Spatial assessment of drought vulnerability using fuzzy-analytical hierarchical process: a case study at the Indian state of Odisha

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ABSTRACT

Droughts can be regarded as one of the most spatially complex geohazards, causing a severe impact on socio-economic aspects. Preparing a comprehensive drought management plan is necessary to mitigate drought risks, and the first step towards achieving it is the preparation of drought vulnerability map. The present study integrates geospatial methods with Fuzzy-Analytical Hierarchy Process (Fuzzy-AHP) technique, to prepare a drought vulnerability map for Odisha, India. Total of 24 parameters under 2 separate vulnerability categories, namely physical and socio-economic, was listed. Spatial layers were prepared for each parameter, and fuzzy membership approach was used to fuzzify each layer, and AHP was used to measure the weights of each parameter using pair-wise comparison matrices. Finally, drought vulnerability maps with five drought vulnerability classes (very-high, high, moderate, low, and very-low) were developed using weighted overlay method. The results show that 33.94% of the region falls under high-drought vulnerability category. Further, the approach was validated using statistical metrics, like area under the Receiver Operating Characteristics curves, Accuracy, Root-Mean-Square-Error and Mean-Absolute-Error. The results imply that the applied method is effective for determining drought vulnerability in the region, which would help the planners for formulating drought mitigation strategies.

KEYWORDS
Drought vulnerability; physical drought vulnerability; socio-economic drought vulnerability; GIS; fuzzy-AHP; Odisha

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1. Introduction

Natural hazards are increasingly becoming frequent with high intensity and severity. To cope up with this environmental changing condition, people need to have a greater resilience to manage the hazardous situation. The losses due to environmental hazard are also increasing day by day. From the 1960s to 1980s the economic damage due to natural disaster has increased 3 times worldwide, with economic loss rising three folds from US$40 billion to US$120 billion (Domeisen 1995). In the 1990s, the economic damage has reached US$400 billion (Carolwicz 1996). Among the extreme climatic hazards, drought is one of the most crucial events which affects a large number of people worldwide (NRC 2013). Drought is deemed as the least understood and most dynamic of all environmental disasters impacting more people than any other hazard (Pulwarty and Sivakumar 2014). The occurrence of droughts is increasing in this age of global warming (Tsubo et al. 2009), affecting millions of people across the globe (Ault 2020). In India, more than 50% of the region is reported vulnerable to severe drought (Kamble et al. 2010), and climate change is likely to alter the country’s current profile of susceptibility to drought (O’Brien et al. 2004). According to estimates by Community Response to Extreme Drought (2016), drought conditions (1900–2016) have impacted almost 1.3 billion people in India. The increase in severity and duration of potential drought events are likely to threaten the country’s water supply and food safety (Ghosh 2019).

Nowadays, water resource management is majorly threatened by water scarcity. Water scarcity is being further diluted by the discordance in rainfall and increase of temperature due to climate change (IPCC 2013). The food security and water resources of the country are likely under threat by the increasing intensity and frequency of the drought event in the future. For these reasons, drought risk area demarcation is very crucial specifically for the agro-economy of India, particularly in the monsoon season. According to an estimation, India’s overall water consumption would rise nearly 32% by 2050 (Amarasinghe et al. 2007) and after using the country’s maximum irrigation capacity, half of the agricultural area would depend on rainfall for cultivation (CRIDA 2007). Through the increasing drought risk, the availability of freshwater and rain-fed agriculture is reported to be vulnerable.

The concept of vulnerability is complex, and most often it includes the exposure and sensitivity to disruptions or exterior stresses and the ability to adapt (Gallopín 2006). According to Intergovernmental Panel on Climate Change (IPCC), the vulnerability of any climate change induced disasters depends on the magnitude, size, and pace of climate change along with the system’s sensitivity and adaptability (Jiang et al. 2012). The above description depicted vulnerability as a multifaceted conception with additional consideration to inequality and poverty (Shi and Stevens 2010). In the 5th assessment of the IPCC report, vulnerability is simply defined as ‘the tendency or disposition to be unfavourably affected’ which mainly denotes the societal risks of any calamity. It is also prejudiced by the coping ability of population regarded as their resource inheritances and exemptions. In the upcoming decades, the vulnerability and risk of drought are expected to grow (Ghosh 2019).

Considering the changing climatic conditions, a proper strategy is required to mitigate the growing vulnerability, and a preventative approach is crucial at different
levels (Chanie et al. 2018). Due to an unanticipated increase in the drought magnitude worldwide, the awareness in the direction of drought risk alleviation and preparation has noticeably amplified in recent years (Maleksaeidi et al. 2017). Drought severity depends on how long the dry condition sustains over an area and it is measured through thresholds of different indices (Leasor et al. 2020). Therefore, drought severity and vulnerability estimation are very much required to frame out any management strategies. ‘Vulnerability assessment’ is one of the major avenues of any drought alleviation scheme, where the identification of victims and causes is necessary.

Over the years, for drought condition analysis, various types of indices have been used in different regions. Several methods, indices and parameters such as, temperature, rainfall, vegetation index, soil moisture have been used to model drought scenario in different region (McKee et al. 1993; Zargar et al. 2011). As drought condition varies from region to region based on climatic types hence their measurement techniques are also different (Bhuiyan 2004; Vicente-Serrano et al. 2012). Drought measuring parameters are sometime linear and sometime nonlinear with respect to each other (Bhuiyan 2004). The PDFs (probability density function) of drought index have been used to demonstrate drought frequency and intensity successfully by Mishra and Desai (2005). Yevjevich (1967) have defined drought condition of a particular number of years when there was no sufficient supply of water resources in those consecutive years with the help of geometric probability distribution. Saldariaga and Yevjevich (1970) have incorporated the time series analysis of drought and developed the run theory to predict the drought occurrence. Sen (1977) has extended the research on run theory to predict the water resource and to evaluate the run sums of the yearly flow data. To identify the stochastic nature of the monthly and yearly drought condition, the Palmer Drought Index (PDI) and some valid stochastic models have used by Rao et al. (1984). For forecasting drought duration and average length of drought, Moye et al. (1988) have used some relevant distribution of probability based on some pertinent equations. Şen (1991) gave some proper distribution function of probability of critical drought condition and also has predicted the duration of some critical drought situation that may come from any hydrological phenomenon. Alternating renewal reward model have been used by Kendel and Dracup (1992) to predict the event of drought. The renewal processes of drought occurrence have been modelled by Loaiciga and Leipnik (1996). Lohani and Loganathan (1997) have used PDSI and also an early warning system to manage the drought condition and to characterize the drought’s stochastic behaviour based on some specific character of drought in a non-homogeneous chain model. To estimate the probability of occurrence of drought event, low-order discrete autoregressive moving average (DARMA) models have been used by Chung and Salas (2000). In the Conchos river basin of Mexico, PDSI have been used as a drought parameter by Kim and Valdés (2003) to forecast the drought. Various aspects of drought such as drought severity, intensity, duration have been predicted in various models. Soil moisture index (SMI), standardized precipitation evapo-transpiration index (SPEI), standardized precipitation index (SPI), normalized difference vegetation index (NDVI), moisture adequacy index are applied to detect the drought condition by some scholars (Ji and Peters 2003; Vicente-Serrano et al. 2010; Hao and AghaKouchak 2013; Rajpoot and Kumars 2019). Yihdego et al. (2019)
have critically analyzed various drought indices and their capability to predict drought. Whereas, Shah and Mishra (2020) have presented the integrated drought index (IDI) for drought monitoring and prediction in India. Physically based models using palmer drought severity index, ARMA model, Pattern recognition technique are also involved to assess and forecast the drought vulnerability (Panu and Sharma 2002). In mitigating the consequences of short-term hydrological and agricultural drought condition, the aforesaid research efforts have provided valuable models and indices.

A large number of research works have been done on predicting and forecasting of the drought condition (Dikshit et al. 2020a, 2020b, 2020d) in different part of the globe rather than the overall vulnerability of drought. Very few works (viz., Raja et al. 2014; Panda 2017) have been conducted to assess the drought prediction in the selected state. Nearly 50% areas of the state of Odisha, India are prone to drought (DH (Deccanherald) 2019). Therefore, for managing the livelihood in this heavily populated region with continuous agricultural extension assessment of drought vulnerability is essential. Wijitkosum and Sriburi (2019), Wijitkosum (2018) and Malik et al. (2020) prepared the drought risk maps based on the analytical hierarchical process (AHP) that have given very good results. Still the works on drought vulnerability is very few. Here drought condition has been measured through SPI and used as important factors with other physical and socio-economic factors. SPI is a widely applied metric to assess meteorological drought at various range of time scale. In shorter time scale it deals with soil moisture, whereas in longer range it is related with groundwater and reservoir storage (John 2018). It has several advantages compared to other drought indices like it uses only precipitation data and along with it is very easy to compute and have consistent spatial interpretation, thus suitable for prediction and risk analysis (Anshuka et al. 2019).

In the present work, the drought vulnerability condition was assessed using physical and socio-economic factors in the state of Odisha, India. For drought vulnerability modelling, a Fuzzy-analytical hierarchical process (Fuzzy-AHP) method was used. The drought vulnerability map was able to demonstrate the vectors of drought in a logical
manner. Fuzzification helps to make the factors unidirectional based on their role, and AHP gives necessary weights of the factors. Therefore, combination of fuzzy and AHP makes the assessment logical and scientific. Besides, this method has an advantage of using expert opinion which is necessary for drought vulnerability assessment. Afterward, the final model was validated by the receiver operating characteristics (ROC), accuracy, mean-absolute-error (MAE) and root-mean-square-error (RMSE). Such work will help the academician and agricultural planner for reducing the impact of drought.

2. Materials and methods

2.1. Study area

Odisha is located on the Eastern coast of India with geographical coordinates ranging from 17.31°N latitude to 22.31°N latitude and 81.31°E longitude to 87.29°E longitude (Figure 1). The region has a 485 km (301 miles) long coastline along the Bay of Bengal. The climate of Odisha is characterized by high temperature, high humidity, moderate to high rainfall and short and mild winters. The state is characterized by a tropical climate, high temperature, medium to high rainfall, and short winters (Panda 2017). The average rainfall of this state is 1451.2 mm and most of this occurs in the months of June till September (Figure 2). Different climatic hazards like floods, droughts and cyclones take place here in almost every year with varying intensity (Chittibabu et al. 2004; Bahinipati 2014; Mohanty et al. 2020; Sam et al. 2020). Odisha is divided into five major regions of physiography such as the Utkal plains, central plateaus, central mountains and highlands, western hills and floodplains. Main rivers of the states are Mahanadi, Brahmani, and Baitarani which flows into the Bay.
of Bengal. As per Census of India (2011), Odisha has the population of 4.2 crores (3.47% of India). For the people of Odisha, the drought event is not new. In some places of Odisha, drought has occurred every year with varying intensity and magnitude. The first extreme drought occurred in the state was in the year of 1866, and after that moderate to extreme drought event was seen 17 times till now. This reveals that in Odisha the moderate to extreme intensity drought happens once in 8 years approximately. In 1866, 1919, 1965 and 2000–2001, the extreme intensity drought happened in the state, and among them 2000–2001 drought event was the most severe. The western and south-central parts of the state have been historically suffering from drought. Therefore, drought vulnerability assessment of this state is very much required in terms of strategic planning and management perspectives.

2.2. Dataset and sources

In the current study, combining physical and socio-economic drought vulnerability using Fuzzy-AHP and geospatial technique, overall drought vulnerability map has been prepared. Total 24 parameters from different data sources under physical and socio-economic drought vulnerability have been considered for generating an inclusive drought vulnerability map. Figure 3 illustrates the methodological framework for this analysis. The data used for this have been collected from various sources and thematic layers of the selected parameters have been prepared using geospatial tools. The details about the data set used for two types of drought have been depicted in Tables 1 and 2.

2.3. Parameters used in vulnerability mapping

For the present work, parameters and specifications were considered after reviewing previous literatures, local context of research, usability and dependability of databases
and their appropriateness to drought (Eklund and Seaquist 2015; Ghosh 2019; Hoque et al. 2020). With various substitutes, the spatial layer has been developed for every parameter. Total 24 spatial data layers of 30 m spatial resolution have been prepared under the two drought vulnerability categories – physical and socio-economic. Natural break classification method of Jenks (1967) has been adopted to classify the maps which decrease the gap inside the similar class data values (Ghosh 2019). It can efficiently represent the spatial pattern of vulnerability, and it has been done using ArcGIS 10.4. The precise details of determining the vulnerability to drought are discussed in the parts below.

### 2.3.1. Parameters used in physical drought vulnerability

Physical drought vulnerability is related to the dried up weather condition (Fowler and Kilsby 2002). In the current study, 12 pertinent criteria highlighted in Figure 3 were considered for physical drought vulnerability mapping. The parameters, their computation and maps (Figure 4) are explained below:

#### 2.3.1.1. Standardized precipitation index (SPI)

The Standardized Precipitation Index (SPI) is a multi-time drought indicator that needs only rainfall data (Cacciamani et al. 2007). The SPI exhibit the abnormal wet and dry condition with the precipitation data, which is given by the user in definite time durations by considering the

| Sl. no. | Variables | Sensitivity/logical consideration | Source | Period |
|---------|-----------|----------------------------------|--------|--------|
| 1       | Annual rainfall | More the rainfall less the vulnerability | Indian Meteorological Department | 1901–2019 |
| 2       | Rainfall trend | Positive trend will suggest wet weather intensification and negative trend would imply dry condition intensification. | Calculated from rainfall data | 1901–2019 |
| 3       | 24 month extreme drought frequency (%) | More frequency means more risk | 1901–2019 |
| 4       | 12 month extreme drought frequency (%) | More frequency means more risk | 1901–2019 |
| 5       | 3 month extreme drought frequency (%) | More frequency means more risk | 1901–2019 |
| 6       | Return period of 24 month extreme drought | Greater recurring periods, lesser risk of drought vulnerability | 1901–2019 |
| 7       | Return period of 12 month extreme drought | Greater recurring periods, lesser risk of drought vulnerability | 1901–2019 |
| 8       | Return period of 3 month extreme drought | Greater recurring periods, lesser risk of drought vulnerability | 1901–2019 |
| 9       | Critical rainfall | More the rainfall needed will raise drought chances | 1901–2019 |
| 10      | Trend of temperature | Rising temperature patterns are suggesting an intensification of dry weather and vice versa | Indian Meteorological Department | 1901–2019 |
| 11      | Wet-day frequency | Decreasing wet day will indicate intensification of dry condition and vice versa | 1901–2019 |
| 12      | Evaporation | Greater the evaporation more the chances of drought | 1901–2019 |

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rainfall departure from the cumulative probability distribution of rainfall over the same period and region (McKee et al. 1993). In order to measure the precipitation deficit over a variety of time scales, the SPI was developed and the SPI of 3, 12, 24 and 48 months’ time stages can be used to characterize the drought of various forms (McKee et al. 1993). There are seven severity classes of SPI which are mentioned in Table 3. The 3 month SPI is applicable for agricultural impact evaluation as it exhibits the short-range seasonal condition of moisture (Ji and Peters 2003). Moderate and long-term moisture condition is reflected by the 12 and 24 months SPI, respectively (Potop et al. 2012). For the vulnerability analysis extreme drought classes of 3, 12 and 24 month SPI have been taken. Here, 3, 12 and 24 month’s SPI has been computed using the following equations (Equations (1)–(9)). Generally, by applying the probability density function to the total precipitation, the estimation of SPI is achieved. For every month and position it was done differently. After that, the standard normal distribution of each probability function has been done (Guttman 1998).

To represent the gamma distribution, the probability function was used:

\[ g(x) = \frac{1}{\beta^a \Gamma(a)} x^{a-1} e^{-x/\beta} \]  

where, the appearance of parameters denoted by \( a \), \( \beta \) denotes the range of the parameter, \( x \) represents the amount of rainfall, and \( \Gamma \) is the gamma function. The \( a \) and \( \beta \) parameters value >0.

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Table 2. Input parameters with their source (socio-economic drought parameters).

| Sl no. | Variables                                      | Sensitivity/logical consideration                                           | Source                                                                 | Period       |
|-------|-----------------------------------------------|---------------------------------------------------------------------------|-----------------------------------------------------------------------|--------------|
| 1     | Cropping intensity (CI)                       | More cropping intensity (CI), more vulnerability                          | Data obtained from District irrigation plan                            | 2016         |
| 2     | % of small and marginal farmers to total worker | More number of small and marginal farmers, more vulnerability             | Odisha, Agriculture Statistics                                         | 2013–2014    |
| 3     | Irrigation intensity (%)                      | More irrigation intensity, more vulnerability                              | A study on Irrigation and Agricultural productivity in Odisha          | 2018         |
| 4     | Total water use                               | More total water use, more vulnerability                                  | Ground water booklet                                                   | 2016         |
| 5     | Water demand                                  | More water demand, more vulnerability                                     | Ground water booklet                                                   | 2016         |
| 6     | Net water availability                        | More water availability, less vulnerability                               | Ground water booklet                                                   | 2016         |
| 7     | Total ground water resource                   | More ground water reserve status, less vulnerability                     | Ground water booklet                                                   | 2016         |
| 8     | Gross Irrigated area (%)                     | More irrigated area, more vulnerability                                  | Data obtained from District irrigation plan                            | 2016         |
| 9     | Population density                            | More population density, more vulnerability                              | Data obtained from District irrigation plan                            | 2016         |
| 10    | Health index                                  | More health index, less vulnerability                                    | Odisha economic journal                                               | 2019         |
| 11    | Income Index                                  | More income Index, less vulnerability                                     | Odisha economic journal                                               | 2019         |
| 12    | Education Index                               | More education index, less vulnerability                                  | Odisha economic journal                                               | 2019         |
Using the Equation (2) the Gamma function $\Gamma(\alpha)$ can be represented.

$$\Gamma(\alpha) = \lim_{n \to \infty} \prod_{v=0}^{n-1} \frac{n!}{y + v} = \int_0^\infty y^{\alpha-1} e^{-y} dy$$  \hspace{1cm} (2)$$

For the adjustment of the gamma distribution, the $\alpha$ and $\beta$ parameters must be calculated. Maximum likelihood results are used to obtain $\alpha$ and $\beta$ as follows (Thom 1958):

Figure 4. Physical drought vulnerability criteria layers: (A) Annual rainfall, (B) Annual we-day frequency, (C) Evaporation, (D) Rainfall trend, (E) Temperature trend, (F) Critical rainfall, (G) 3 month extreme drought frequency, (H) Return period of 3 month extreme drought, (I) Return period of 12 month extreme drought, (J) 12 month extreme drought frequency, (K) Return period of 24 month extreme drought, and (L) 24 month extreme drought frequency.
After that, to detect the increasing probability distribution function $G(x)$ of a given timescale $\alpha$ and $\beta$ parameters are implemented:

$$G(x) = \int_{0}^{x} g(x)dx = \frac{1}{\beta^a \Gamma(a)} \int_{0}^{x} x^{\alpha} e^{-x/\beta} dx$$  \hspace{1cm} (6)$$

By substituting $x/\beta$ with $t$, the Equation (6) can be reduced as follows:

$$G(x) = \frac{1}{r(\bar{x})} \int_{0}^{x} t^{\alpha-1} e^{-1} dt$$  \hspace{1cm} (7)$$

Edwards (1997) introduced the true feasibility of non-exceedance $H(x)$ can be achieved as follows:

$$H(x) = q + (1-q)G(x)$$  \hspace{1cm} (8)$$

Where, the possibility of a zero event is represented by $q$, and frequency of zeros by $m$ in the time series dataset of rainfall. Following Equation (9) $q$ can be estimated (Thom 1966):

$$q = \frac{m}{n}$$  \hspace{1cm} (9)$$

**Percentage drought frequency (DF):** DF has been applied to calculate the drought accountability for a sample time period (Wang et al. 2014). Employing the Equation (10) percentage drought frequency has been calculated.
\[ N_{i,100} = \frac{N_i}{i \times n} \times 100 \] (10)

where, \( N_{i,100} \) = drought number in 100 years for a timescale \( i \).
\( N_i \) = for a time scale \( i \) the number of months with droughts in the \( n \) year set.
\( i \) = time scale (31,224 months)
\( n \) = total number of years

**Annual rainfall:** With the increasing rainfall the drought vulnerability will be low (Antwi-Agyei et al. 2012). Sum of total monthly precipitation of each district have been calculated and the annual average of the precipitation has been generated.

**Rainfall trend:** Both positive and negative trends suggest intensification in both wet and dry weather respectively (Wang et al. 2010). In these calculations, the precipitation of each year has been taken and then linear regression has been done to identify the trend of the rainfall over the region.

**Rainfall threshold/critical rainfall:** The initiation of drought can be understood by calculating the threshold rainfall or critical rainfall (Paulo and Pereira 2006). To get the critical rainfall value, at first we have to calculate the mean (\( \overline{X} \)) and standard deviation (\( \sigma \)) for a definite time period for a particular location and then we have to set the required SPI (say -1.5) and then place the values into Equation (11).

\[ X_i = \sigma SPI + \overline{X} \] (11)

Negative SPI values (> -0.99) indicate the occurrence of drought. Here we have calculated the critical rainfall value considering the SPI value of -1.5.

**Return period of drought:** The vulnerability will be high if the return period of drought is more frequent, and with an increasing gap between two drought years the vulnerability will get reduced (Bonaccorso et al. 2003). At first all the SPI values have been arranged in ascending order and rank has been given. Subsequently, the return periods were calculated by dividing the total year with each rank. Return period of 3, 12 and 24 month extreme drought were calculated for the present study.

**Wet-day frequency:** Like with the rainfall, wet-day occurrence is also an important parameter in determining vulnerability to drought (Murthy et al. 2015). Increasing wet day frequency in a year will decrease the dry condition (Groisman and Knight 2008). Drought condition cannot easily affect a region with more number of wet day frequencies and vice-versa.

**Temperature trend and evaporation:** In identifying drought vulnerability, temperature and evaporation are two significant parameters (Mpelasoka et al. 2008). With increasing temperature and evaporation will also increase and with increasing evaporation the dryness as well as vulnerability of a region will rise. In this analysis, linear regression has been used to measure the trend of the temperature.

### 2.3.2. Parameters used in socio-economic drought vulnerability

In the present study, 12 parameters, (Figure 3) have been taken for mapping the socio-economic drought vulnerability. The parameters and their maps (Figure 5) are explained below:
Cropping intensity (CI): Cropping intensity is the ratio between the gross cropped area and net crop area. With the increasing cropping intensity, the drought intensity will also increase (Gumma et al. 2014). More vulnerability of drought will be seen in the areas having high cropping intensity. More amount of crop will be destroyed due to the scarcity of water.

Percentage of small and marginal farmers: Even though there are more small and marginal farmers, they would be more impacted by the drought (Alam 2015). As most of the farmers have a very small amount of landholding for agriculture and they do not use high technology for production so, the drought condition will highly affect them in compared to large farmers.

Figure 5. Socio-economic drought vulnerability criteria layers: (A) Health index, (B) Education index, (C) Income index, (D) Population density, (E) Gross irrigated area, (F) Cropping intensity, (G) Total ground water resource, (H) Net water availability, (I) Total water use, (J) Small and marginal farmer, (K) Irrigation intensity, and (L) Water demand.
**Irrigation intensity:** The drought will more affect the high irrigation intensity area as normally those regions have more water demand (Pattanayak and Mallick 2018). More amount of crop will be negatively affected due to the dry conditions.

**Total water use:** Total water use has a direct relation with drought vulnerability, as in high water use areas the water demands will also be higher in dry periods (Blum 2005). So, the regions marked as significantly higher water use zones will have to face more severity of drought in compare to the lower water use areas.

**Water demand:** Where the water demand is high, the drought will badly affect those areas (Fernandes et al. 2015). Here the total water demand has been calculated by adding the domestic water demand, crop water demand, and livestock water demand, industrial water demand (Fernandes et al. 2015). We obtained the water demand (domestic water demand, crop water demand, livestock water demand, and industrial water demand) data from groundwater booklet, 2016.

**Net water availability:** If there has a supply of high amount of water all-round the year, the drought cannot easily affect those regions (Sala and Tenhunen 1996). Even if there is rainfall deficiency in a year in a particular region from other sources of water the region can manage the water deficit. But if there are no other sources of water except rainfall, then drought will severely affect those areas.

**Total ground water resource:** To defeat the drought effect, the groundwater is a major source (Peters et al. 2005). With the increasing ground water storage the drought vulnerability will be low as groundwater supply will mitigate the issue of water demand during drought period. Over-exploitation of groundwater can significantly affect the drought-induced damages due to reduced water level.

**Gross Irrigated area:** Drought vulnerability is largely controlled by the LULC (Kaplan 2014) as higher the irrigated area the more will be the vulnerability as with the increasing irrigated area the water demand will be more.

**Population density:** Where the population density is very high, water requirement will also be high and drought will be more vulnerable there and vice versa (Heidari et al. 2020). So, it is directly related with drought severity as more people will get affected by this.

**Health, Income & Education Index:** Drought vulnerability largely depends on the development of the local resident. With the increasing development of health, education and income opportunities, the drought vulnerability will be lowered in an area (Miyan 2015). Human development is reflected by the Health index, Education index, and Income index. With the increasing values of those indices, the adaptive power of that region to vulnerable condition will also increase.

### 2.4. Application of fuzzy AHP

Fuzzy-AHP is the application of fuzzy theory on AHP, which was developed by Saaty (1980). AHP is a commonly employed decision-taking method in numerous concerns...
related to multi-criteria decision making (MCDM). This takes the pair-wise analysis of separate solutions according to several parameters and makes a weighting judgement for issues. As basic AHP cannot comprise uncertainty for individual decisions, fuzzy logic can solve the issue. In F-AHP, the weights of directional raster have been calculated, which can give better results in MCDM problems. van Laarhoven and Pedrycz (1983) first showcased the fuzzy AHP applications. For the pair-wise comparisons, van Laarhoven and Pedrycz (1983) explained the triangular membership functions. Afterwards, Buckley (1985) added to the theme by ascertaining the fuzzy priorities of pair-wise comparisons having triangular membership functions. Although several additional techniques have been added in Fuzzy-AHP to determine comparative weights of importance for both the normal and the replacement, but Buckley’s approach has been implemented here. In the following section, the F-AHP method is discussed. The procedure is described below:

**Step 1**: Through linguistic conditions, judgement makers compare the criteria or substitute as shown in Table 4 (Batuhan Ayhan 2013). For example, if the decision maker states that ‘parameter1 (P1) is less significant compared to parameter 2 (P2)’, then (2, 3, 4) is taken on a fuzzy triangular scale. On the other hand, the relation of C2 to C1 would take the fuzzy triangular scale as (1/4, 1/3, 1/2) in the pair wise contribution matrices of the parameters (Batuhan Ayhan 2013). The pair-wise contribution matrix has been demonstrated in Equation (4). Where, \( \tilde{d}_{ij} \) shows the preference of the \( k^{th} \) decision maker of \( i^{th} \) parameter over \( j^{th} \) criterion, by using fuzzy triangular numbers. \( d_{12} \) depicts the first decision maker’s preference of the first parameter over the second parameter, and equals to, \( d_{12} = (2, 3, 4) \).

\[
\tilde{d}^k = \begin{bmatrix}
\tilde{d}_{11}^k & \tilde{d}_{12}^k & \cdots & \tilde{d}_{1n}^k \\
\tilde{d}_{21}^k & \tilde{d}_{22}^k & \cdots & \tilde{d}_{2n}^k \\
\vdots & \vdots & \ddots & \vdots \\
\tilde{d}_{n1}^k & \tilde{d}_{n2}^k & \cdots & \tilde{d}_{nn}^k
\end{bmatrix}
\]  

(12)

**Step 2**: If there is more than one judgement maker, average priority is granted to each decision maker \( d_{ij}^k \) and measured as in the Equation (13).
\[
\tilde{d}_{ij} = \frac{\sum_{k=1}^{K} \tilde{d}_{kj}^k}{K}
\] (13)

**Step 3:** Pair-wise contribution matrix is modified which is consistent with mean priorities as shown in Equation (14).

\[
\tilde{A} = \begin{bmatrix}
\tilde{d}_{11} & \cdots & \tilde{d}_{1n}
\vdots & \ddots & \vdots \\
\tilde{d}_{n1} & \cdots & \tilde{d}_{nn}
\end{bmatrix}
\] (14)

**Step 4:** As Buckley stated, the geometric average of fuzzy comparative values for each criterion is determined by Equation (15). Here \(\tilde{r}_i\) still depicts triangular values.

\[
\tilde{r}_i = \left( \prod_{j=1}^{n} \tilde{d}_{ij} \right)^{1/n}, i = 1, 2, \ldots, n
\] (15)

**Step 5:** By combining next 3 sub steps, the fuzzy weights of each criterion could be computed with Equation (18).

**Step 5a:** Computed the vector summation of each \(\tilde{r}_i\)

**Step 5b:** Find the (-1) power of aggregate vector. Change the fuzzy triangular number, to make it increase.

**Step 5c:** Multiply every \(\tilde{r}_i\) with this reverse function to get the \(i(\tilde{w}_i)_i\) parameters’ fuzzy weight.

\[
\tilde{w}_i = \tilde{r}_i \otimes (\tilde{r}_1 \oplus \tilde{r}_2 \oplus \cdots \oplus \tilde{r}_n)^{-1} = (l_{w_i}, m_{w_i}, u_{w_i})
\] (16)

**Step 6:** Since \(\tilde{w}_i\) are still fuzzy triangular numbers, they need to de-fuzzified by centre of area method anticipated by Chou & Chang, using the Equation (17)

\[
M_i = \frac{l_{w_i} + m_{w_i} + u_{w_i}}{3}
\] (17)

**Step 7:** \(M_i\) is a non-fuzzy number, but it needs to be standardized by following Equation (18).

\[
N_i = \frac{M_i}{\sum_{i=1}^{n} M_i}
\] (18)

The proper weights of all parameters and alternatives can be calculated by following these 7 measures. The ratings are then calculated for each alternative by integrating each alternative weight with the relevant parameters. In accordance with these results, the decision-maker assigns the alternative with the optimum score.


2.5. Fuzzification of the criteria layer

Fuzzification is the method of altering an input into fuzzy value (Jain 2014). If indistinctness is happened because of uncertainty, ambiguity or vagueness, then the variable is possibly fuzzy and can be signified by a membership function. The degree of membership is decided by fuzzification. Here, we have converted all the criteria layer of physical and socio-economic drought vulnerability into fuzzy layer by employing the fuzzy membership function in the ArcGIS environment, according to their contribution (positive or negative) in determining the drought vulnerability. The directionality of influence of each parameter is described as below in the Tables 5 and 6.

2.6. Calculating the weight of the parameters by AHP

Employing the AHP method weights of the physical and socio-economic parameters have been calculated for assessing the overall drought vulnerability of Odisha. Depending on the contribution of each parameter to the magnitude of the drought, pair-wise comparison matrixes have been planned. After determining the ranking position of each parameter, the weight has been calculated. The rank and their certain weight of parameters and the decision matrix for two drought vulnerability categories (physical and socio-economic) is given in the following Tables 7–10.

2.7. Vulnerability assessment

By employing the weighted overlay method, the drought vulnerability classes were found through individual parameter’s weights. After that, the resultant maps were divided into five categories, namely very-high, high, moderate, low and very-low to generate the final maps of physical and socio-economic drought vulnerability. Then, the overlay technique was applied to produce the map of overall drought vulnerability, which merged both the drought category maps. To produce the overall drought vulnerability map, physical drought vulnerability has been given more weightage than socio-economic drought, as socio-economic conditions are the secondary determinants of drought vulnerability. The logic applied here is that if an area is very much susceptible to physical drought and the socio-economic conditions are also poor, then the area has been demarcated as very high drought vulnerable zone. Secondly, in spite of having poor socio-economic conditions if the physical drought susceptibility of a region is very-low, then the overall drought vulnerability will also be low. In this way, the produced overall drought vulnerability map has been divided into very high, high, moderate, low and very low five groups.

2.8. Validation of vulnerability assessment

2.8.1. Receiver operating characteristics (ROC)

ROC curve is a threshold dependent approach which is widely and competently applied in the evaluation of the presentation of a classified outcome (Ramyachitra and Manikandan 2014). Area under the curve (AUC) characterizes model competency
AUC value closer to the 1 denotes faultless prediction ability of the models and < 0.5 denotes poor performance (Shatnawi 2017).

### 2.8.2. Discrimination accuracy measures: efficiency

The ratio between gully presence and gully absence pixels which were appropriately categorized can be explained as (Gutiérrez et al. 2009). The formula of calculation is expressed as below (Equation (19)):

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}
\]  

(19)

where, True Positive (TP) and True Negative (TN) are the properly categorized areas as drought prone and drought absence consequently. False Positive (FP) reflects the amount of non-drought vulnerable areas that were wrongly categorized as drought prone areas and False Negative (FN) applies to the amount of drought prone villages that were imperfectly identified as non-drought vulnerable.

### 2.8.2.1. Root mean square error (RMSE)

The square root of the ratio between the difference between enumerated values and truly executed values is RMSE (Roy et al. 2014). The formula is articulated in below (Equation (20)):

\[
\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(V_{\text{predict}} - V_{\text{observe}})^2}{N}}
\]

(20)

where, N is the number of sample, \(V_{\text{predict}}\) is predicted and \(V_{\text{observe}}\) is the pragmatic values of the dependent variable.

### 2.8.2.2. Mean absolute error (MAE)

Like RMSE, the mean absolute error (MAE) was computed as the summing up of total values of difference among practical and enumerated values excluding their directions (Deo et al. 2016). The formula is expressed in Equation (21):

| Sl no. | Variables                                | Directionality of influence |
|-------|------------------------------------------|------------------------------|
| 1     | Rainfall                                 | Inverse                     |
| 2     | Rainfall trend                            | Inverse                     |
| 3     | 24 month extreme drought frequency (%)   | Direct                      |
| 4     | 12 month extreme drought frequency (%)   | Direct                      |
| 5     | 3 month extreme drought frequency (%)    | Direct                      |
| 6     | Return period of 24 month extreme drought | Inverse                     |
| 7     | Return period of 12 month extreme drought | Inverse                     |
| 8     | Return period of 3 month extreme drought  | Inverse                     |
| 9     | Critical rainfall                         | Direct                      |
| 10    | Temperature                              | Direct                      |
| 11    | Wet-day freq.                            | Inverse                     |
| 12    | Evaporation                              | Direct                      |

Table 5. Physical drought vulnerability parameters with their directionality of influence in assessing drought vulnerability.
Table 6. Socio-economic drought parameters with their directionality of influence in assessing drought vulnerability.

| Sl no. | Variables                                           | Directionality of influence |
|--------|-----------------------------------------------------|----------------------------|
| 1      | Cropping intensity (CI)                             | Direct                     |
| 2      | % of small and marginal farmers to total worker     | Direct                     |
| 3      | Irrigation intensity (%)                            | Direct                     |
| 4      | Total water use                                     | Direct                     |
| 5      | Water demand                                        | Direct                     |
| 6      | Net water availability                              | Inverse                    |
| 7      | Total ground water resource                         | Inverse                    |
| 8      | Gross Irrigated area (%)                            | Direct                     |
| 9      | Population density                                  | Direct                     |
| 10     | Health index                                        | Inverse                    |
| 11     | Income Index                                        | Inverse                    |
| 12     | Education Index                                     | Inverse                    |

Table 7. Resulting weights for the criteria based on your pair-wise comparison.

| Sl. No | Variables                                           | Weight | Rank |
|--------|-----------------------------------------------------|--------|------|
| 1      | Rainfall                                            | 0.122  | 3    |
| 2      | Rainfall trend                                      | 0.173  | 1    |
| 3      | 24 month extreme drought frequency (%)             | 0.078  | 5    |
| 4      | 12 month extreme drought frequency (%)             | 0.054  | 7    |
| 5      | 3 month extreme drought frequency (%)              | 0.042  | 11   |
| 6      | Return period of 24 month extreme drought          | 0.065  | 6    |
| 7      | Return period of 12 month extreme drought          | 0.050  | 10   |
| 8      | Return period of 3 month extreme drought           | 0.041  | 12   |
| 9      | Critical rainfall                                   | 0.050  | 9    |
| 10     | Temperature trend                                   | 0.161  | 2    |
| 11     | Wet-day freq                                        | 0.053  | 8    |
| 12     | Evaporation                                         | 0.112  | 4    |

Table 8. The resulting weights are based on the principal eigenvector of the decision matrix.

| Parameters | 1 | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  | 11  | 12  |
|------------|---|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1          | 1 | 0.5 | 3   | 2   | 2   | 1   | 2   | 2   | 3   | 0.25| 2   | 4   |
| 2          | 2 | 1   | 3   | 3   | 3   | 3   | 4   | 4   | 2   | 2   | 1   | 3   |
| 3          | 0.33| 0.33| 1   | 3   | 2   | 2   | 3   | 3   | 0.5 | 0.33| 2   | 0.33|
| 4          | 0.5 | 0.33| 0.33| 1   | 1   | 1   | 1   | 1   | 0.33| 2   | 1   |     |
| 5          | 0.5 | 0.33| 0.5 | 1   | 1   | 0.5 | 0.5 | 1   | 1   | 0.33| 1   | 0.5 |
| 6          | 1  | 0.33| 0.5 | 1   | 2   | 1   | 2   | 2   | 0.33| 1   | 0.5 |
| 7          | 0.5 | 0.25| 0.33| 1   | 2   | 0.5 | 1   | 1   | 2   | 0.5 | 1   | 0.33|
| 8          | 0.5 | 0.25| 0.33| 1   | 1   | 0.5 | 1   | 1   | 0.33| 1   | 0.33|
| 9          | 0.33| 0.5 | 2   | 1   | 1   | 0.5 | 0.5 | 1   | 1   | 0.33| 0.5 | 0.5 |
| 10         | 4  | 0.5 | 3   | 3   | 3   | 3   | 2   | 3   | 3   | 1   | 4   | 1   |
| 11         | 0.5 | 1   | 0.5 | 0.5 | 1   | 1   | 1   | 1   | 2   | 0.25| 1   | 0.2 |
| 12         | 0.25| 0.33| 3   | 1   | 2   | 2   | 3   | 3   | 2   | 1   | 5   | 1   |

\[ MAE = \frac{1}{N} \sum_{i=1}^{n} \left| V_{\text{predict}} - V_{\text{observe}} \right| \] (21)
### Table 9. Resulting weights for the criteria based on your pair-wise comparison.

| Sl. No | Variables                              | Weight | Rank |
|--------|----------------------------------------|--------|------|
| 1      | Cropping intensity                     | 0.132  | 2    |
| 2      | Irrigation intensity                   | 0.073  | 6    |
| 3      | Total water use                        | 0.045  | 10   |
| 4      | Water demand                           | 0.06   | 7    |
| 5      | Net water availability                 | 0.185  | 1    |
| 6      | Total ground water resource            | 0.115  | 4    |
| 7      | Gross irrigated area                   | 0.094  | 5    |
| 8      | Population density                     | 0.123  | 3    |
| 9      | Health index                           | 0.028  | 12   |
| 10     | Income Index                           | 0.055  | 8    |
| 11     | Education Index                        | 0.038  | 11   |
| 12     | % of small and marginal farmers to total worker | 0.051 | 9    |

### Table 10. The resulting weights are based on the principal eigenvector of the decision matrix.

| Parameters | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|------------|---|---|---|---|---|---|---|---|---|----|----|----|
| 1          | 1 | 2 | 3 | 3 | 0.33| 1 | 3 | 2 | 4 | 2  | 2  | 3  |
| 2          | 0.5| 1  | 3 | 2 | 0.33| 0.33| 0.33| 0.5| 0.33| 3  | 1  | 2  | 0.5|
| 3          | 0.33| 0.33| 1 | 1 | 0.33| 0.33| 0.33| 0.33| 0.33| 2  | 2  | 3  | 3  |
| 4          | 0.33| 0.5 | 1 | 1 | 0.33| 0.33| 0.33| 0.33| 0.33| 2  | 2  | 3  | 3  |
| 5          | 3  | 3  | 3  | 3 | 1 | 2 | 2 | 3 | 3  | 3  | 4  | 3  | 3  |
| 6          | 1  | 3  | 3  | 3 | 0.5 | 1 | 2 | 0.5 | 3 | 2  | 3  | 3  | 2  |
| 7          | 0.33| 3  | 2  | 3 | 0.5 | 0.5 | 0.5 | 1  | 0.33| 2  | 3  | 3  | 2  |
| 8          | 0.5 | 2  | 3  | 3 | 0.33| 2 | 3 | 1 | 3  | 3  | 3  | 1  | 3  |
| 9          | 0.25| 0.33| 0.33| 0.33| 0.5 | 0.33| 0.33| 0.5 | 0.33| 1  | 0.33| 0.33| 0.5 |
| 10         | 0.5 | 0.33| 1  | 0.5 | 0.33| 0.5 | 0.33| 0.33| 3  | 1  | 2  | 3  | 3  |
| 11         | 0.5 | 0.5 | 0.5 | 0.33| 0.25| 0.33| 0.33| 0.33| 3  | 0.5 | 1  | 1  | 1  |
| 12         | 0.33| 1  | 2  | 0.33| 0.33| 0.33| 0.5 | 0.5 | 1  | 2  | 0.33| 1  | 1  |

1 = Cropping intensity, 2 = Irrigation intensity, 3 = Total water use, 4 = Water demand, 5 = Net water availability, 6 = Total ground water resource, 7 = Gross irrigated area, 8 = Population density, 9 = Health index, 10 = Income Index, 11 = Education Index, 12 = % of small and marginal farmers to total worker.

### 3. Results

#### 3.1. Physical drought vulnerability mapping

The physical drought vulnerability map (Figure 6) depicts that in the western part of the study region nearly 35.08% (54,653.16 km²) area is fallen under the high to very-high drought vulnerable category. The western parts of Odisha are characterized by low precipitation, high temperature, and high evaporation (The Hindu 2018). Moderate drought vulnerable zone comprises about 12.18% (18,965.11 km²) area in mainly south eastern part and also some isolated patches of these categories are found in the eastern and northern part of this region. Whereas, areas with low to very-low vulnerability cover 52.72% (82,088.73 km²) area in northeastern and southern part of the study region (Table 11). The north-eastern and southern parts of the study area are mainly characterized by high precipitation, low temperature, and low evaporation as compared to the western part.
3.2. Socio-economic drought vulnerability mapping

The produced socio-economic drought map (Figure 7) reveals that very high and high vulnerable areas occupy approximately 6.11% (9509.03 km\(^2\)) and 25% (40,296.97 km\(^2\)) of Odisha, respectively. The moderately vulnerable zone covers approximately 23.18% (36,092.88 km\(^2\)) of the study region. Near about 31.67% (49,313.96 km\(^2\)) and 13.16% (20,484.81 km\(^2\)) area is fallen under the low and very-low drought vulnerable zone mainly in the southern, southeastern, northwestern and northern part (Table 12). Except for the very-low and Low vulnerable zones, other three categories are spread all over the region haphazardly.

3.3. Overall drought vulnerability

After combining the physical and socio-economic drought vulnerability maps overall drought vulnerability map was prepared. In the drought vulnerability map (Figure 8) it is found that 15.87% (25,956.36 km\(^2\)) and 18.07% (28,136.25 km\(^2\)) of the study area comes under very high and high vulnerable zones, respectively. These two zones mainly cover the extreme western part of the region (Outlook 2018). The moderately vulnerable zone comprises 12.73% (18,575.85 km\(^2\)) of the study region; mainly a narrow stripe in the central part and an isolated pocket in the north eastern portion are fallen under this zone. 27.00% (42,040.89 km\(^2\)) and 26.33% (40,997.65 km\(^2\)) in the
eastern and southern part has fallen under the low and very-low vulnerable category, respectively (Table 13). In general, almost the entire region can be considered as a drought-prone area, but the western part is highly vulnerable to drought.

### 3.4. Validation of drought vulnerability assessment

Without validation through reliable statistical measures, it is not justified to say the model is good. In this analysis through the ROC, MAE, RMSE and accuracy measures the effectiveness of drought vulnerability map has been assessed. The AUC value of 0.843 suggests that a drought vulnerability map produced by Fuzzy-AHP is very accurate and its prediction accuracy is 84.3% (Figure 9). The values of RMSE and MAE are 0.315 and 0.467, respectively. The accuracy value of our model is 0.774. From the calculated AUC, RMSE, MAE and accuracy value of our model, it can be said that, the employed model is reliable and suitable for assessing the drought vulnerability of a region.

### 4. Discussion

Significant amount of the researches have been conducted regarding the drought prediction and susceptibility (Sheffield and Wood 2008; Gidey et al. 2018; Spinoni et al. 2018; Al Adaileh et al. 2019; Ghosh 2019; Hoque et al. 2020; Quenum et al. 2019; Bhunia et al. 2020). Drought mitigation and policy development studies for India have been done by various scientists (Bandyopadhyay et al. 2020; Gupta et al. 2020). Whereas drought vulnerability assessment considering a wide range of physical and socio-economic parameters are not in practice. The study has been conducted in the state of Odisha, where drought is a major threat (The Hindu 2018; Sam et al. 2020). Here, droughts have been assessed based on two types of parameters – physical and socio-economic where physical parameters are used to find out the drought-prone regions and socio-economic parameters are applied to portray the probable damage due to drought. If in any place drought occurs due to physical parameters, then what will be its impact on the socio-economic condition of that region has been the prime aim of this study. To perform this study, a wide range of physical and socio-economic parameters (twelve for each) have been taken so that all the probable avenues of drought can be covered. The consideration of SPI based drought is well practiced, and it has been used for both analysis and prediction of drought (Karimi et al. 2019; Kalisa et al. 2020). The parameters have been selected based on the previous literatures and its assessment has been done using well-appreciated MCDM techniques like fuzzy and AHP. Although there are some limitations of AHP like it cannot deal with the non-straight models and it does not consider the uncertainty (Karthikeyan et al. 2019).

### Table 11. Area under different physical drought vulnerability zones.

| Physical drought vulnerability classes | % of area | Actual area in km² |
|---------------------------------------|-----------|---------------------|
| Very high                             | 18.52     | 30,394.01           |
| High                                 | 16.58     | 24,259.15           |
| Moderate                              | 12.18     | 18,965.11           |
| Low                                   | 28.91     | 45,014.89           |
| Very low                              | 23.81     | 37,073.84           |
It is mainly over-dependent on decision maker’s choice which makes the ranks biased. In spite of that it is able to assess the priority value of the factors quite efficiently. Fuzzy AHP is a synthetic expansion of the traditional AHP system where the fuzziness of decision-makers is considered. Fuzzy logic can be regarded as a precise logic of imprecision and uncertainty. Fuzzification of the parameters has been done based on their relevance to drought occurrence and impacts and AHP gives the necessary weights to the parameters. Combination of fuzzy logic and AHP have helped to increase the accuracy of the drought vulnerability model. After preparing the drought vulnerability maps of these two categories with the help of F-AHP method, a general overlay has been done to prepare the combined drought vulnerability map for the entire Odisha state. The parameterization is unique, which covers almost each and every possible facet of droughts so that a holistic view of drought scenario can be presented in front of the planners and strategy developers. This work

Figure 7. Socio-economic drought vulnerability map of study area.

Table 12. Area under different socio-economic drought vulnerability zone.

| Socio-economic vulnerability | % of area | Actual area in km² |
|------------------------------|-----------|--------------------|
| Very high                    | 6.11      | 9513.70            |
| High                         | 25.88     | 40,296.97          |
| Moderate                     | 23.18     | 36,092.88          |
| Low                          | 31.67     | 49,312.41          |
| Very Low                     | 13.16     | 20,491.04          |
will surely help to formulate drought alleviation strategies in Odisha and will guide the future drought research especially from the perspective of strategy development.

Therefore, three maps have been prepared - overall drought vulnerability map, physical and socio-economic parameter based drought vulnerability maps which are classified into five categories using Jenks (1967) natural break method (Figures 6–8). According to the classification, the north-western parts of the state (15.87%) have very high vulnerability to drought mainly because of increasing temperature, decreasing rainfall, high frequency of extreme drought, low water availability, low groundwater, high evaporation and high demand of water. On the other hand, the eastern part of the state has very-low vulnerability to drought as it is located in the coastal belt of Bay of Bengal.

The large number of climate-change-impact studies, often referred to as first-generation vulnerability assessment (Füssel and Klein 2006; Raut et al. 2020) was carried out considering socio-economic characteristics and climatic conditions through the

![Overall drought vulnerability map of study area.](image)

**Table 13. Area under different overall drought vulnerability zone.**

| Drought vulnerability class | % of area | Actual area in km² |
|----------------------------|-----------|--------------------|
| Very Low                   | 26.33     | 40,997.65          |
| Low                        | 27.00     | 42,040.89          |
| Moderate                   | 12.73     | 18,575.85          |
| High                       | 18.07     | 28,136.25          |
| Very High                  | 15.87     | 25,956.36          |
use of a composite index to understand socio-economic vulnerability to climate change. Vulnerability determinants are necessarily dynamic, and vary according to stimulus consideration and locations system-specific (Smit and Wandel 2006). There were few attempts (viz., Raja et al. 2014; Panda 2017) to assess the drought of Odisha where 50% of the state is drought prone (DH (Deccanherald) 2019). Therefore, we need to strengthen our awareness of the possibility of drought in this region where population growth and agricultural activities are rapidly increasing. Nonetheless, the characterization of drought, which enables operations such as early alert of drought (Kogan 2000) and risk mitigation of drought, which allows for better readiness and disaster planning (Hayes et al. 2004), is important for a region’s comprehensive evaluation of drought.

The profile of livelihoods among farmers in the study region, as a drought-prone and economically backward zone, revealed that income-diversification activities were restricted to non-farm operations, small business and agricultural labour. Farmers recorded lack of availability of non-farm sources of income and thus a large number of households are heavily dependent on agriculture and related activities for their livelihood. In drought vulnerable areas, socio-economic conditions (e.g. income, health, and education index) are in the most vulnerable situation, as our study confirmed with the similar findings of Eklund and Seaquist (2015) carried out in Duhok Governorate, Iraqi Kurdistan region. Physical drought vulnerability indices (viz. annual rainfall, evaporation trend, rainfall trend, drought intensity, and temperature trend) regulate the overall drought vulnerability in this study area as like the work Ghosh (2019), Hoque et al. (2020). In drought prone areas cropping intensity as well as agricultural production (Raja et al. 2014) is very-low that severely affects farmer’s income (Panda 2016). Fuzzy-AHP, a semi-quantitative method used in this study,
provided good accurateness of the vulnerability model. In this regard, delineation of potential rainwater harvesting site, potential artificial groundwater recharge sites and integration with the drainage and canal networks will not only help for managing the water demand and groundwater table but also drought vulnerability condition of the study area. The agricultural insurance has been recognized as one of the important measures for farmers to insure them in case of unexpected crop failure and increasing their adaptive capacity (Panda et al. 2013). In the future, there are scopes for further inclusion of parameters and indices which can portray the drought vulnerability more precisely. There is continuous advancement of drought predicting techniques, and scholars can follow this work and make it better with their additional inputs (Dikshit et al. 2020c). The accuracy of the models can be further increased with more ground level data. However, such work will help the urban planners; especially agricultural planners for taking the suitable strategies in the highly drought vulnerable area.

5. Conclusion

In this study, Fuzzy-AHP, a multi-criteria approach was used to assess the drought vulnerability condition of Odisha. The drought vulnerability map was authenticated by using ROC, accuracy, RMSE and MAE methods employing validation datasets. The overall drought vulnerability map revealed the Bargarh, Balangir, Deogarh, Jharsuguda, Kalahandi, Nabarangapur, Nuapara, Sambalpur and Sudargarh districts have very high to high drought vulnerability. Spatial drought vulnerability map provides geographic bases for the identification of vulnerable hotspots on a sub-state scale. Such type of vulnerability map is very important particularly in India where a large portion of population depends on agriculture. It also encourages decision makers to offer priority to adaptive and reactive agricultural adaptation policies in response to drought. The method that was applied here can be used to forecast vulnerability under potential climate change scenarios and evaluate the long-term impacts of droughts agriculture. As the agricultural sector is mainly affected by the drought so, it is important to formulate robust strategies by the policy makers for the farmers by strategies such as land-use change to grow the most drought-resistant crops and varieties, sufficient water facilities to combat water shortage. The limitation of our study is that the authentication of the outcomes of our study has been done collecting the information published in different reports instead of using direct field data due to time constrain and lack of funding. However, such shortcoming does not reduce the accuracy of the develop model. However, this work will be helpful in taking drought management schemes. This validated mapping approach may also be applied in other areas to assess spatial drought vulnerability by altering the parameters and associated datasets.

Disclosure statement

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Data availability statement

Raw data were generated at University of Gour Banga, India. Derived data supporting the findings of this study are available from the corresponding author [B.P.] on request.

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