to significantly increase in the near future under the optimistic scenario and slightly decrease in the far future under the pessimistic scenario (Fig. 12-A and B). The gradual increase in precipitation amount and frequency of wet days can potentially contribute to reducing the intensity of future droughts events at some places in the GRB.

Some sub-basins (Indravati, Lower Godavari, Sabari, Wardha,

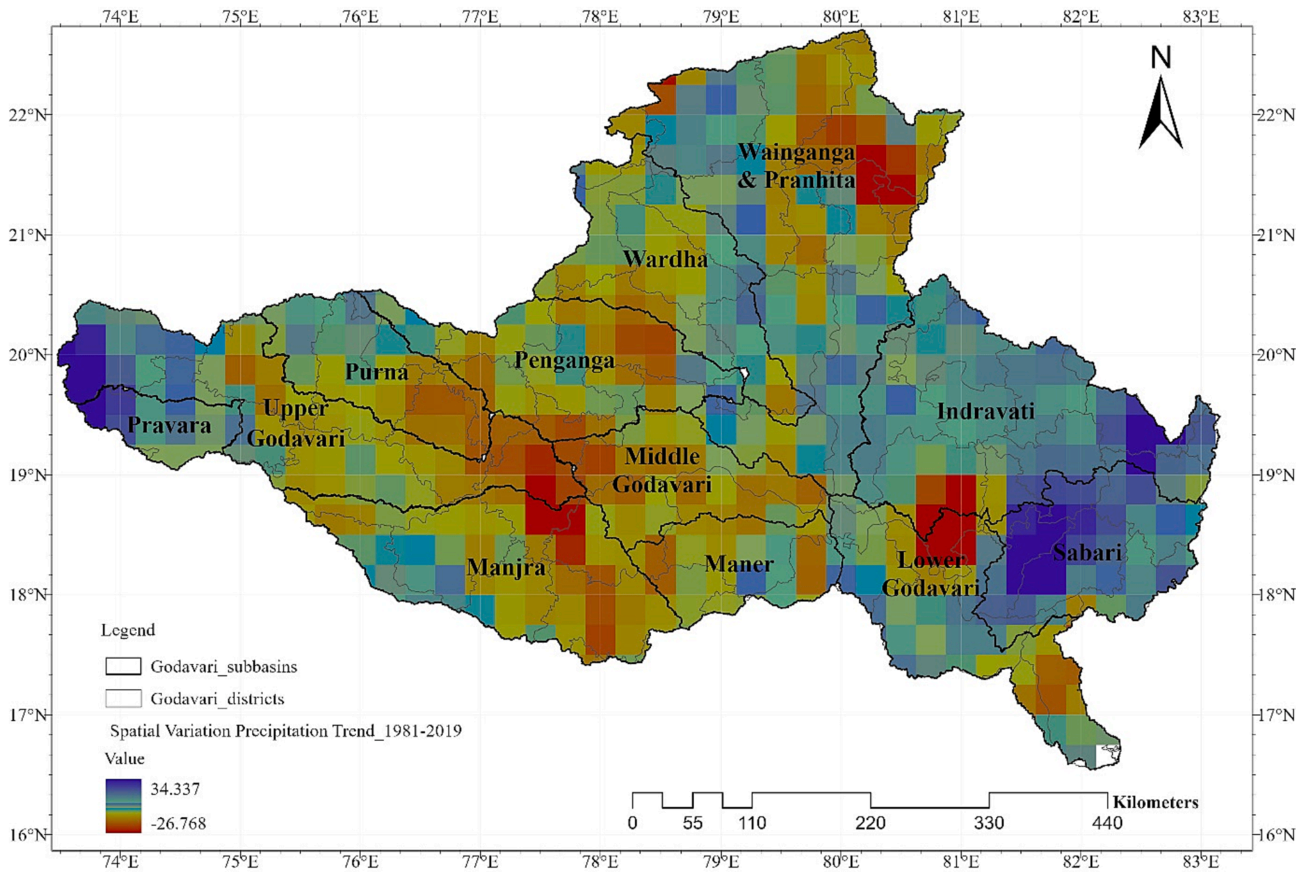


Fig. 6. Trend of spatial variation of rainfall over a baseline (1981–2019) reference period.

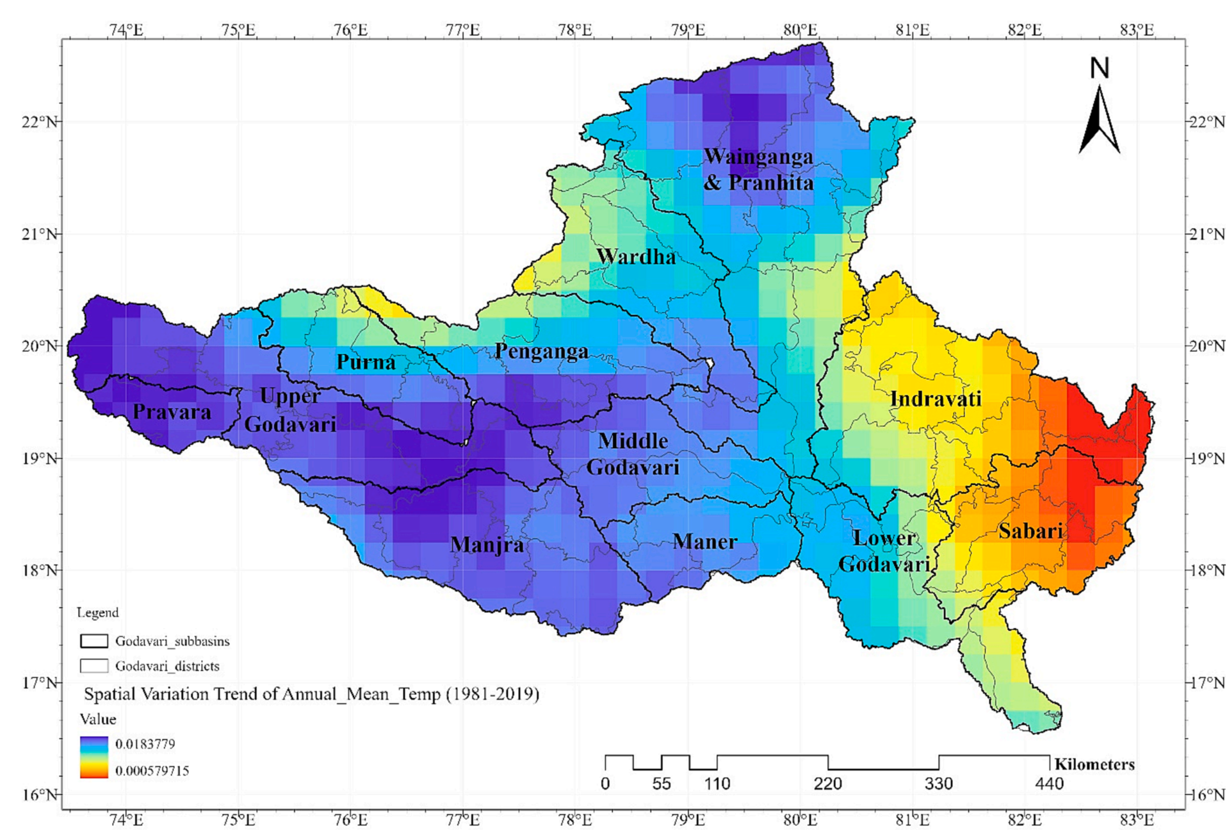


Fig. 7. Trend of spatial variation of rainfall and annual mean temperature over a baseline (1981–2019) reference period.

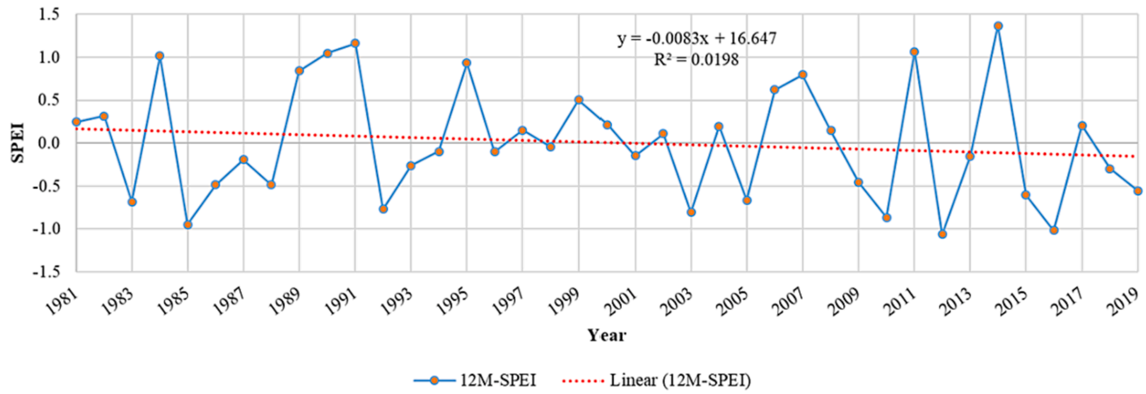


Fig. 8. Intra-annual variability of SPEI over a baseline (1981–2019) reference period at GRB.

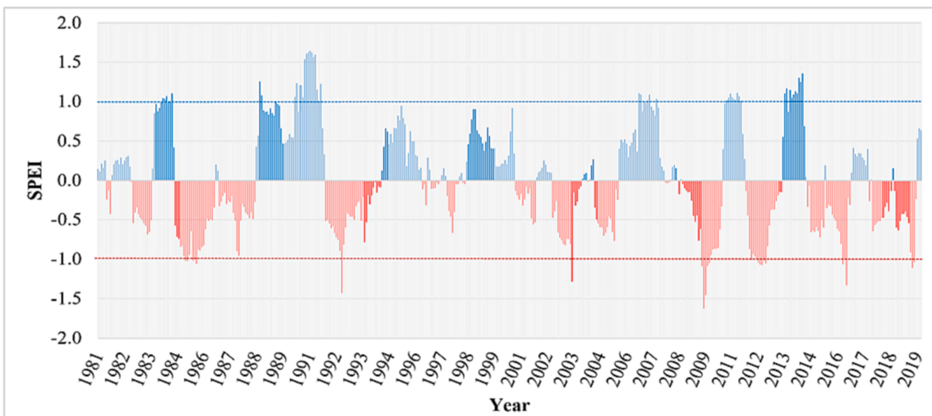


Fig. 9. Dry and wet episodes according to time-series SPEI over a baseline (1981–2019) reference period.

Table 6
Major drought and flood events based on SPEI values.

Number	Major drought events	Major flood events
	SPEI	SPEI
1	1985	1984
2	1992	1988
3	2003	1990
4	2009	1991
5	2011	2006
6	2012	2007
7	2016	2010
8	2019	2011
9		2013
10		2014

Wainganga, and Pranitha) showed an increasing frequency of total and severe-to-extreme droughts under the optimistic scenario (+2 K). Whereas under the pessimistic scenario (+4 K), they showed a decrease in the frequency of total droughts and a gradual rise in the frequency of severe-to-extreme droughts (Fig. 12-C and D). This implies that if global warming continues, an extreme drought situation will likely occur in the future over the GRB. Therefore, it is crucial to understand the persistence of drought and its impact to determine which sub-basins are more vulnerable considering their socio-economic activities, and hence SPEI values over both scenarios have been used to conduct spatial analysis.

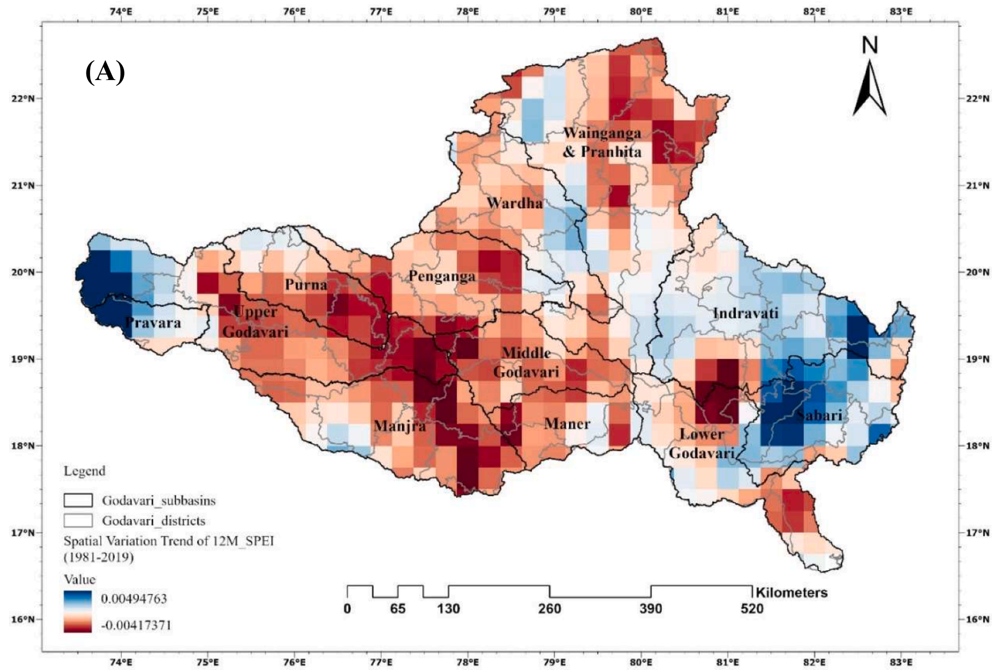
Fig. 13 demonstrates the results for the probability of drought occurrences and its spatial variation in the future under the impact of increasing warming, and it indicates that more drought episodes are likely to occur at the central belt, particularly over the sub-basins of Wardha, Wainganga, Pranitha, and part of Indravati and Lower Godavari. Therefore, the results suggest that drought mitigation measures should prioritise these areas. This spatiotemporal analysis was also used to test the hypothesis "dry become drier and wet become wetter in the future" for future climate change scenarios. The hypothesis was demonstrated to be true over most sub-basins. The sub-basins of Penganga, Wardha, and Wainganga-Pranhita, located at the north-western part of GRB, were predicted to present lower precipitation (drier) in the future, whereas the sub-basins of Sabari, Indravati, and the southwest part of Pravara and Upper Godavari were predicted to present a gradual increase in precipitation (wetter) in the future (Fig. 13-A and B).

The hypothesis was considered negative (false) in a few locations, including the lower south and lower southeast districts of the GRB. This also confirms that the climate change impacts vary with location and time. Therefore, there is a need for local assessments of climate change risks and impacts. Accordingly, this study performed a comprehensive assessment of drought risks and impacts on agriculture.

Drought risk assessment and impacts analysis

The agricultural community is a major vulnerable community in the GRB. Because of the uneven rainfall distribution, it is difficult for farmers to understand the drought situation and the associated impact. Therefore, to identify the level of risk and response capacity, we analysed the comprehensive drought risk assessment using various geospatial data. The results of the drought risk assessment were helpful in the identification of areas at higher drought risk and more vulnerable to the potential climate change impacts, which was used to further evaluate socio-economic impacts under the worst-case drought scenarios.

The assessment was based on the conceptual approach proposed by the United Nations Development Program (Prabnakorn et al., 2019) and applied by Sun et al. (2020). It consists of assessing the hazard, exposure,



(B)

Sub basins	M-K Trend	Remark
Manjara	-0.00147	Decreasing
Wardha	-0.00042	Decreasing
Wainganga & Pranhita	-0.00077	Decreasing
Upper Godavari	-0.00072	Decreasing
Sabari	0.00136	Increasing
Purna	-0.00131	Decreasing
Pravara	0.001107	Increasing
Penganga	-0.00121	Decreasing
Middle Godavari	-0.0015	Decreasing
Maneru	-0.00127	Decreasing
Lower Godavari	-0.00084	Decreasing
Indravati	0.000339	Increasing

Fig. 10. Spatial variation of trend (Fig-A) in drought occurrences based on M–K trend using12-month SPEI over sub-basins of GRB (Fig- B) during a baseline (1981–2019) reference period.

and societal vulnerability, which are then combined to determine the risk of significant impacts from any hazards. The results of the 12-month SPEI were further analysed to illustrate the level of drought hazard risk and to identify the worst-case drought scenario across each sub-basin over the GRB. Based on the drought indices (SPEI-12) during the baseline period (1981–2019), we identified drought years (severe-to-extreme) and normal years. The year 2012 and 2009 faced a higher frequency of total drought events, at 57 and 56, respectively. Many researchers suggested that the vegetation condition can be used as an indicator for the identification of the drought condition of an area, and the Normalized Difference Vegetation Index (NDVI) has been widely used to identify the drought-related stress to the vegetation (Artikanur et al., 2022; Gumma et al., 2019; Nejadrekabi et al., 2022). Therefore, this study used the Normalized Difference Vegetation Index (NDVI) as the main vegetation indicator to evaluate drought conditions during the severe drought years at GRB. The NDVI values were derived using MODIS-16-day composites (from, https://modis.gsfc.nasa.gov/), and the maps were illustrated for these two severe droughts years (Fig. 14). The range of the NDVI values indicates the drought severity, and based on the drought index scale, the areas affected by drought indicated by low NDVI values. Whereas the high NDVI values represent less drought-related stress to the vegetation, and hence represent the low-drought severity and risk over such areas.

NDVI maps from 2009 and 2012 indicated the onset and extent of the drought effect on agricultural areas. According to the findings, the droughts in 2009 (Fig. 14-A) and 2012 (Fig. 14-B) had the greatest impact on agricultural areas (Fig. 14-C) compared to other land use types in the Godavari River Basin (Fig. 14-D). The major portion of the agricultural area covering the sub-basin of Pravara, Upper Godavari, Purna, Penganga, Manjra, Middle Godavari, Maner, Wardha, and

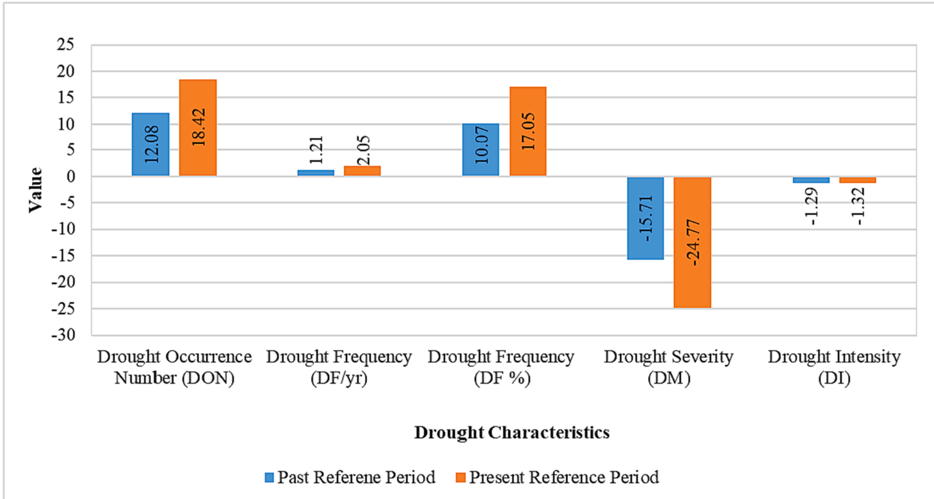


Fig. 11. Drought characteristics over the baseline (1981–2019) included past (1981–2010) and present (2011–2019) reference periods.

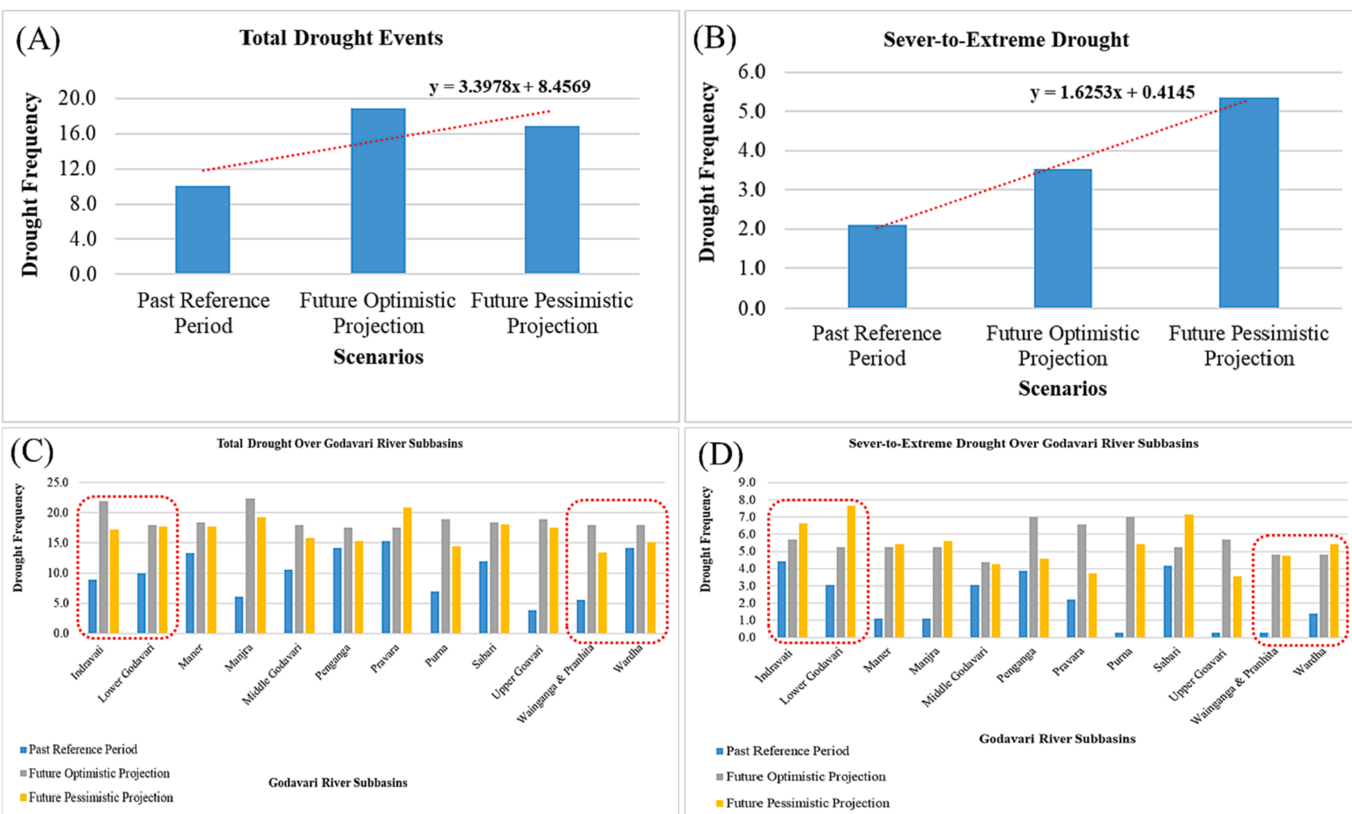


Fig. 12. Evaluation of the impacts of climate change on droughts using the drought frequency for total drought events (Fig. A and C), and severe-to-extreme drought events (Fig. B and D), over the past and future periods.

northern Wainganga & Pranhita has shown higher drought severity compared to the other areas during these two sever-drought years at GRB. Therefore, the occurrence of drought is well associated with reduced vegetation area and mean NDVI values during these both severe drought years. This also validated the results of drought hazard estimation using SPEI-12 over GRB. However, in the category of severe-to-extreme droughts, 2009 faced a higher frequency of events (28) than in 2012. Therefore, the SPEI computation in 2009 was considered the worst-case scenario for the vulnerability assessment, which was used to determine the most affected sub-basin and highly vulnerable districts. Using the criteria provided in Table 4, the severity of drought hazard was mapped, and the hazard risk map was generated to illustrate the low, medium, high, and very high drought risks for the agricultural sector (crop production and economic loss of the farming community). The results showed that approximately 92% of the GRB area was affected by the drought in 2009. Each sub-basin and district faced risks with different levels of degree of vulnerability, based mostly on the assets directly exposed to the effects of drought, such as crops. Because agriculture is the most impacted sector by droughts in this area, and it is primarily rainfed and mostly dependent on rainfall, we used land-use type as an indicator to analyse the agricultural drought risks. The land-use types were divided into agricultural land and others because

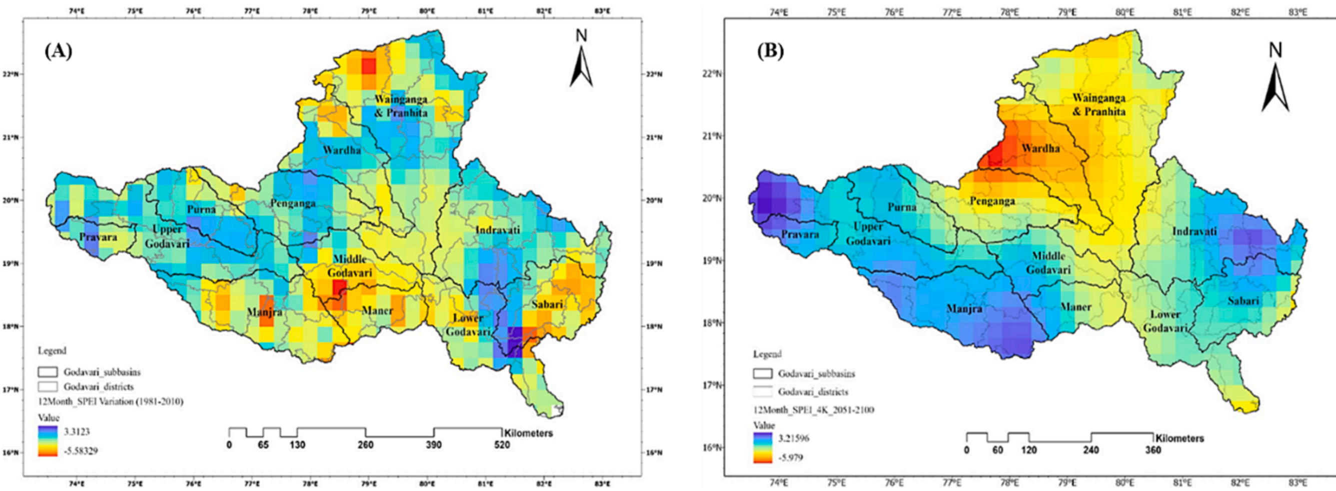


Fig. 13. Spatial variation of drought occurrences over the past and future periods at GRB, illustrated in Fig (A) and (B), respectively under future warming scenarios.

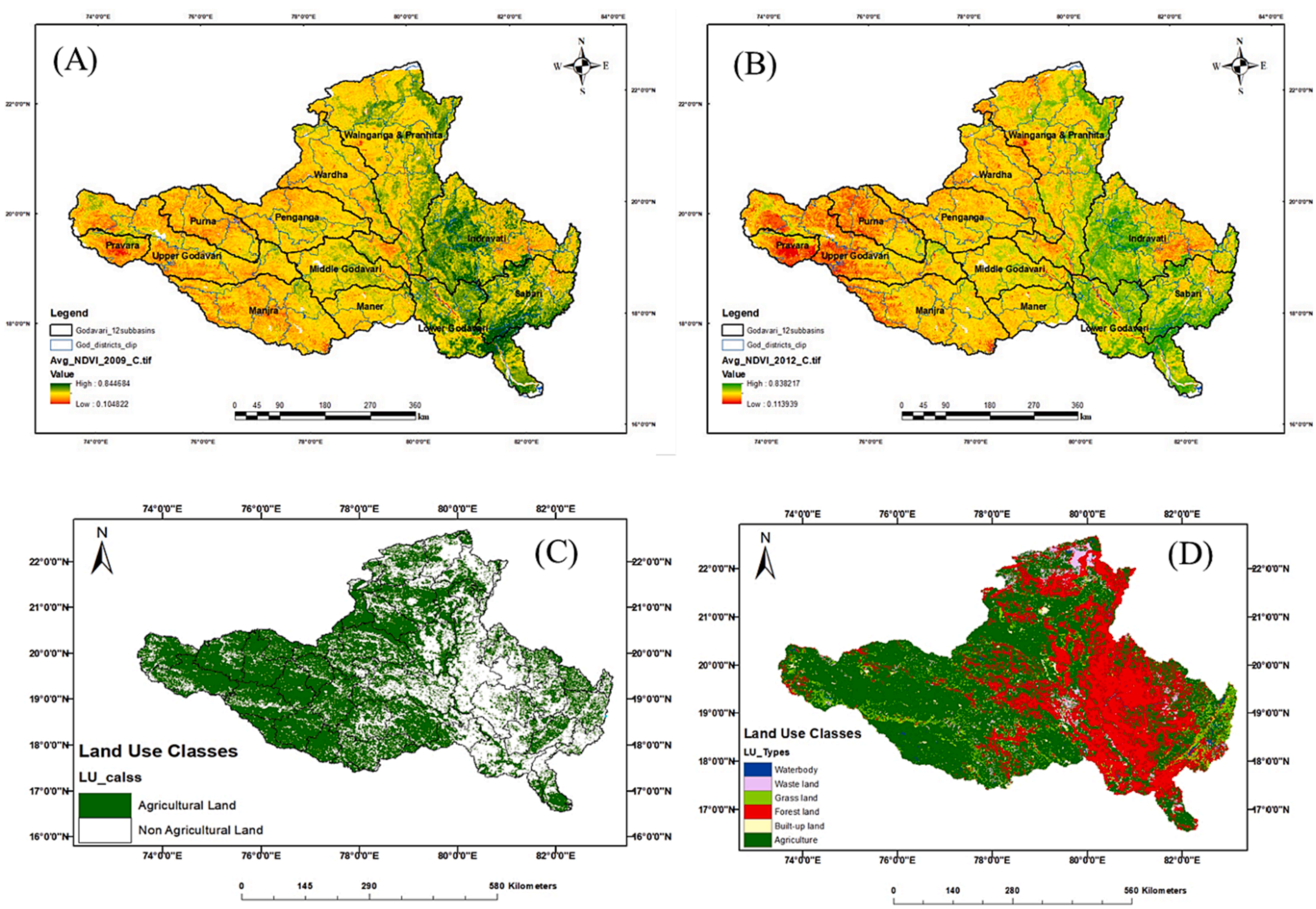


Fig. 14. NDVI maps showing the onset of drought and its spatial extent of effects on agricultural areas during the severe drought years of 2009 and 2012 at GRB.

whenever there is a drought, the area under agricultural land is at risk. Accordingly, the land-use map was categorised into two categories: risk class, representing the land cover under agriculture; and no risk class, representing the land cover other than agriculture; and they were used to define the exposure risk map.

The sensitivity risk is the degree of dependency on resources that are affected by the hazards. Therefore, to analyse the drought sensitivity risk, population density (PD) was considered a resource affected by drought (i.e. economic and health risk). People are affected by water scarcity and food insecurity as a result of crop yield reduction and economic loss caused by droughts. Therefore, the PD data (people/km^2) was obtained over the same period as the worst-case drought year for the hazard risk assessment. The PD was further reclassified into four classes based on the percentile distribution (Table 4), and the risk was further assessed. The districts with higher number of people per square kilometre were considered more vulnerable and more sensitive to droughts hazard in terms of the degree of damage caused to individuals, particularly for water requirements and economic loss. The areas with comparatively smaller number of people per square kilometre were considered less vulnerable to drought risks and associated impacts. Accordingly, a sensitivity risk map was prepared and overlayed with the exposure risk map to assess the level of vulnerability risk over the sub-basins of GRB more precisely.

The final drought risk map for agriculture over the GRB area was prepared (Fig. 15), and it represented the level of drought risk at each district in each sub-basin. This map was prepared using the overlay analysis of classified drought hazard and drought vulnerability map (Drought Risk = Drought Hazard × Drought Vulnerability (Exposure × Sensitivity)) using the two-dimensional table of overall risk score (Table 5).

The results show that 22 districts, which covered approximately 30% of the total GRB area, were classified as safe from drought risk (although the area was only 7.5% when calculated considering only the drought hazard (SPEI)). This demonstrates the importance of considering the vulnerability and exposure components in a risk analysis for a precise risk assessment. A lower area of approximately 8% presented low risk, whereas an area of approximately 11% (covering six districts) presented very high risk, as highlighted in dark red in Fig. 15. Thirteen districts in the middle and the north-western parts of the state were classified at medium risk (yellow), whereas the remaining ten districts in the north and east were classified at low risk (light green) owing mostly to their lower PD and higher share of non-agricultural land.

According to the agriculture drought risk assessment, the areas highlighted in dark red in Fig. 15 are the most affected and highly vulnerable districts, which are expected to experience maximum drought frequency with higher drought severity under the worst-case drought scenario. They will likely be more impacted by droughts under the influence of climate change. Therefore, the East Godavari district (one of the worst-affected districts; densely populated with highly coastal vulnerability) was identified and considered for the analysis of drought impact. The crop production statistics (production and prices) were analysed to investigate the extent of the impacts of such a severe drought over the GRB. By selecting one crop, we can quantify the spatial and temporal impacts more precisely. Therefore, among crop categories, the rice crop was selected because it is the major staple food in India, and the major crop at the Godavari River Basin. Moreover, Rice is a more water-sensitive crop than many other crops, as it requires more water for optimum growth throughout the growing season, hence, therefore, represents a higher risk of experiencing economic loss in drought. District-level rice production and prices were used as indicators to evaluate the risk and impacts of drought on rice crops. The trends for annual and seasonal production were plotted, as shown in Fig. 16.

The rice production decreased drastically during the drought years compared to the production in previous normal years, as highlighted by the dotted bar in Fig. 16. Rice is a more water-sensitive crop than many crops, as it requires more water for optimum growth throughout the growing season. Rice crops accounted for 41.02% production loss, estimated at approximately 48 million Rs. (67,000 USD), during a single drought year in 2009 compared to the production of the previous year in 2008 (Fig. 16a). The results were cross-validated with the losses and impacts reported by other sources. In 2010, the Ministry of Agriculture of the Government of India reported that the 2009 drought was one of the worst droughts considering the preceding 37 y. The overall agriculture growth in 2009 decreased because of this drought (DOAC, 2010). The sown area under Kharif food grain declined by 11.78%. Approximately 30 million-hectare crops and 120.5 million people were affected during this severe 2009 drought year (DOAC, 2010). The overall agricultural production was reduced by 20–40%, in which rice output was reduced by 15 million tonnes compared to the previous season, and food grain scarcity triggered an inflation of 17–20% owing to this single severe drought in India.

Droughts do not create instant impacts, and the beginning drought events may be mistaken for a short dry spell. The analysis indicated that droughts are a long-lasting disaster with long-term impacts. They can generate greater impact in the following seasons or months, as evidenced by the lower production in the dry (rabbi) season than in the

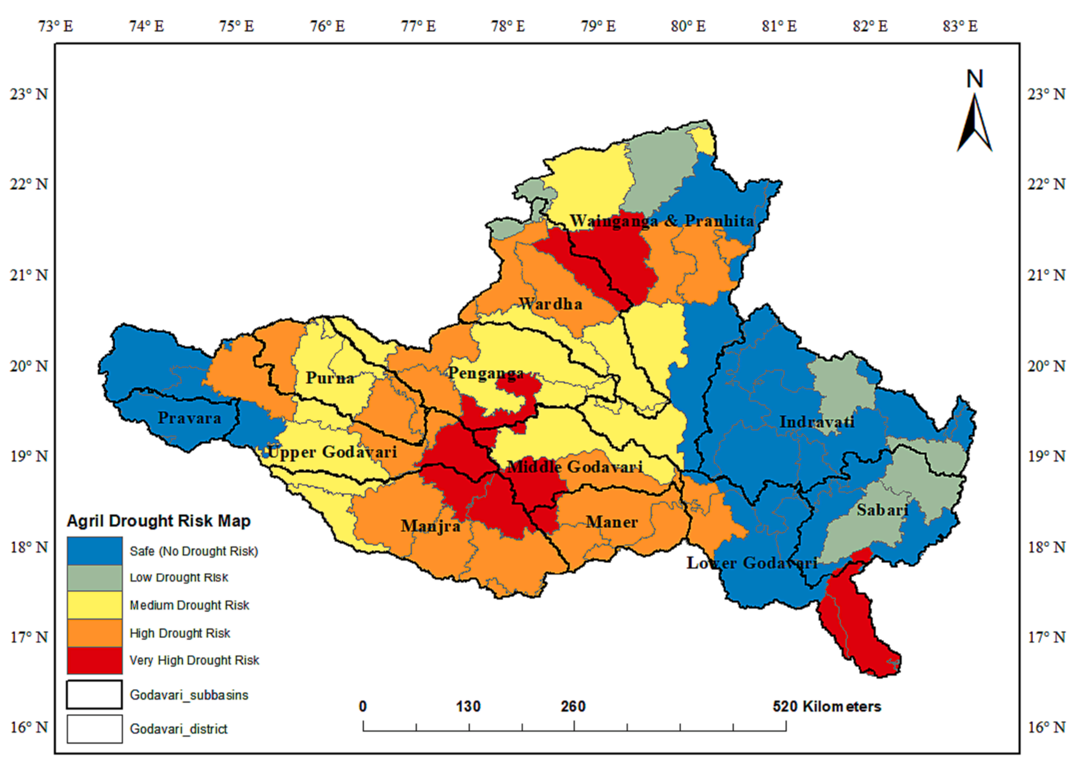


Fig. 15. The final district-level agricultural drought risk map over GRB.

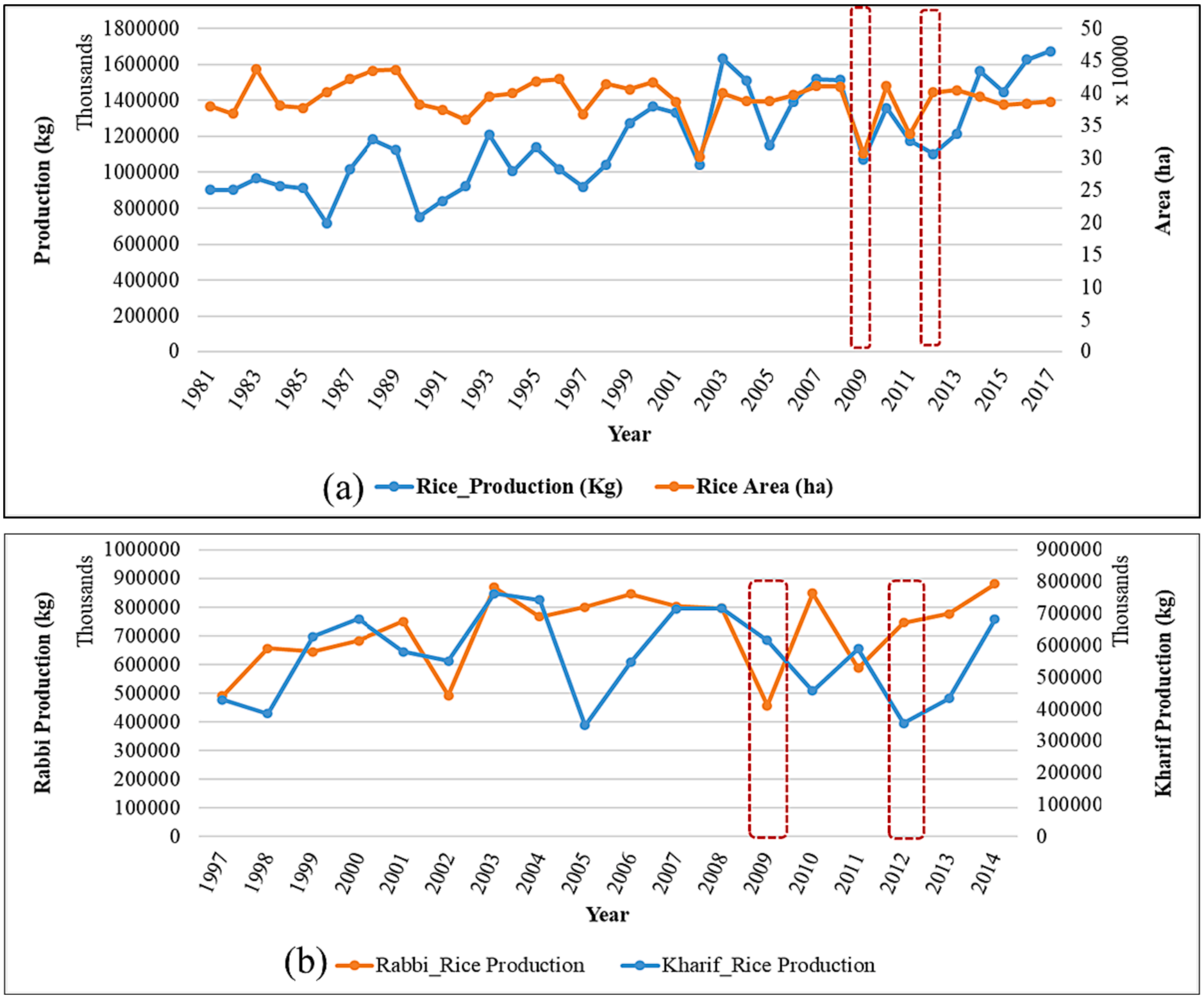


Fig. 16. (a) Annual and (b) seasonal rice production at East Godavari for 1981–2017 and 1997–2014, respectively.

rainy (kharif) season during the same drought year over the East Godavari district in the GRB, as shown in Fig. 16b. This risk may be addressed by implementing a crop rotational adaptation strategy, which includes introducing crops that demand less water and provide greater benefits without increasing economic or resource demands. Rainwater harvesting and storage would also be effective in preventing the drought crisis during the rabbi (dry) season because the drought in the rainy season may last throughout subsequent dry (rabbi) seasons owing to soil moisture loss. Therefore, proper rainwater storage could help address this issue. Moreover, the evaluation of risks to crop production and the economy can assist in investigating the amount of losses incurred from drought in the worst-affected locations, which can be used to justify mitigation strategies for drought risk and associated impacts.

Conclusions

The impacts of climate change vary with space and time. Thus, there is always a need to perform precise climate change risk assessments, and hence the spatio-temporal assessment of climate change impacts on drought is crucial. In this study, we focused on the assessment of impacts of climate change on drought and its consequences on the agricultural crops production across each sub-basin over the Godavari River Basin, India. For this purpose, this study has used long-term high spatial gridded observed datasets over historical period and d4PDF scenarios over future period for comprehensive assessment of climate variability, and drought occurrences. The results showed that, the locations that experience dry episodes are likely to predict more intense droughts in the future over Godavari River Basin. The magnitude and intensity of the drought are varying from one sab-basin to another sub-basin in GRB mainly due to the rapid variability in rainfall and temperature. The decreasing amount of annual rainfall during a recent period (2015–2019), with a higher contribution (80–85%) during the monsoon period (4 months-June to September) adds extra pressure on water resource management. The abrupt changes in the amount of intra-annual rainfall have brought maximum numbers of droughts over the Godavari River Basin during recent past 40 years. Both, the intensity and magnitude of drought have been observed increased during the present period (2011–2019) than in the past three decadal periods. The 9 sub-basins out of 12 (around 75% of the area) showed higher vulnerability for drought risk, whereas only 3 sub-basins (around 25 % area) have shown a lower risk and less vulnerability for drought occurrences from 1981 to 2019 across each sub-basin in GRB.

Future warming increases the drought frequency and severity, as it has shown a significant increasing trend of drought in the future under both future (+2K) and (+4K) warming scenarios over the Godavari River Basin. The severe-to-extreme droughts category has shown continuously increased frequency under both warming scenarios. In terms of spatial risk, more drought episodes are likely to be predicted in the central belt, particularly over the sub-basins of Wardha, Wainganga, and Pranitha, and a partial portion of Indravati and Lower Godavari sub-basins. Six districts showed the highest drought risk due to their total dependence on agriculture production and located with a dense population. A sharp decline in rice production (41.02 %), resulting in an economic loss of 67,000 USD was estimated during a single worst-case severe drought year. The drought has impacted significantly maximum on food crops than other crop categories like fodder, cash, and oilseeds crops in the East Godavari district. The farmers can switch from high-water-intensive crops such as rice to crops that require less water for optimum growth and can sustain within the drought spell with a minimum water supply such as maize or cotton. Moreover, the crops like maize and cotton are less-duration crops (100 and 165 days, respectively), and require less water for optimum crop growth (Praharaj et al., 2016; Doorenbos and Pruitt, 1977). Therefore, the crop that needs less water, and can sustain within a dry spell with minimum water supply can be considered a crop rotational mitigation strategy here. This could minimize the risk of drought, and even farmers could able to save their economy rather than wasting it by producing rice crops during the drought year.

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CRediT authorship contribution statement

Khagendra P. Bharambe: Conceptualization, Methodology, Formal analysis, Data curation, Software, Investigation, Visualization, Writing – original draft, Writing – review & editing. **Yoshihisa Shimizu:** Conceptualization, Methodology, Supervision, Writing – review & editing, Funding acquisition. **Sameh A. Kantoush:** Conceptualization, Methodology, Writing – review & editing, Funding acquisition. **Tetsuya Sumi:** Conceptualization, Methodology, Writing – review & editing, Funding acquisition. **Mohamed Saber:** Conceptualization, Methodology, Writing – review & editing, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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