ANALYSING FLOOD RISK ZONATION USING ANALYTICAL HIERARCHY PROCESS (AHP) IN BHAGIRATHI BASIN, INDIA

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in

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I hereby declare that this thesis contains literature survey and original research work by the undersigned candidate, as part of my Master of Engineering degree in Water Resources & Hydraulic Engineering, Jadavpur University during the academic session 2020-22.

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Abstract

Flood is a very commonly occurring disaster in Bhagirathi Basin. As a result, many people lost their life & properties. Proper flood control management is required to get out of this problem. It is not possible to fully control the flood damages. But by taking some physical measures, it is possible to prevent the flood damage to some extent. Identification of flood zone is very much essential for this reason. So, flood vulnerability and risk assessment are crucial strategies. Some physical and social parameters are selected to calculate. Those parameters are most influential during the flood. To evaluate flood vulnerability and risk zonation Analytical Hierarchy Process has been used, which is a beneficial process for evaluating flood risk zonation. So, the objective of this study is to assess flood risk zonation using the analytical hierarchy process in the GIS framework. The parameters considered for flood hazard are Drainage Density, Distance from River, Elevation, Slope, Topographical wetness Index, Modified Normalized Difference Water Index (MNDWI), Roughness, Rainfall, Modified Fournier Index (MFI), Normalized Difference Vegetation Index (NDVI), Soil and Sediment Transport Index (STI). And the parameters taken for Vulnerability Assessments are Total Population, Child population Under six years of age, Total female population, Distance from flood centre, Land Use Land Cover (LULC), Distance from Hospital, Distance from Road, Road Density, Illiteracy Rate and Employment Rate. The map has been prepared for each parameter, and a pairwise comparison matrix is prepared to calculate the weightage value for each parameter, which is applied in the AHP process. The result of this analysis shows that lower region of the basin is most susceptible, vulnerable and risk zoning area, due to low range value of distance from river and high value of drainage density. All most 60% area of the lower region is highly flood susceptible, 40% are flood vulnerable and almost 25% are risk zoning area. So, in future this study will help to build and implement various Government policies during flood.

Keywords: Flood; Analytical hierarchy process; Hazard; Vulnerability; Risk

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1 Introduction

Floods are natural disasters often caused by heavy rains and excessive river flow, accumulation of water in low lying areas, and they become disasters when they cause significant loss of life and property. In monsoon tropical and subtropical regions, floods are the most damaging, widespread, and frequent natural disasters (Sanyal and Lu 2006; Islam and Dharanirajan 2017). Flooding currently affects around 21 million people worldwide and this number is estimated to increase to 54 million by 2030 (Kazakis et al. 2015). Climate change has accelerated the pace of flooding in riparian regions across the world during the last three or four decades, owing to growing human strain on riparian zones (Kourgialas and Karatzas 2011). The prevalence of flooding in developing countries in Southeast Asia is more than 80% due to monsoons. Flooding affects about 13 million people each year, mainly in India, Bangladesh, China, Indonesia, Myanmar and other countries (Sanyal and Lu 2004). Climate change, population growth in riverine areas, messy and unscientific construction, depletion of the water storage capacity of rivers, lack of dredging and scientific river management are all factors. causing flooding (Ghosh and Kar 2018; Chakraborty and Mukhopadhyay 2019). Due to this circumstance, Asian countries have previously reported that they suffer more than 85% of disasters and disasters each year, with about 90% of the population dying. Floods are natural disasters that cannot be completely avoided. However, scientific processes can help reduce the amount of damage (Ali et al. 2019; Rahman et al. 2019; Vignesh et al. year 2021). Risk is based on the idea of minimizing damage to an area by determining the extent of flooding. The risk factor, random, works by detecting flood-prone locations and devising precise river management methods based on local climate, precipitation, flows, and topography (Danumah et al. 2016; Baky et al. 2020; Dandapat and Panda 2017; Xiao et al. 2017; Sar et al. 2015). The storm hazard map is designed to help people prepare for impending flooding and minimize flood damage (Ouma and Tateishi 2014; Elsheikh et al 2015; Chen et al 2011; Sinha et al. 2008). The susceptibility of flood prone locations is illustrated and the hazard should include locations beyond it. However, there is no physical separation between the two locations and the terrains are identical. Usually, flood extent and volume are determined according to their sensitivity and hazard (An et al. 2021; de Brito et al. 2018). Tingsanchali and Karim (2005) investigated food hazards, vulnerabilities and risks in the Southwestern region of Bangladesh. However, they made the mistake of assuming that vulnerability is proportional to population density, which does not accurately represent dietary damage data, casting doubt on vulnerability outcomes. and risks. The vulnerability measurement strategy must first address the risk factors and then estimate the damage function. In addition, flood-affected areas around the world, especially Southeast Asian countries, are now implementing low-cost, long-term river management systems based on risk assessment methodologies, rather than the conventional flood control strategy of constructing various structures (Stefanidis and Stathis 2013; Khosravi et al. 2016; Das 2018).

Recently, some milestones have been seen in food risk and susceptibility studies, but not in food risk studies. It is becoming more common to use hydraulic models to assess food safety. For example, Affetal. (2019), Zinetal. (2018) and Tyrna et al. (2018) and various hydrodynamic models are used to study the dangers of food. At the same time, priority is given to land use and community-based research on food vulnerability. The study by Masood and Takeuchi (2012b) is comprehensive and provides a clear approach for conducting food risk assessments. This study shows the application of a one-dimensional hydraulic model for hazard assessment, land use analysis for vulnerability assessment, and final determination of food risk from hazards and vulnerabilities. Expert-based models include frequency ratio (FR) (Sarkar and Mondal 2020), information value (IV) (Ul Moazzam et al. 2020), certainty factor (CF) (Cao et al. 2020), and logical regression. (LR) is included.) (Fustos et al. 2017), Weight of Evidence (WOE) (Tehrany et al. 2017), Fuzzy Logic (Perera and Lahat 2015), Neuro fuzzy Logic (K Hydrological Engineering Center, etc. Hydrological Models-River Analysis System HEC-RAS (Namara et al. 2021) and soil water assessment tools (SWAT) (Nasir et al. 2020) are also used to determine flood vulnerability. Analytical Hierarchy Process (AHP) as a knowledge-based expert model (Hammami et al. 2019; Goumrasa et al. 2021) is one such methodology among Flood vulnerability and risk mapping or research have been carried out in various parts of the world by following multiple statistical methods. he reason is that the AHP model can be used quickly and it can be used to provide a realistic picture of inundation in any location. The size and extent of a flood anywhere is expressed in multidimensional terms, and the idea of risk is easily conveyed by disasters (Kittipongvises et al. 2020; Ghezelsofloo and Hajibigloo 2020; Dung and associates 2020). The idea of flood risk in an area based on a number of interrelated spaces in the process of social, economic and geographical continuum, is easily expressed through the AHP (Seejata) model. et al. 2018 Wubalem et al. Year 2020). It is now much easier to identify flood hazards and vulnerable areas using the widespread use of analytical tools in GIS. GIS detects floodplains by helping to make decisions about specific parameters, as well as identifying and predicting future floodplains (Dash and Sar 2020; Hategekimana et al. 2018). The efficiency and effectiveness of the AHP model are significantly enhanced when used together with GIS (Souissi et al. 2020; Goumrasa et al. 2021; Hammami et al. 2019; Allafta and Opp 2021; Franci et al. 2016). Furthermore, it was found that the combination of AHP model with GIS can make good predictions and quickly identify locations prone to future flooding in many cases (Akay 2021; Tella et al. Balogun 2020).

India has a monsoon climate, which not only affects the social, economic and geographical sectors of the nation, but also plays an important role in flood control. Flood prone areas of the Ganges Delta in north and northeast India include West Bengal, Bihar, Assam, Uttar Pradesh and Orissa (Dhar and Nandargi 2003; Sahoo and Sreeja 2015). In addition, floods have submerged more than 3.3 million hectares of Indian land in Maharashtra and Gujarat in western India, as well as several flooded districts in Tamil Nadu and Karnataka in the south (Patel et al. 2017). The floodplains of India are the Bhagirathi-Hooghly basins in the South Bengal floodplains of eastern India and the Ganges delta. Every year, floods claim the lives and livelihoods of about 3.5 to 4 lakh people. The Bhagirathi-Hooghly River flows through West Bengal, India, and is recognized as an important tributary of the Ganges. It splits from the Ganges in the Mithipur block of Murshidabad district and empties into the Bay of Bengal, including Kolkata (Ghosh et al. 2020). (Ghosh et al. 2020). This river system is known as the lifeline of West Bengal and it played an important role in the development of irrigation, industrialization and human settlement. However, as the water flow of the main river has decreased gradually over time, tributaries of the Chhotanagpur Plateau such as the Ajay and Damodar have concentrated a lot of material and deposited them in the Bhagirathi-Hooghly River. In addition, the river's traffic capacity has been severely reduced due to unscientific dredging and the continued encroachment of urban structures.

On the other hand, the lower part of the Bhagirathi-Hooghly Basin is socially and economically developed and overpopulated in terms of agrarian economy, industrialization and communication systems. Due to its high rice production, the region is known as the granary of West Bengal. Severe floods occur every year during the monsoon season, disrupting the daily lives of local people and destroying crops, causing them to suffer economic losses afterwards (Sanyal and Lu 2005; 2006; Jha and Bairagya 2013; Mujiburrehman 2015; Ghosh and Kar 2018). In addition, for most of the year, much of the area is flooded by floodwaters, making life in the floodplains uninhabitable. Flood risk and sensitive areas should be identified to ensure the location of flood risk areas to minimize flood-related hardship. Accordingly, the current literature uses spatial change-based mapping to assess flood severity, disaster and risk such as hazard and disaster in the Bhagirathi basin to identify locations prone to future flooding. and prioritize flood management strategies. Food risk factors will be disaggregated into seven data-based areas: hydrological and hydrogeological characteristics, geomorphological characteristics, meteorological characteristics, cover characteristics, soil characteristics, and infrastructure. strata and socioeconomic characteristics. The purpose of this article is to review, analyze, evaluate and synthesize the causative factors of food and their influence into a unified whole, as well as to make recommendations on the causative factors of food. Factors contributing to food production according to socio-economic characteristics of each type. Land. These results are very useful for future studies on determining criteria and calculating their weight in food hazard partitioning by AHP method in different fields, especially for sparse data.

1.1 Objective

The objective of the present study is:

1. To analyses the severity, catastrophe and risk levels of floods as a hazard and disaster along the Bhagirathi basin with the help of mapping based on spatial changes to identify flood-prone areas in the future and prioritize flood management policy.
2. To identifies the parameters that help in the occurrence of floods and increase their severity and then reviews them geographically according to their significance and importance.

2 Literature Review

[Abah and Clemate, 2013]

Flood is a natural disaster that causes significant damage, disrupts daily life and poses human, social, economic and environmental risks. Inundation is defined as an increase in water levels in coastal areas, reservoirs, streams and canals. Floods injured more than 350 million people worldwide. Flood damage is expected to increase by 2050. It is one of the most dangerous environmental risks to society, and it has piqued the curiosity of many researchers who want to know. more about the growing consequences of environmental change. The growing population along with the accumulation of assets in densely populated areas increases the risk of flooding. Floods will have a bigger impact in the future as the population increases.

[Rehman et al., 2019]

The impact on people living nearly 100 kilometers from the coast is expected to be significantly greater by 2030. Many issues are related to climate change and the impact of human activities on the climate. global has arisen after recent floods. Flooding is expected to become more frequent as the population grows. The valuable surface has been turned into a waterlogged area due to population growth, leading to increased erosion, natural precipitation, and flooding. In recent years, the average flood damage has increased to more than fifty billion dollars. According to the study, the number of floods increased from 2010 to 2013, 2014, 2015, 2017, 2018 and 2019.

In 2000, 2007, 2014 and 2015, floods affected a large number of people. Between 2010 and 2020, about 3.6 billion people, or 56% of the world's population, were flooded. About 820,000 people in South and North America alone were affected by floods between 2010 and 2020. Catastrophic floods in the LDCs have created terrible conditions leading to enormous human suffering, massive loss of ancillary structures, life-threatening hazards and commercial development.

[Kourgialas and Karatzas 2011]

From last three to four decades, worldwide rate of flooding increases due to climate change and increase in population. The prevalence of flooding in emerging Southeast Asia is more than 80% due to monsoons.

[Chakraborty and Mukhopadhyay 2019]

Climate change, population growth in riparian areas, unregulated and unscientific development, depletion of river water capacity, lack of dredging and scientific management of rivers are all factors that cause flooding. The food risk analysis in this study focused on the basic characteristics of hazard intensity and food susceptibility, which were found to ultimately affect the spatial distribution of food risk. As a result, all three key food management inputs: food risk, vulnerability, and hazard are thoroughly analyzed and mapped, providing decision-making systems with ready-to-use tools for tracking disasters. It is trusted because it is properly validated and can be used to identify key areas of priority when developing mitigation and response plans.

Since this study is based on a wide range of efficient criteria derived from multiple research efforts in different parts of the world, this data-poor region direct document presented before the larger scientific forums. Can be considered as. The efficiency of AHP-GIS binding has proven to be high again and can be recommended as a reliable method of food risk assessment, especially in areas with low data. In this food-sensitive area, more research is undoubtedly needed to better understand the nature, timing, causes and nature of the hydrological systems of the major rivers that flow through it.

[Abu Reza Md. Towfiqul Islam et al., 2020]

For the first time, this study used two new hybrid ensemble models, Dagging and RS, and three benchmark models such as ANN, RF, and SVM to estimate flood vulnerability mapping in the Teesta River basin in Bangladesh (north). did. In this study, a total of 413 flood sites were selected, with 12 parameters affecting the flood, including Elevation, slope, curvature, aspect, SPI, TWI, STI, LULC, precipitation, distance to river, TWI, and soil type. The relevance of flood control parameters was evaluated using the IGR approach, Multicollinearity Diagnostic Test (VIF), and Pearson Correlation Matrix. The impact of flood control parameters was assessed using a feature selection approach such as: B. Evaluated information acquisition rate. Based on the training and validation dataset, we used the Friedman test, Wilcoxon signed rank test, T-pair test, and RoC curve to validate the flood-prone model. Depending on the use of the ROC curve in the result validation phase, the daggering model shows maximum efficiency compared to other models (AUC = 0.863-training phase; AUC = 0.873-validation phase). However, all models worked well when mapping flood vulnerabilities. According to the conclusions of the study, daggering is one of the most powerful tools for modeling flood risk. According to the best model, a total area of 29.62% is at high risk of flooding. However, some factors such as SPI and land use are so dynamic that the implementation of these models does not take into account the changes in these factors over time. Future research on these aspects will be based on the availability of temporal information.

[Abhishek Ghosh et al, 2018]

This study uses multi-criteria statistical techniques to quantitatively investigate the key components and triggering mechanisms underlying flood risk and vulnerability. Floodplains have had a significant impact on the floodplains of the lower Ganges over time. The devastation caused by floods emphasized the importance of risk assessment to gain better knowledge of the factors that create flood hazards. This study shows how an analytic hierarchy process (AHP) -based flood risk assessment approach can improve existing risk assessment approaches. This article also recommends using AHP-led weights to assess flood risk and vulnerability and incorporating socio-economic factors along with physical factors. This study attempts to reasonably combine geomorphological and hydrological factors with the intensity of flood risk and demographic, socio-economic and infrastructure factors with the degree of vulnerability. Both are needed to create risk intensity classes that help identify effective planning and security action priorities.

The results clearly show that the flat and less active lowland areas are mainly at risk due to the high probability of flood risk and the concentration of population, agricultural expansion, and insufficient resilience to hazardous situations, covering almost the entire Northwest and Southwest parts of the district. Accordingly, the study's findings could be useful in identifying resilience building factors, which can then be taken into account in future flood risk management planning options. Furthermore, this type of study can be carried out at the district and watershed levels, allowing for a more complete risk map and a better assessment of riparian flood risk.

[Dhekra Souissi et al, 2018]

Floods are classified as major natural disasters due to their devastating level, causing many socio-economic losses. The objective of this project was to create a flood risk sensitivity map for the Gabès region using a "multi-criteria decision-making process" model in a geographic information system. Elevation, land use/land cover, lithology, rainfall intensity, drainage density, distance from the drainage network, slope, and groundwater depth are all used in the flood simulation. Weights were used to analyze the effect of each flood risk contributor using a hierarchical analytical process approach. The results show that elevation (22.5%) is the most important factor of flooding, about 15% of the entire area is flooded and the equivalent flood hazard index is 6.30. The results were confirmed using the sensitive zone histogram, which showed that 74.51% of the measured floodplains were mostly in the moderate to extreme sensitive zone.

[Yared Abayneh Abebe et al, 2018]

Disaster risk reduction is an important issue for small island developing governments, as discussed in this article. Risk mitigation measures are based not only on the magnitude of the physical hazard, but also on the exposure and susceptibility of the community. Flood risk management practices on Sint Maarten, a Caribbean Island, were studied using a combination of flood and agent models. Agent-based modeling is used to simulate the behavior of actors in urban planning and policy in order to reduce flood risk, vulnerability, and community exposure. Flood patterns are influenced by the behavior of actors such as the construction of new buildings and the adoption of risk mitigation measures, as these actions alter the course of stormwater runoff. Then, flood maps from the modified flood model simulations will be used to analyze the impact and modify the characteristics and behavior of the actors. The results of the simulations show that the lowlands are densely populated, which increases the vulnerability and the number of sensitive settlements is also large. The implementation of risk mitigation measures is therefore the most important of the four policies. Flood risks can be minimized by widening existing drainage channels, developing new channels and embanking levees to protect against coastal flooding, which will reduce the number of houses inundated. The Building and Housing Ordinance is an important policy to reduce vulnerability as it impacts all families on the island. Overall, the combined model's results can be used to guide policy decisions and provide insight to island leaders.

[Ratan Kumar Samanta et al, 2018]

Flood sensitivity mapping is essential for long-term and appropriate management of urban hydrology. In the FR model, a GIS-based BSA was used to quantify the relationship between flooding and the categories of each harmonic factor. To provide a more accurate assessment of flood susceptibility maps of the lower and middle Subarnarekha River basins, the FR model was applied using two-variable probability-weighted and classified independent variables. (India). Quantitative methods were used to rank each variable, and FR probabilistic models were used to evaluate the association between each class with flood occurrences. Finally, flood susceptibility maps are generated and grouped into four categories: very low, low, medium, high and very high. The results of the developed model were evaluated using ground data (30% flooded area) and area under the curve (AUC). The AUC for the calculated success rate was 84.80%, while the prediction rate was calculated as 81.20%. Researchers, planners, and local governments may find flood susceptibility maps created with FR models useful in developing methods for flood mitigation.

[Surjit Singh Saini et al, 2016]

This study described that Urban flooding is more expensive and difficult to control than rural flooding, depending on land use and the functional characteristics of buildings. Flooding is an unavoidable hazard in many Indian cities. Haryana is a state in India. Flood Risk Modeling and Flood Impacts Using Geographic Information Systems & # 40; GIS & # 41; provided to the most important area. Flood probabilities are calculated over return periods of 2, 5, 10 and 20 years using the Weibull cell location formula and the maximum possible discharge is 500, 1000, 1200 and 1500 m3 is used to predict flood levels using Hydraulics and the River Engineering Center Analytical System &; HEC-RAS &; The software is based on maximum discharge data from the Tangri River over the past 21 years. Using observed flood depth data, flood depth was estimated using spatial interpolation. According to the model results, the flooded areas are 690, 1135, 1530 and 2300 ha, respectively, and the predicted impacts on land use and population are also estimated respectively. The magnitude of the expected return of flooding in 5 years is confirmed using data from the most recent flood, including remote sensing images and field surveys, from July 2010. Accordingly, these results can be used by urban authorities, planners and local policymakers to help decision-making in risk-sensitive land use planning by including scenarios climate change to limit the negative impact of flooding in the urban environment.

[Marı´a Bermu´dez et al, 2018]

At the microscopic scale, this modeling experiment allows researchers to analyze and compare two sources of uncertainty in a flood loss model. The sensitivity of the common flood loss modeling setup to the computer grid representation of buildings in the 2D flood modeling approach, as well as the mechanism for assigning flow depth from simulation results for the specific structure. Estimates of flood damage generated by the two risk allocation systems investigated in this study vary widely. The sensitivity of the distribution method to forecasted flood damage is equivalent to the sensitivity of the vulnerability curve. The results suggest the need to include these sources of uncertainty in small-scale flood risk prediction methods.

3 Study Area

The Bhagirathi Basin covers three states – West Bengal, Jharkhand and Bihar in India (24°51'45.36"N, 87°41'0.03"E - 22°15'42.63"N, 88° 9'48.14"E in North-South and 24°27'31.15"N, 86°15'59.65"E - 23°58'32.86"N, 88°42'42.41"E) with a length of 294 km in north-south and 270 km in east west direction. The region is composed of recent Pleistocene sediments and is geologically located in the Rarh region, below the shattered delta sector of the Bengal basin (Ghosh et al. 2020). Along the river's path, the region was first covered with sand, clay, and sand. In the plain's flat area, fine silt, sandy loam, and loamy soil have all been discovered. The area experienced catastrophic floods during British rule, and subsequent floods significantly exacerbated property damage. Causes of riverbank erosion include heavy to heavy rainfall, tropical monsoon storms, invasion of river channels into urban areas, excessive sedimentation, illogical embankment construction, and civil engineering work along riverbanks. The Bhagirathi Hooghly River dominates this basin, along which tributaries such as the Khari, Jalangi and Churni rivers flow from side to side. The main river and its three tributaries form the entire catchment area of 27,000 square kilometers. Since the entire study area is a floodplain, the hydrodynamic conditions are significantly different from other areas. The problem of bank erosion is caused by the horizontal displacement of the bank, which is visible by the meandering river flow and vice versa. Other floodplain features include marshes, wide arc lakes, and shoal formations (Sanyal and Lu 2005; 2006; Jha and Bairagya 2013; Mujiburrehman 2015). Due to the area's modest slope, rainfall flows into the river fairly quickly. The region experiences 110 to 124 wet days per year, with an average annual rainfall of 1400 to 1800 mm, due to the tropical monsoon environment. Analysis of the average annual rainfall pattern from 1985 to 2020 shows that rainfall has increased significantly in recent times. The reason is that the erratic weather has significantly increased the number of cyclones and tropical depressions over the past 10 years. During the rainy season, these showers can produce between 150 and 250 mm of rain per day, rapidly raising river levels and affecting travel. The Bhagirathi Basin covers many 152 blocks spanning the 14 districts of West Bengal, Jharkhand and Bihar. Only the Chakai block in Jamui district is included in this basin. These rock formations are prone to flooding in some places and mud erosion in others. In some locations, the elevation exceeds that of the surrounding natural plain due to the embankment along the shore. However, during the monsoon period, water accumulates in the low lying areas close to the embankment in front of the river. Most mouzas along riverbanks are prone to flooding, but only when flooding occurs over a considerable distance. Sedimentation reduces river mobility, while heavy rains upstream raise water levels and cause flooding. Peak flows and river sediments developed together between 1985 and 2020, suggesting that the area has undergone significant sedimentation due to faster sediment concentrations from upstream to currents. peak flow.

In the region, flooding is more prolonged and potentially more destructive during the year when there is more rainfall, according to the comparison between precipitation and runoff data. The Indo-Bangladesh Water Treaty and the Farakka Dam are responsible for the water flow of the Bhagirathi-Hooghly River, which is decreasing day by day even though the river's origin is a tributary of the Ganges. Changes in land use are also attributed to the arbitrary and uncontrolled construction of shoreline housing and to continued urban expansion. The risk of flooding in this area may be increased due to the hasty installation of the jetty and the rampant mining of sand from the riverbed.

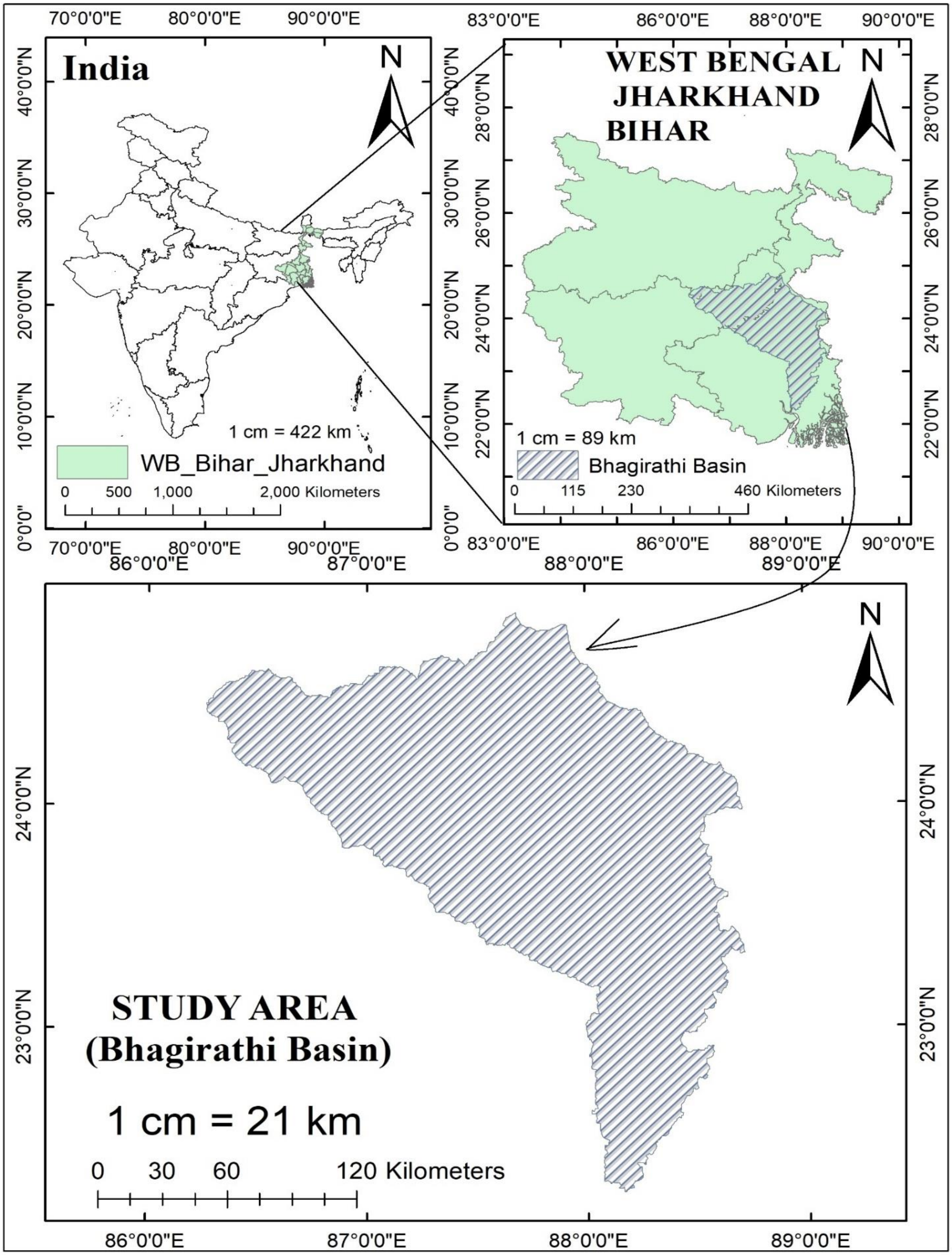


Figure 1:Location of the study

4 Data Used

The AHP model requires a lot of data that needs to be interpolated in one place to explain the dangers, vulnerabilities, and risks of floods. This is because floods provide a multidimensional view of the hydrodynamic state of the area. Using data from the District Census Handbook, vulnerability mapping requires knowledge of the region's population and its characteristics (ability to work, education and unemployment rate, total number of women and men) from District Census Handbook (2011). We collected survey responses from East Burdwan, Hooghly, and Nadia districts and created a vulnerability map. Then all the data was sorted using the attribute table created by Geospatial Mouzas. The USGS Landsat 8 OLI (Operational Land Imager), a land use and land cover map (LULC) for the pre-monsoon season (February 18, 2020), has been geo-corrected for the purpose of identifying various geographic and communication parameters. Created from. A map (path and row-138/44, cell size-30 m) was used. Additionally, the height, land slope, river flow direction, and several other hydrological characteristics of the entire area have been determined using the ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) DEM (Digital Elevation Model) (1 arc second horizontal resolution). The entire DEM was then mosaicked and the ArcGIS Hydrology toolset was used to prepare for flood hazards, vulnerabilities, and risk zoning. In the Arc-GIS v10.4.1 program, these images and base maps are projected using Universal Transverse Mercator projection using Zone 45 North (UTM 45N) and World Geodetic System Survey 1984 (WGS 1984). The images are from various sources and are not geometrically corrected for accuracy. A geometric correction with a root-mean squared error (RMSE) of ±0.5 pixels has been added to adjust the image for the image registration process. The FAO soil map was used to extract soil suitable for the current study area and its distribution. Average annual rainfall in this region was calculated using information from IMD, Pune. Vulnerability indicators, on the other hand, primarily on social, socio-economic and communicative media, as well as data and their distribution collected from specific regions. Also, collected data, including the number of floods organized from 1985 to 2020, the amount of damage and the number of affected areas, and the amount of flooded area, were collected from the District Disaster Management Plan of the Government of West Bengal.

5 Methodology

Hazard, vulnerability and risk are three general terms in flood control management in recent days. When an event hits the entire human society financially, socially and culturally and in some cases leads to the loss of human life, that situation is known as a hazard. Again, in some cases, the characteristics and conditions of human society are such that they are perceived as much more sensitive to hazards, then it turns into vulnerability. When it comes to risk management, the concept of vulnerability needs to be good because hazards often become disasters that can become vulnerable to human society. On the other hand, risk is a multidimensional trend based on social, economic, geographical, and environmental factors. However, the risk (R) is based on a combination of hazard (H) and vulnerability (V) parameters (Fig. 4) (Souissi et al. 2020; Dano 2021; Ghosh and Kar 2018; Chakraborty and Mukhopadhyay 2019; Swain et al. 2020). $R = H \times V$ (1) Discussion of flood hazards and vulnerabilities in any region is the key to knowing the flood risk of that region. However, hazard and vulnerability largely depend on certain factors, known as indicators. These indicators are used as a system to measure hazards and vulnerability on a small scale. The hazard elements can be visualized, which helps to create the material and suitable environment for disaster. Though the components of vulnerability cannot imagine, they can be felt and help increase the future range of flooding. After considering the current study area's geographical, environmental and socio-economic conditions and the literature review of various old works, 12 and 10 indicators were approved to assess the hazard and vulnerability.

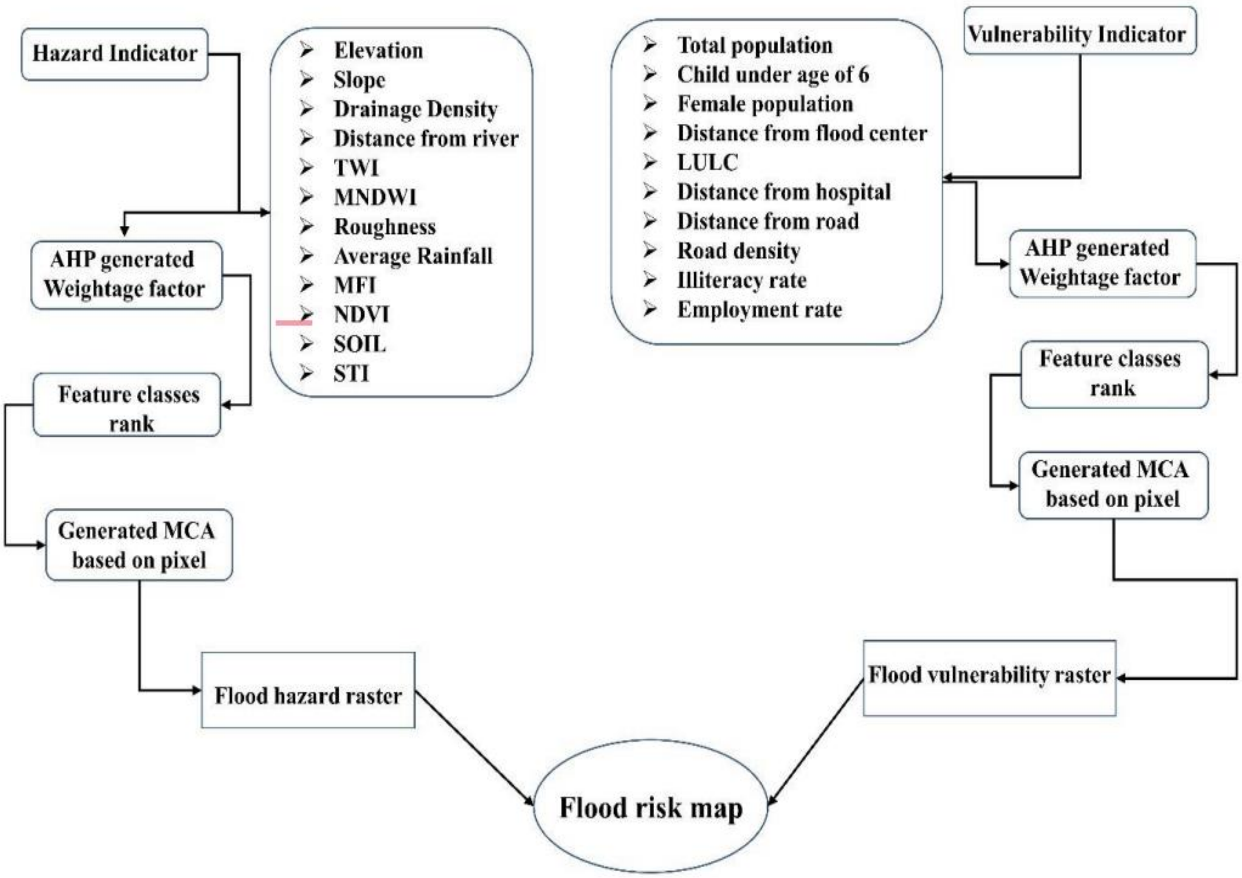


Figure 2:Methodology framework for the study

5.1 Indicator of hazard

Hazard and its derivative indicators for disaster are based on geographical and environmental factors. Also, these indicators have been used to determine the weightage, which helps create the AHP model (Table 2 and Fig. 4 a-l). These indicators are - 1. Distance from river (measured by the ring of radial buffer at intervals of 500 m from the river up to 3945 m), 2. Drainage density (measured using DEM's ArcGIS density analysis tool), 3. Elevation (based on data from ASTER-DEM 1 arc second void filled and mosaic of ArcGIS raster tools. However, being a floodplain area, the height here is much lower), 4. Slope (measured using

ArcGIS's Surface Analysis Tool based on DEM), 5. TWI or Topographical wetness index (created in Arc GIS with the help of a raster calculator based on DEM and the water flow equation), 6. MNDWI or modification of normalized difference water index and 7. Roughness (measured by DEM. Since this is a floodplain region, the roughness is much less), 8. Average rainfall (based on weather information from IMD, Pune. This region belongs to the tropical monsoon; therefore, the amount of rainfall is much higher here), 9. MFI or Modified Fournier Index (mainly used to measure rainfall intensity. During the rainy season, this region receives heavy rainfall in a brief time.), 10. NDVI or normalized difference vegetation index (LANDSAT OLI band 4 and 5) has been used to calculate NDVI, whereas bands 3 and 7 have been used to calculate MNDWI. If the value of NDVI decreases and at the same time the value of MNDWI increases, there is the possibility of flood), 11. Soil (has been extracted from the FAO soil map), 12. STI or Sediment transport index (based on unit stream-power theory and length-slope factor in the revised universal soil loss equation (RUSLE) (where the slope of the land is less than 100 m and the slope is less than 140).

A. Distance to stream:

Euclidean distance buffer tool was applied to extract the stream buffer map in ArcGIS.

Buffer

Multi-buffer ring

Path distance

The adjacent parts of the main river are more vulnerable to flood.

B. Drainage density

The drainage density is one of the primary factors that causes flood occurrence.

When the drainage density is high, the runoff rate is important, therefore, the flood hazard becomes higher.

C. Elevation:

The flooding is inversely related to the elevation.

Higher the elevation, lower the chances of occurrences of flooding, and vice versa.

D. Slope:

The slope plays a significant role in studying flood risks since it controls the velocity of water flow and the surface runoff infiltration.

Therefore, according to the classification process, the area with the lowest slope is very highly affected by floods.

No.	Class	Symbol	Description
1.	0 to 5°	A	Very gentle
2.	5° to 10°	B	Gentle
3.	10° to 15°	C	Moderate
4.	15° to 25°	D	Moderately steep
5.	25° to 35°	E	Steep
6.	>35°	F	Very steep

Slope (degrees)	Description	Groundwater potentiality
< 2	Flat	Very high
2–8	Undulating	High
8–15	Rolling	Moderate
15–30	Moderately steep	Low
30–60	Steep	Very low

E. Topographic Wetness Index (TWI):

The topographic wetness index (TWI, ln(a/tanβ)), which combines local upslope contributing area and slope, is commonly used to quantify topographic control on hydrological processes. Obviously the highest values are in channels, the lowest on ridges.

$\ln(a/\tan\beta)$

where a is the local upslope area draining through a certain point per unit contour length and tanβ is the local slope

F. Modified Normalized Difference Water Index (MNDWI):

Normalize Difference Water Index (NDWI) is use for the water bodies analysis. The index uses **Green and Near infra-red bands** of remote sensing images. The NDWI can enhance water information efficiently in most cases. It is sensitive to build-up land and result in over-estimated water bodies. The NDWI products can be used in conjunction with NDVI change products to assess context of apparent change areas.

Water bodies having low reflectance. It only reflects within visible portion of the electromagnetic spectrum. Water bodies in their liquid state are generally high reflectance on Blue (0.4 - 0.5 µm) spectrum than Green (0.5 -0.6 µm) and Red (0.6 – 0.7 µm) spectrum. Clear water having greatest reflectance in the blue portion of the visible spectrum. So, water appear blue. Turbid water has higher reflectance in visible spectrum. There is no reflection in Near Infrared (NIR) and beyond. NDWI is developed by Gao(1996) to enhance the water related features of the landscapes. This index uses the near infrared (NIR) and the Short-Wave infrared (SWIR) bands. NDWI can be calculated by following formula:

NDWI = (NIR – SWIR) / (NIR + SWIR)

For Landsat 7 data, NDWI = (Band 4 – Band 5) / (Band 4 + Band 5)

For Landsat 8 data, NDWI = (Band 5 – Band 6) / (Band 5 + Band 6)

But result appear form above formula is poor in quality. The pure water neither reflects NIR nor SWIR. The formula of NDWI then modified by Xu (2005). It uses Green and SWIR band.

MNDWI = (Green – SWIR) / (Green + SWIR)

For Landsat 7 data, NDWI = (Band 2 – Band 5) / (Band 2 + Band 5)

For Landsat 8 data, NDWI = (Band 3 – Band 6) / (Band 3 + Band 6)

Similarly, Normalize Difference Water Index (NDWI) value lies between -1 to 1. Generally, water bodies NDWI value is greater than 0.5. Vegetation has much smaller values which distinguishing vegetation from water bodies easily. Build-up features having positive values lies between 0 to 0.2.

G. Roughness:

Roughness $= \frac{(FS_{\text{mean}} - FS_{min})}{(FS_{max} - FS_{min})}$

Higher roughness implies higher surface run-off

H. Normalized Difference Vegetation Index (NDVI):

The Normalized Difference Vegetation Index (NDVI) is the most commonly used vegetation index for observe greenery globally. Other commonly used vegetation indices Enhanced Vegetation Index (EVI), Perpendicular Vegetation Index (PVI), Ration Vegetation Index (RVI).

In general, Healthy vegetation is good absorber of electromagnetic spectrum in visible reason. Chlorophyll contains in a greeneries highly absorbs Blue (0.4 - 0.5 µm) and Red (0.6 - 0.7 µm) spectrum and reflects Green (0.5 – 0.6 µm) spectrum. Therefore, our eye perceives healthy vegetation as green. Healthy plants having high reflectance in Near Infrared (NIR) between 0.7 to 1.3 µm. This is primarily due to internal structure of plant leaves. High reflectance in NIR and high absorption in Red spectrum, these two bands are used to calculate NDVI.

Class Range of NDVI:

So, following formula gives Normalized Difference Vegetation Index (NDVI).

NDVI = (NIR – Red) / (NIR + Red)

For Landsat 7 data, NDVI = (Band 4 – Band 3) / (Band 4 + Band 3)

For Landsat 8 data, NDVI = (Band 5 – Band 4) / (Band 5 + Band 4)

The NDVI value varies from -1 to 1. Higher the value of NDVI reflects high Near Infrared (NIR), means dense greenery. Generally, we obtain following result:

NDVI = -1 to -0.1 represent Water bodies

NDVI = -0.1 to 0.1 represent Barren rocks, sand, or snow

NDVI = 0.2 to 0.5 represent Shrubs and grasslands or senescing crops

NDVI = 0.6 to 1.0 represent Dense vegetation or tropical rainforest

The NDVI rate can be calculated using raster calculator in ArcGIS.

I. Sediment Transport Index (STI):

The sediment transport index (STI) described by Moore and Burch (1986).

The index combines upslope contributing area (As), under the assumption that contributing area is directly related to discharge, and slope (B).

The index is calculated as:

$$\mathrm{STI} = \left(\frac{A_s}{22.13}\right)^{0.6} \left(\frac{\sin\beta}{0.0896}\right)^{1.3}$$

Equation 1

Where As is the specific catchment area (i.e. the upslope contributing area per unit contour length) estimated using one of the available flow accumulation algorithms in the Hydrology toolbox;

B is the local slope gradient in degrees; the contributing area exponent, m, is usually set to 0.6 and the slope exponent, n, is usually set to 1.3.

Table 1: Parameter's weightage of flood susceptibility or hazard

SL NO	Parameters	AHP Weight	Class	Range	Flood Level	Area in SQKM	Area in %	Rating
1	Distance from river (km)	0.267	1	0 - 200	Very high	3568.277	12.01467	0.50
			2	201 - 500	High	5054.14	17.01768	0.26
			3	501 - 1,000	Medium	7593.496	25.56789	0.13
			4	1,001 - 2,000	Low	10281.57	34.61885	0.07
			5	2,001 - 4,603	Very Low	3201.857	10.7809	0.03
2		0.192	1	0.02 - 0.11	Very Low	246.7566	0.830849	0.05

	Drainage Density (km2/sqkm)		2	0.12 - 0.20	Low	2282.355	7.684867	0.09
			3	0.21 - 0.28	Medium	9896.515	33.32233	0.15
			4	0.29 - 0.37	High	15727.57	52.95594	0.26
			5	0.38 - 0.46	Very high	1546.149	5.206003	0.45
3	Elevation	0.123	1	0-44	Very high	16844.74	56.71767	0.42
			2	44-106	High	4738.962	15.95649	0.26
			3	106-179	Medium	3226.906	10.86527	0.16
			4	179-256	Low	3373.642	11.35934	0.10
			5	256-726	Very Low	1515.031	5.101238	0.06
4	Slope	0.122	1	0-2	Very high	16488.76	55.51904	0.44
			2	2-8	High	12145	40.89325	0.26
			3	8-15	Medium	870.9122	2.932435	0.15
			4	15-30	Low	182.9093	0.615871	0.09
			5	30-55	Very Low	11.70259	0.039404	0.05
5	TWI	0.087	1	3.10 - 5.70	Very Low	1057.195	3.559666	0.05
			2	5.71 - 7.70	Low	13363.3	44.99535	0.09
			3	7.71 - 14.90	Medium	14650.41	49.32917	0.15
			4	14.91 - 22.80	High	615.208	2.071458	0.26
			5	22.81 - 25.33	Very High	13.17516	0.044362	0.44
6	MNDWI	0.063	1	-0.72 - -0.2	Very Low	782.0262	2.633142	0.06
			2	-0.19 - -0.14	Low	5404.989	18.19901	0.10
			3	-0.13 - -0.073	Medium	7261	24.44835	0.16
			4	-0.072 - 0.062	High	7490.818	25.22216	0.26

			5	0.063 - 0.47	Very High	8760.519	29.49734	0.43
7	Roughness	0.044	1	0.11-0.24	Very high	5177.325	20.76295	0.44
			2	0.25-0.37	High	5715.598	22.92162	0.26
			3	0.38-0.48	Medium	6625.745	26.57164	0.16
			4	0.49-0.59	Low	5367.163	21.52426	0.09
			5	0.60-0.89	Very Low	2049.575	8.219536	0.06
8	Rainfall	0.028	1	1,140 - 1,262	Very Low	2094.152	7.051174	0.06
			2	1,263 - 1,383	Low	13388.27	45.07935	0.09
			3	1,384 - 1,504	Medium	10181.61	34.28228	0.16
			4	1,505 - 1,625	High	3023.667	10.18092	0.27
			5	1,626 - 1,746	Very high	1011.641	3.406276	0.43
9	MFI	0.028	1	2.33 - 14.46	Very Low	4076.419	13.72562	0.05
			2	14.47 - 26.6	Low	5617.274	18.9138	0.09
			3	26.61 - 38.73	Medium	6784.431	22.84371	0.15
			4	38.74 - 50.87	High	8281.234	27.88356	0.26
			5	50.88 - 63	Very High	4939.983	16.63331	0.44
10	NDVI	0.015	1	-0.28-0.021	Very high	483.9021	1.629336	0.42
			2	0.022-0.13	High	4548.64	15.31562	0.26
			3	0.14-0.18	Medium	11222.15	37.78584	0.16
			4	0.19-0.25	Low	9275.804	31.23235	0.10
			5	0.26-0.51	Very Low	4168.856	14.03686	0.06
11	Soil	0.015	1	Meadow Soil	Low	11862.41	39.9614	0.11

			2	Young Soil with Alluvial Deposit	High	13213.43	44.51264	0.31
			3	Loamy Soil	Moderate	4608.831	15.52596	0.58
12	STI	0.015	1	0.00 - 0.01	Very high	16403.01	55.23033	0.50
			2	0.02 - 3.69	High	13029.63	43.87188	0.26
			3	3.70 - 11.07	Medium	175.404	0.5906	0.13
			4	11.08 - 22.14	Low	41.3296	0.13916	0.07
			5	22.15 - 10,992.23	Very Low	49.90276	0.168027	0.03

5.2 Indicator of vulnerability

The vulnerability is also developed by some indicators like a hazard or other several indicators. However, the only difference is that vulnerability indicators are based on people's social, socioeconomic status, and communication systems. In the case of vulnerability like hazard, ranking is also done by creating AHP weightage (Table 2 and Fig. 5 a-j). Indicators of Vulnerability are - 1. Total Population, 2. Child under the age of 6, 3. Female population, 9. Illiteracy Rate, 10. The employment rate (prepared based on the data gathered from the district and village based census of the year 2011 for Nadia, Hooghly and East Burdwan district), 4. Distance from flood centre (Based on the information obtained from the District Disaster Management Plan of the above communities and prepared through radial ring buffer at a distance of 500 meters), The vulnerability is also developed by some indicators like a hazard or other several indicators. However, the only difference is that vulnerability indicators are based on people's social, socio-economic status, and communication systems. In the case of vulnerability like hazard, ranking is also done by creating AHP weightage (Table 2 and Fig. 5 a-j). Indicators of Vulnerability are - 1. Total Population, 2. Child under the age of 6, 3. Female population, 9. Illiteracy Rate, 10. The employment rate (prepared based on the data gathered from the district and village-based census of the year 2011 for Nadia, Hooghly and East Burdwan district), 4. Distance from flood centre (Based on the information obtained from the District Disaster Management Plan of the above commnities and prepared through radial ring buffer at a distance of 500 meters),

A. Shelters and hospitals

The availability of shelters and health-care facilities in hazard-prone areas is a vital indicator of coping capacity of a particular community.

B. Children and elderly population/dependent population

Age group of 0–14 and above 60 are generally dependent population and they are highly vulnerable to natural hazards because of their restricted mobility and difficulty with evacuation during emergencies (Cutter and Emrich 2009).

C. Illiteracy

The number of illiterate population (males and females) was used with the assumption that illiterate people are dependent on others to prepare and evacuate themselves during a forthcoming disaster. Thus, the highest illiteracy rates of the district were given the highest importance when allocating weight in the decision hierarchy.

D. Land Use and Land Cover:

Landsat

Or Sentinel

ESRI LULC 2020

https://www.arcgis.com/home/item.html?id=d6642f8a4f6d4685a24ae2dc0c73d4ac

E. Distance to road

QGIS- OSM to shape

Euclidean distance buffer tool was applied to extract the road buffer map in ArcGIS.

Buffer

Multi-buffer ring

Path distance

The adjacent parts of the main road are less vulnerable to flooding.

F. Road Density

Infrastructure facilities such as roads and rail networks are in the category of "lifeline" and play a significant role in evacuation and post event relief and recovery. As these networks are important in determining the lifeline of a community.

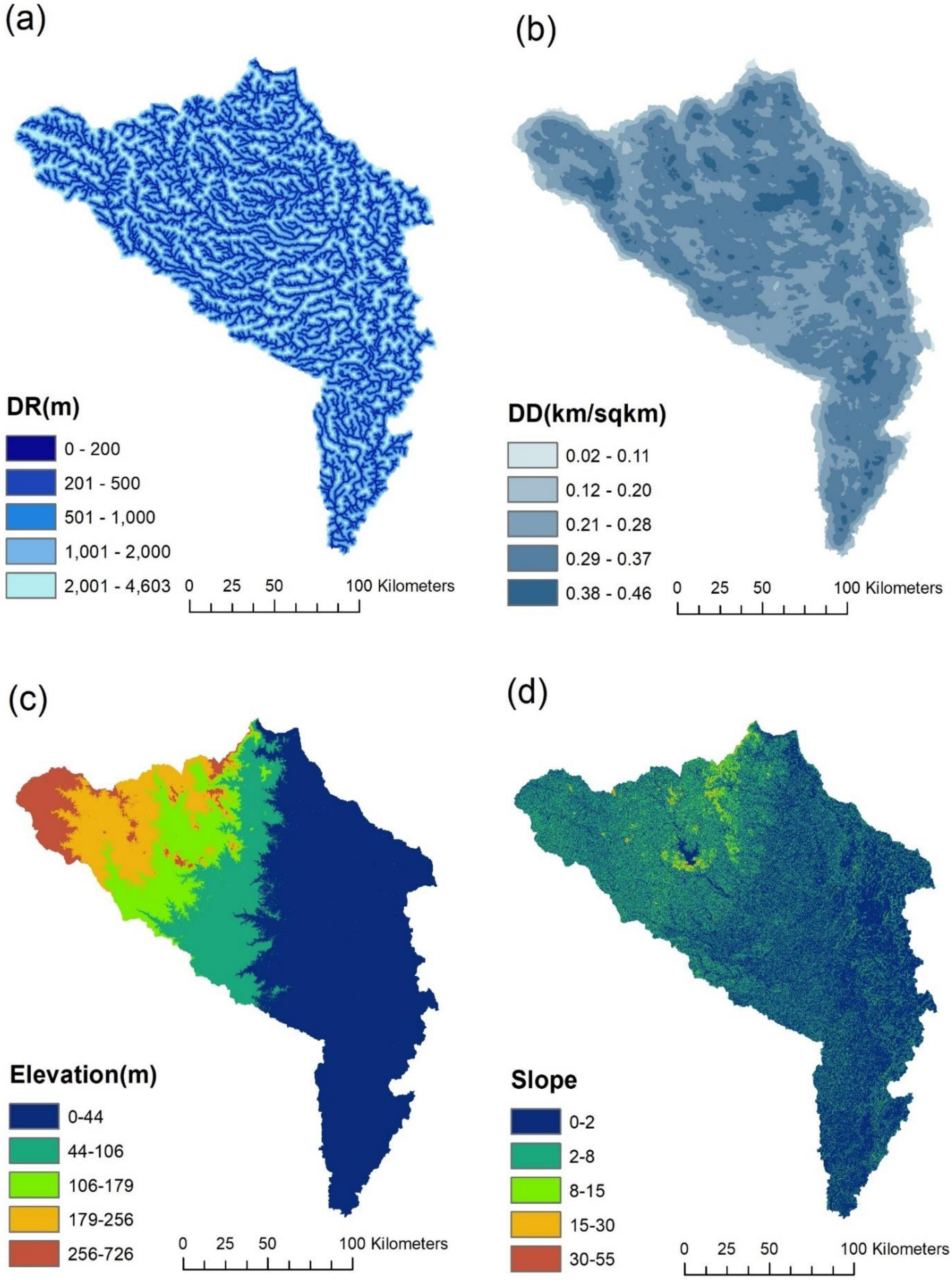
Table 2:Parameter's weightage of flood vulnerability

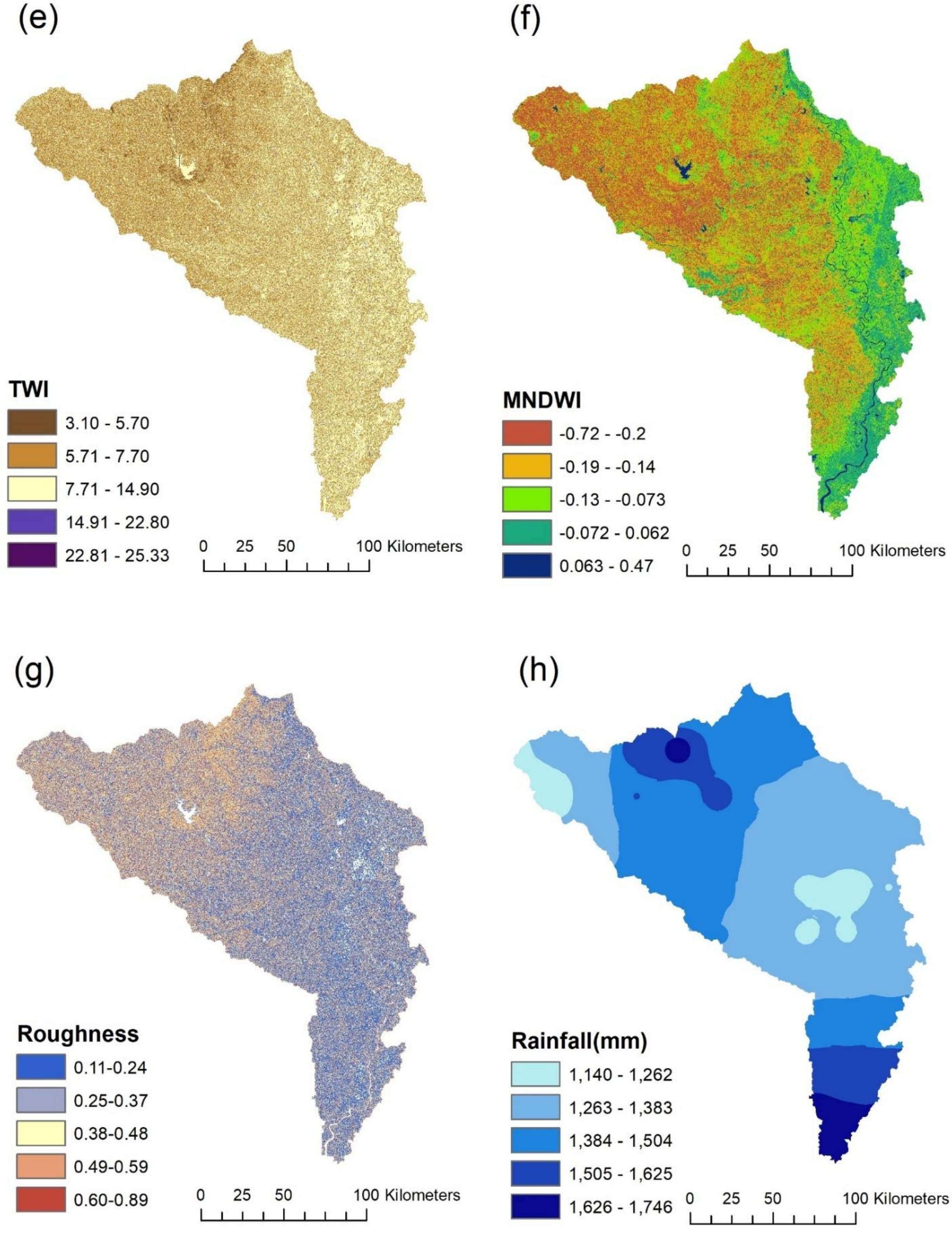
SL NO	Parameters	AHP Weight	Class	Range	Flood Level	Area in SQKM	Area in %	Rating
1	**Total Population**	0.3041	1	2,760 - 119,363	Very Low	7255.095	24.42913	0.059
			2	119,364 - 196,164	Low	17667.01	59.4878	0.097
			3	196,165 - 294,628	Medium	4359.186	14.67812	0.159
			4	294,629 - 543,126	High	383.8689	1.292552	0.259
			5	543,127 - 47,127,124	Very High	33.381	0.1124	0.426
2	**Child under 6**	0.1892	1	322 - 18,539	Very Low	7255.095	24.42913	0.056
			2	18,540 - 32,969	Low	17667.01	59.4878	0.096
			3	32,970 - 62,846	Medium	4359.186	14.67812	0.157
			4	62,847 - 103,412	High	383.8689	1.292552	0.257

			5	103,413 - 4,190,450	Very High	33.381	0.1124	0.434
3	**Female Population**	0.1588	1	1,377 - 58,842	Very Low	5698.946	19.18932	0.050
			2	58,843 - 95,693	Low	12055.99	40.59456	0.088
			3	95,694 - 143,709	Medium	8322.699	28.02394	0.151
			4	143,710 - 263,342	High	3587.52	12.07979	0.259
			5	263,343 - 21,856,505	Very High	33.381	0.1124	0.451
4	**Distance_Floodcentre**	0.1077	1	0 - 27,781	Very Low	19409.790	65.354	0.053
			2	27,782 - 55,561	Low	4180.374	14.076	0.089
			3	55,562 - 83,342	Medium	3698.067	12.452	0.153
			4	83,343 - 111,122	High	1526.830	5.141	0.262
			5	111,123 - 138,903	Very High	884.284	2.977	0.444
5	**LULC**	0.0760	1	Waterbody	Very Low	1200.43	4.04192	0.035
			2	Vegetation	Moderate	9747.47	32.8203	0.134
			3	Urban area	Very High	10328	34.775	0.260
			4	Fallow land	Low	873.144	2.93993	0.068
			5	Agricultural land	High	7550.48	25.4229	0.503

6	**Distance_Hospital**	0.0526	1	0 - 3,420	Very Low	18087.600	60.902	0.036
			2	3,421 - 8,851	Low	8649.374	29.123	0.081
			3	8,852 - 17,903	Medium	1509.827	5.084	0.146
			4	17,904 - 30,577	High	875.901	2.949	0.269
			5	30,578 - 51,296	Very High	576.639	1.942	0.467
7	**Distance from Road**	0.0352	1	0 - 1,567.01	Very Low	17076.58	57.49816	0.042
			2	1,567 - 4,526	Low	9616.807	32.38053	0.094
			3	4,526 - 12,361	Medium	2370.826	7.982753	0.147
			4	12,361- 25,942.	High	366.975	1.235633	0.257
			5	25,942 - 44,398	Very High	268.164	0.902929	0.461
8	**Road Density**	0.0352	1	0 - 1.32	Very High	13625.34	45.88728	0.459
			2	1.33 - 2.57	High	10026.44	33.76693	0.259
			3	2.58 - 4.72	Moderate	4585.545	15.44315	0.150
			4	4.73 - 9.44	Low	1010.534	3.403268	0.085
			5	9.45 - 17.71	Very Low	445.2075	1.499365	0.047
9	**Illiteracy Rate**	0.0240	1	14.88 - 26.98	Very Low	3028.951	10.30229	0.047

			2	26.99 - 37.81	Low	6395.116	21.75154	0.086
			3	37.82 - 47.05	Medium	8385.633	28.52184	0.149
			4	47.06 - 60.11	High	5784.697	19.67534	0.262
			5	60.12 - 96.1	Very High	5806.346	19.74898	0.456
10	**Employment Rate**	0.0174	1	23.14 - 33.04	Very Low	3954.865	13.3167	0.043
			2	33.05 - 38.22	Low	8926.177	30.05595	0.101
			3	38.23 - 42.72	Medium	8698.928	29.29076	0.169
			4	42.73 - 49.02	High	4951.622	16.67295	0.267
			5	49.03 - 80.52	Very High	3166.945	10.66364	0.420


(a)
DR(m)
0 - 200
201 - 500
501 - 1,000
1,001 - 2,000
2,001 - 4,603
0 25 50 100 Kilometers
(b)
DD(km/sqkm)
0.02 - 0.11
0.12 - 0.20
0.21 - 0.28
0.29 - 0.37
0.38 - 0.46
0 25 50 100 Kilometers
(c)
Elevation(m)
0-44
44-106
106-179
179-256
256-726
0 25 50 100 Kilometers
(d)
Slope
0-2
2-8
8-15
15-30
30-55
0 25 50 100 Kilometers


(e)
TWI
3.10 - 5.70
5.71 - 7.70
7.71 - 14.90
14.91 - 22.80
22.81 - 25.33
0 25 50 100 Kilometers
(f)
MNDWI
-0.72 - -0.2
-0.19 - -0.14
-0.13 - -0.073
-0.072 - 0.062
0.063 - 0.47
0 25 50 100 Kilometers
(g)
Roughness
0.11-0.24
0.25-0.37
0.38-0.48
0.49-0.59
0.60-0.89
0 25 50 100 Kilometers
(h)
Rainfall(mm)
1,140 - 1,262
1,263 - 1,383
1,384 - 1,504
1,505 - 1,625
1,626 - 1,746
0 25 50 100 Kilometers

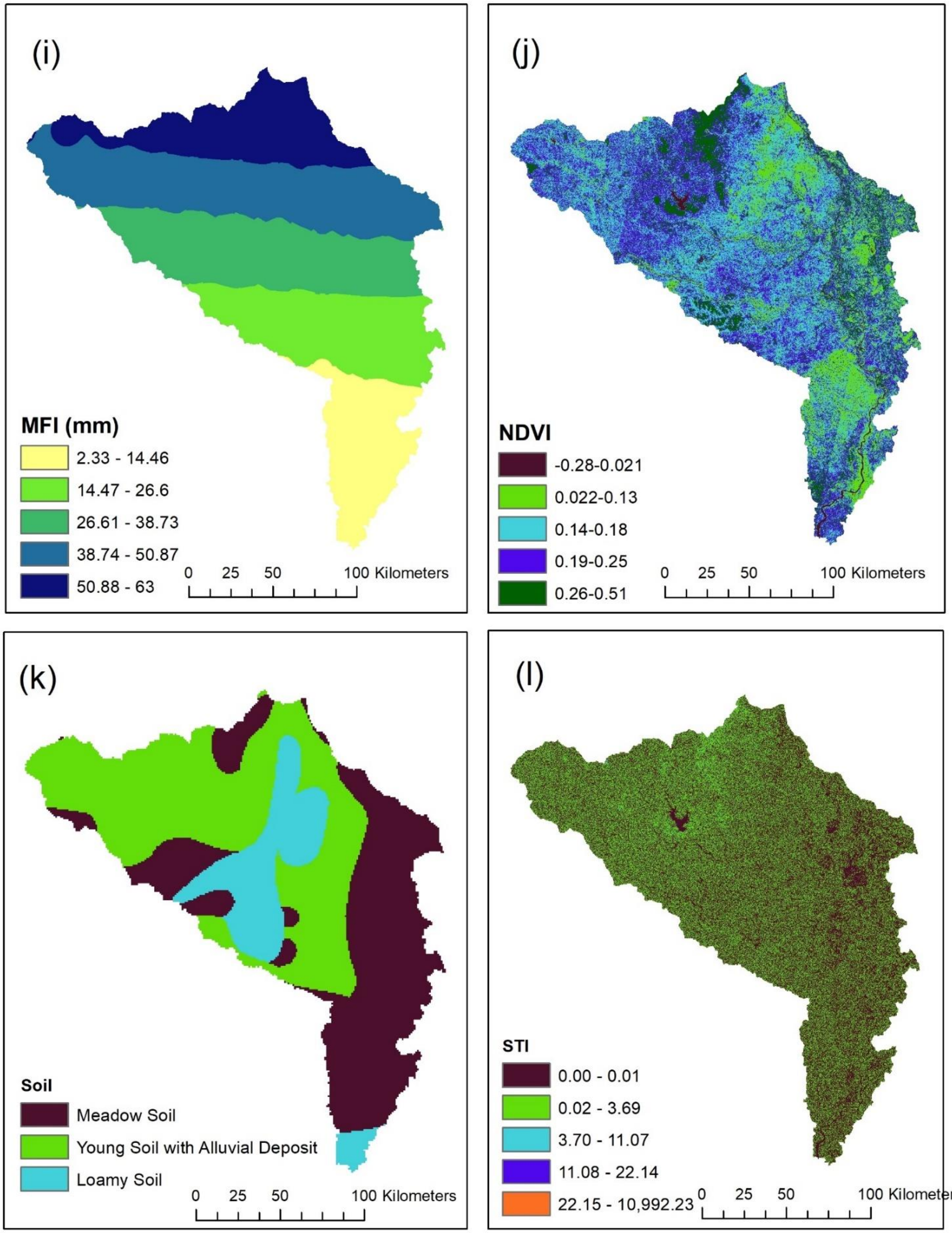
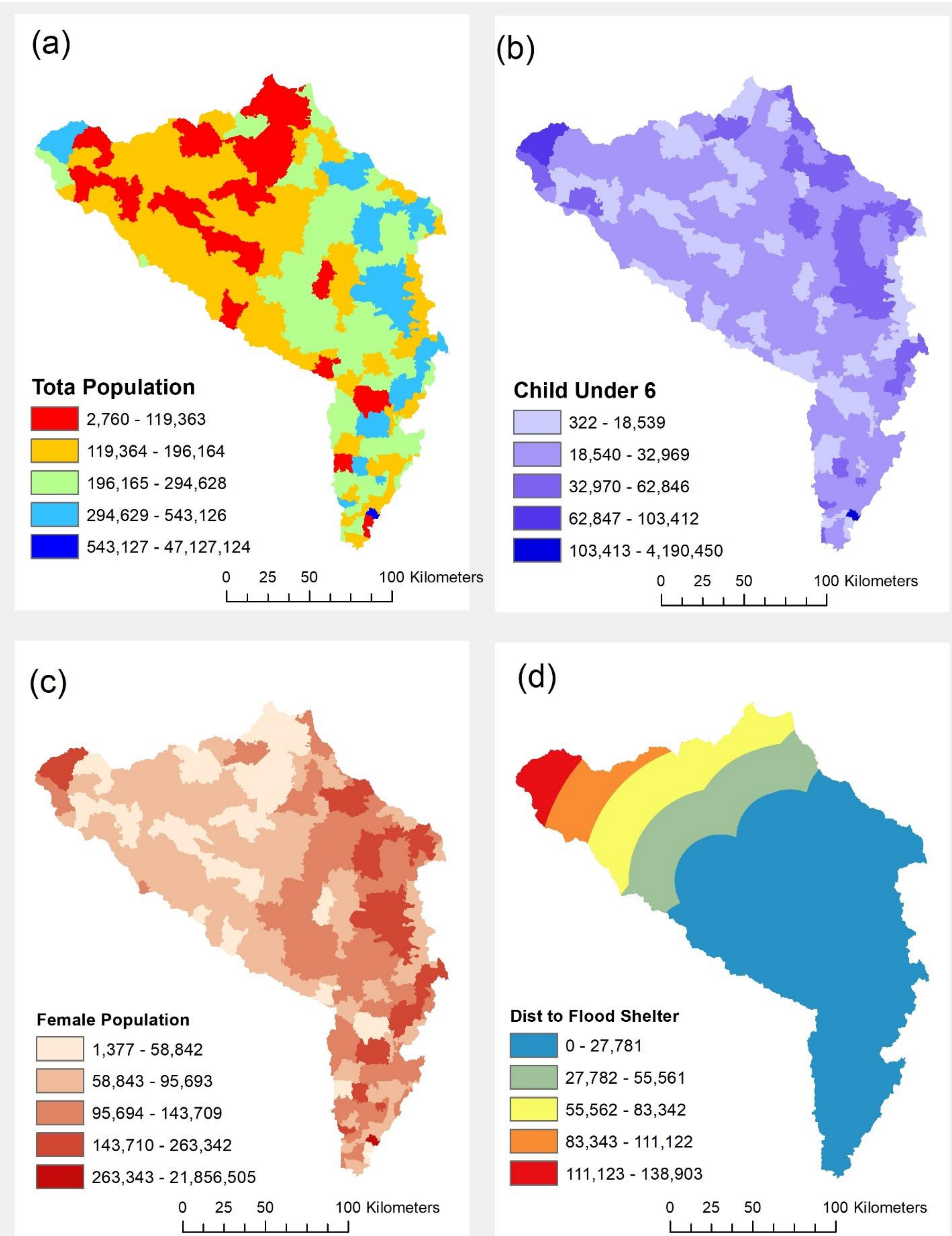
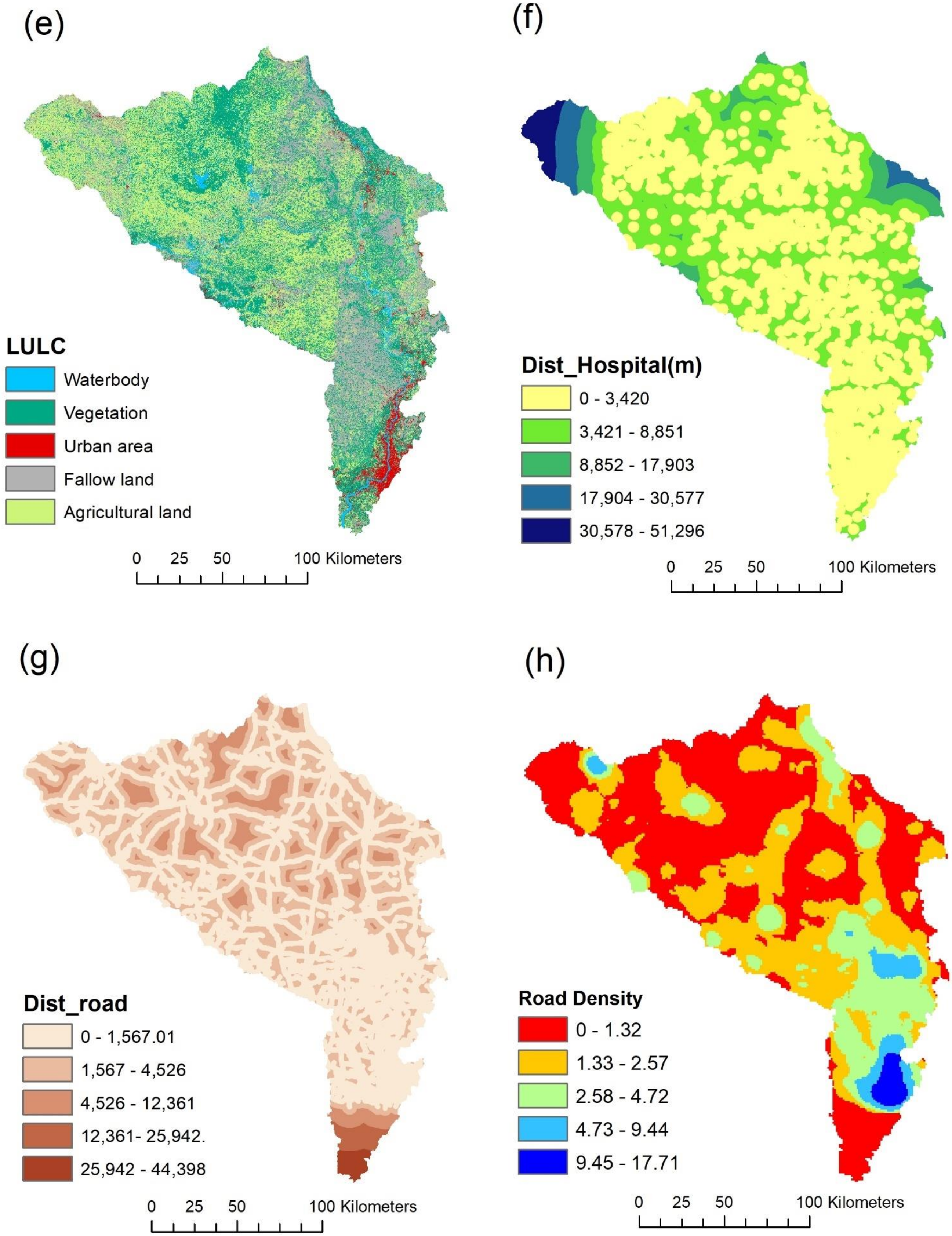


Figure 3Spatial distribution of flood hazard indicator in the study area


(a)
Tota Population
2,760 - 119,363
119,364 - 196,164
196,165 - 294,628
294,629 - 543,126
543,127 - 47,127,124
0 25 50 100 Kilometers
(b)
Child Under 6
322 - 18,539
18,540 - 32,969
32,970 - 62,846
62,847 - 103,412
103,413 - 4,190,450
0 25 50 100 Kilometers
(c)
Female Population
1,377 - 58,842
58,843 - 95,693
95,694 - 143,709
143,710 - 263,342
263,343 - 21,856,505
0 25 50 100 Kilometers
(d)
Dist to Flood Shelter
0 - 27,781
27,782 - 55,561
55,562 - 83,342
83,343 - 111,122
111,123 - 138,903
0 25 50 100 Kilometers


(e)
LULC
Waterbody
Vegetation
Urban area
Fallow land
Agricultural land
0 25 50 100 Kilometers
(f)
Dist_Hospital(m)
0 - 3,420
3,421 - 8,851
8,852 - 17,903
17,904 - 30,577
30,578 - 51,296
0 25 50 100 Kilometers
(g)
Dist_road
0 - 1,567.01
1,567 - 4,526
4,526 - 12,361
12,361- 25,942.
25,942 - 44,398
0 25 50 100 Kilometers
(h)
Road Density
0 - 1.32
1.33 - 2.57
2.58 - 4.72
4.73 - 9.44
9.45 - 17.71
0 25 50 100 Kilometers

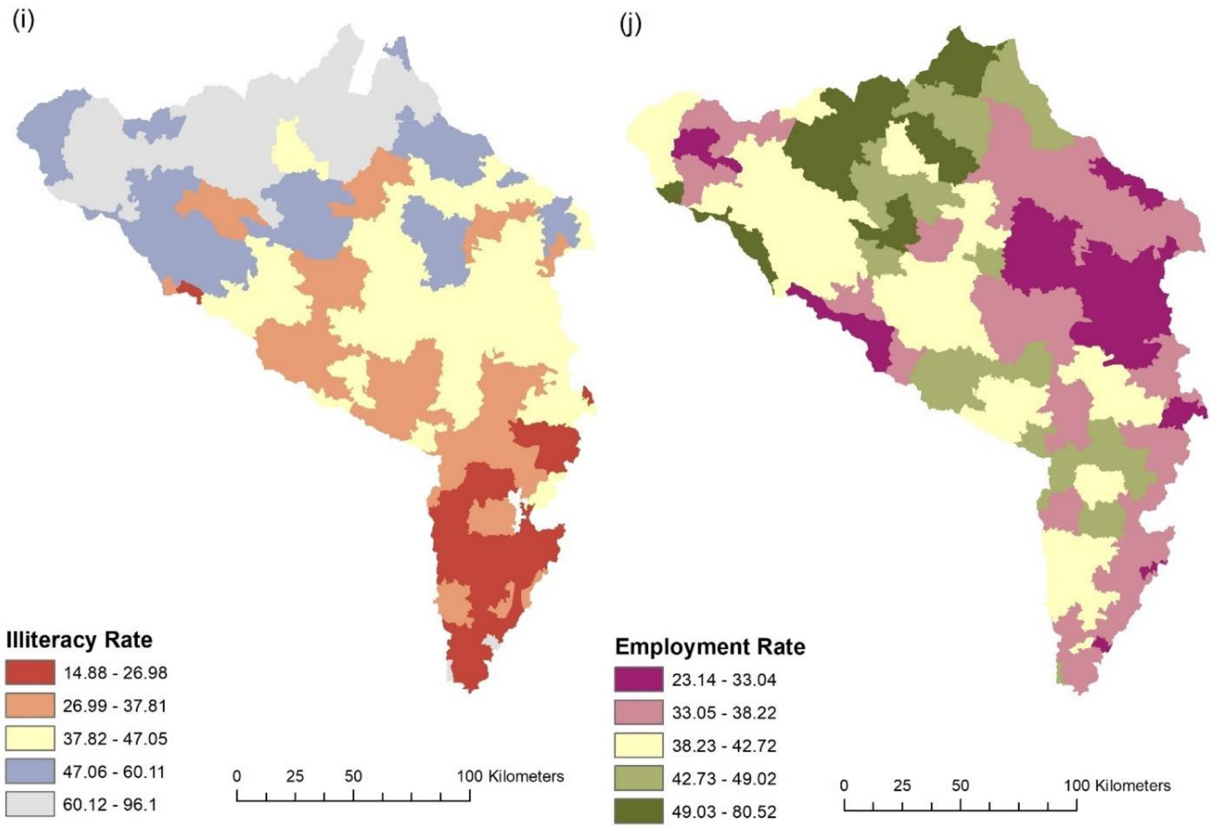


Figure 4:Spatial distribution of flood vulnerability indicator in the study area

5.3 Multicollinearity analysis

Since the AHP model is based on the dependence or relationship of different independent variables, it is essential to note that the value of the relationship between the independent variables should not be too high (Toebe and Filho 2013). If the relationship value between the independent variables is too high, then multicollinearity is created through the possibilities of breakdown (O'Brien 2007). This multicollinearity problem often arises when the risk factor is shown through the prediction according to the AHP model, and the linear correlation parameters reduce the prediction ability of the AHP model. Tolerance (TOL) and Variance Inflation Factor

(VIF) is used to test the multicollinearity of the indicators used for the AHP model (Table 4). The model indicator sees the multicollinearity problem if the TOL is less than 0.10 and the VIF is more than 5.0. But the multicollinearity test between the hazard and vulnerability indicators in the current study area shows that the variables are free of linear correlation parameters (Ahmad et al. 2021).

Table 3: Multicollinearity on hazard and vulnerability indicator

Hazard Parameter	**Collinearity Test**		**Vulnerability Parameter**	**Collinearity Test**	
	TOL	**VIF**		**TOL**	**VIF**
Elevation	0.854	1.301	Total Population	0.741	1.21
Slope	0.786	1.272	Child Below 6	0.689	1.185
Drainage Density	0.383	2.612	Female Population	0.914	1.521
Distance from river	0.373	2.681	Distance from flood centre	0.939	1.065
TWI	0.717	1.396	LULC	0.873	1.146
MNDWI	0.679	1.473	Distance from hospital	0.892	1.121
Roughness	0.964	1.038	Distance from road	0.637	1.571
Average Rainfall	0.973	1.028	Road density	0.472	2.119
MFI	0.754	1.32	Illiteracy rate	0.628	1.594
NDVI	0.667	1.500	Employment rate	0.807	1.240
Soil	0.814	1.741			
STI	0.810	1.234			

5.4 Weightage analysis of hazard and vulnerability parameter through AHP

AHP is a multidimensional, multi-purpose multi-criteria decision analytics (MCDA) criterion that allows one to arrive at the proper conclusion by comparing different dimensional decisions and choices with the above (Souissi et al.2020; Akay 2021; Tella and Balogun 2020). A hierarchical structure is created by combining the different paths obtained through group discussions and is fulfilled through the AHP model to achieve a particular purpose. The primary regulators of activity are modelled according to their efficiency with equal importance. The preference matrix (Saaty 1977; 1990; 2008; Sar et al. 2015; Ghosh and Kar 2018) measures the controllers of a specific action and compares the significance of the controllers based on their preferences (Table 5). The AHP model develops an alternative causation approach by reviewing the purpose and subject matter of each specific activity and variable. The weightage of hazard and vulnerability indicators in the current study area is determined using the AHP model. The indicators are compared pairwise, and the matrix generates a specific score based on their importance. Each factor is measured according to its relative importance (Table 6 a and b). A priority vector table is then created according to the normalized Eigenvector of the matrix (Saaty 1977; 1990; 2008; Sar et al. 2015; Ghosh and Kar 2018). The weight of the objective sequence is calculated based on the average obtained from it to measure flood hazards and vulnerability (Table 7 a and b). In the created comparison matrix table, consistency ratio (CR) is used to see if all the parameters are compatible with the AHP model. According to this index, if CR => 0.10, the performance of that model is consistent (Saaty 1977; 2008; Chakraborty and Mukhopadhyay 2019).

$$CR = CI/RI \tag{2}$$

Where, CI is the consistency index, RI is the random index (basically it is the number of indicator or parameter). The CI is also defined as (Saaty 1977; 2008; Chakraborty and Mukhopadhyay 2019),

$$CI = (\lambda max - n)/(n - 1) \tag{3}$$

Where, λmax is the largest eigen value of comparison matrix table, n is the number of criteria. In this study, with 12 and ten hazard and vulnerability indices criteria, the CR and CI values are calculated as 0.077 and 0.115. But in the case of vulnerability, the measured CR and CI values are 0.034 and 0.051. But surprisingly, despite the difference in the number of criteria, the RI value is the same (1.48) in both hazard and vulnerability cases.

Table 4: Scale of preferences (Saaty 1977)

Intensity Importance	Description
1	Equal Importance
3	Moderate importance
5	Strong importance
7	Very strong and demonstrated importance
9	Extreme importance
2,4,6,8	Intermediate values
Reciprocals	Inverse comparison

Table 5:Comparison matrix table for flood hazard

Matrix	DR	DD	E	S	TWI	MNDWI	Roughness	Rainfall	MFI	NDVI	Soil	STI
DR	1.00	3.00	4.00	4.00	5.00	6.00	7.00	8.00	8.00	9.00	9.00	9.00
DD	0.33	1.00	3.00	4.00	4.00	5.00	6.00	7.00	7.00	8.00	8.00	8.00
E	0.25	0.33	1.00	1.00	3.00	4.00	5.00	6.00	6.00	7.00	7.00	7.00
S	0.25	0.25	1	1.00	3	4	5.00	6.00	6.00	7.00	7.00	7.00
TWI	0.2	0.25	0.333333	0.3333333	1.00	3	4.00	5.00	5.00	6.00	6.00	6.00
MNDWI	0.166667	0.20	0.25	0.25	0.33333333	1.00	3.00	4.00	4.00	5.00	5.00	5.00
Roughness	0.142857	0.17	0.2	0.2	0.25	0.3333333	1.00	3.00	3.00	4.00	4.00	4.00
Rainfall	0.125	0.14	0.166667	0.1666667	0.2	0.25	0.3333333	1.00	1.00	3.00	3.00	3.00
MFI	0.125	0.14	0.166667	0.1666667	0.2	0.25	0.3333333	1	1.00	3.00	3.00	3.00
NDVI	0.111111	0.13	0.142857	0.1428571	0.16666667	0.2	0.25	0.3333333	0.3333333	1.00	1.00	1.00
Soil	0.111111	0.13	0.142857	0.1428571	0.16666667	0.2	0.25	0.3333333	0.3333333	1	1.00	1.00
STI	0.111111	0.13	0.142857	0.1428571	0.16666667	0.2	0.25	0.3333333	0.3333333	1	1	1.00

Sum	2.93	5.86	10.55	11.55	17.48	24.43	32.42	42.00	42.00	55.00	55.00	55.00

λ_{max}	N	CI	CR
13.2608	12	0.11462	0.077446

Table 6:Comparison matrix table for flood vulnerability

Matrix	Total_Pop	Child_6	F_Pop	Dis_floodcentre	LULC	Dis_Hospital	Dis_Road	Road Density	Illiteracy Rate	Employment Rate
Total_Pop	1.00	3.00	3.00	4.00	5.00	6.00	7.00	7.00	8.00	9.00
Child_6	0.33	1.00	1.00	3.00	4.00	5.00	6.00	6.00	7.00	8.00
F_Pop	0.33	1.00	1.00	2.00	3.00	4.00	5.00	5.00	6.00	7.00
Dis_floodcentre	0.25	0.33	0.5	1.00	2	3	4.00	4.00	5.00	6.00
LULC	0.2	0.25	0.333333	0.5	1.00	2	3.00	3.00	4.00	5.00
Dis_Hospital	0.166667	0.20	0.25	0.3333333	0.5	1.00	2.00	2.00	3.00	4.00
Dis_Road	0.142857	0.17	0.2	0.25	0.33333333	0.5	1.00	1.00	2.00	3.00
Road Density	0.142857	0.17	0.2	0.25	0.33333333	0.5	1	1.00	2.00	3.00
Illiteracy Rate	0.125	0.14	0.166667	0.2	0.25	0.3333333	0.5	0.5	1.00	2.00
Employment Rate	0.111111	0.13	0.142857	0.1666667	0.2	0.25	0.3333333	0.3333333	0.5	1.00
Sum	**2.81**	**6.38**	**6.79**	**11.70**	**16.62**	**22.58**	**29.83**	**29.83**	**38.50**	**48.00**

λmax	N	CI	CR
10.4563	10.00	0.0507	0.0343

Table 7:Normalized matrix table for flood hazard

Matrix	DR	DD	E	S	TWI	MNDWI	Roughness	Rainfall	MFI	NDVI	Soil	STI
DR	0.34	0.51	0.38	0.35	0.29	0.25	0.22	0.19	0.19	0.16	0.16	0.16
DD	0.11	0.17	0.28	0.35	0.23	0.20	0.19	0.17	0.17	0.15	0.15	0.15
E	0.09	0.06	0.09	0.09	0.17	0.16	0.15	0.14	0.14	0.13	0.13	0.13
S	0.09	0.04	0.09	0.09	0.17	0.16	0.15	0.14	0.14	0.13	0.13	0.13

TWI	0.07	0.04	0.03	0.03	0.06	0.12	0.12	0.12	0.12	0.11	0.11	0.11
MNDWI	0.06	0.03	0.02	0.02	0.02	0.04	0.09	0.10	0.10	0.09	0.09	0.09
Roughness	0.05	0.03	0.02	0.02	0.01	0.01	0.03	0.07	0.07	0.07	0.07	0.07
Rainfall	0.04	0.02	0.02	0.01	0.01	0.01	0.01	0.02	0.02	0.05	0.05	0.05
MFI	0.04	0.02	0.02	0.01	0.01	0.01	0.01	0.02	0.02	0.05	0.05	0.05
NDVI	0.04	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02
Soil	0.04	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02
STI	0.04	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02

Table 8: Normalized matrix table for flood vulnerability

Matrix	Total_Pop	Child_6	F_Pop	Dis_floodcentre	LULC	Dis_Hospital	Dis_Road	Road Density	Illiteracy Rate	Employment Rate
Total_Pop	0.36	0.47	0.44	0.34	0.30	0.27	0.23	0.23	0.21	0.19
Child_6	0.12	0.16	0.15	0.26	0.24	0.22	0.20	0.20	0.18	0.17
F_Pop	0.12	0.16	0.15	0.17	0.18	0.18	0.17	0.17	0.16	0.15
Dis_floodcentre	0.09	0.05	0.07	0.09	0.12	0.13	0.13	0.13	0.13	0.13
LULC	0.07	0.04	0.05	0.04	0.06	0.09	0.10	0.10	0.10	0.10
Dis_Hospital	0.06	0.03	0.04	0.03	0.03	0.04	0.07	0.07	0.08	0.08
Dis_Road	0.05	0.03	0.03	0.02	0.02	0.02	0.03	0.03	0.05	0.06
Road Density	0.05	0.03	0.03	0.02	0.02	0.02	0.03	0.03	0.05	0.06
Illiteracy Rate	0.04	0.02	0.02	0.02	0.02	0.01	0.02	0.02	0.03	0.04
Employment Rate	0.04	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.02

5.5 Developing flood hazard, vulnerability and risk index

Since the flood risk is determined based on hazard and vulnerability, the flood risk has been developed through spatiality after creating the hazard and vulnerability index. The hazard and vulnerability index are created after ranking according to the weightage of the hazard and vulnerability indicators from the comparison matrix table. The flood hazard index (FHI) is measured as (Souissi et al. 2020; Dano 2021; Ghosh and Kar 2018; Chakraborty and Mukhopadhyay 2019; Swain et al. 2020),

$$
\begin{aligned}
FHI = {} & (wE \times E) + (wS \times S) + (wDD \times DD) + (wDR \times DR) \\
& + (wTWI \times TWI) + (wMNDWI \times MNDWI) \\
& + (wRoughness \times Roughness) + (wRainfall \times Rainfall) \\
& + (wMFI \times MFI) + (wNDVI \times NDVI) + (wSoil \times Soil) \\
& + (wSTI \times STI)
\end{aligned} \tag{3}
$$

Where, E, S, DD, DR refers to the elevation, slope, drainage density and distance from river, respectively. wE, wS , wDD, wDR, wTWI, wMNDWI, wRoughness, wRainfall, wMFI, wNDVI, wSoil and wSTI are the corresponding weightage of the hazard indicators. The flood vulnerability index (FVI) is measured as (Souissi et al. 2020; Dano 2021; Ghosh and Kar 2018; Chakraborty and Mukhopadhyay 2019; Swain et al. 2020),

$$
\begin{aligned}
FVI = {} & (wTOTP \times TOTP) + (wC6 \times C6) + (wFP \times FP) \\
& + (wDFC \times DFC) + (wLULC \times LULC) + (wDFH \times DFH) \\
& + (wDFR \times DFR) + (wRD \times RD) + (wIR \times IR) \\
& + (wER \times ER)
\end{aligned} \tag{4}
$$

Where, TOTP is the total population, C6 is the total count of child below the age of 6, FP is the female population, DFC is the distance from flood centre, LULC is the land use and land cover, DFH is the distance from hospital, DFR is the distance from road, RD is the road density, IR is the illiteracy rate, and ER is the employment rate. wTOTP, wC6, wFP, wDFC, wLULC, wDFH, wDFR, wRD, wIR and wER are the corresponding weightage of the vulnerability indicators. Information on hazards and vulnerability from the above indexes is served after reclassification and normalization. The current study area's hazard and vulnerability index have been classified into four sections, Natural Break (NB), Equal Interval (EI), Quantile (QN) and Geometric Interval (GI) through ArcGIS's symbology tool. Showing through different reclassifications means sharing equal values, groups, features and geometric intervals. It is elementary to understand how many areas are included in hazard, vulnerability or risk. After reclassifying, all the data is converted into a gridded raster with a spatial resolution of 30m X 30m according to spatiality. On the other hand, the flood risk index (FRI) is measured using the Arc GIS Map

Algebra tool (Ghosh and Kar 2018; Chakraborty and Mukhopadhyay 2019; Swain et al. 2020).

$$FRI = FHI \times FVI \quad (5)$$

In the case of FRI, after reclassification and normalization in the same way, it is converted into gridded raster data on the basis of spatiality.

5.5.1 Sensitivity analysis

It is possible to evaluate the effect of each indicator on the hazard and vulnerability index through the sensitivity analysis of the single indicator (O'Brien 2007; Toebe and Filho 2013; Ahmad et al. 2021). The sensitivity test is essential here because each indicator has been worked out with its arbitrary numerical value. In the case of FHI and FVI indexes, sensitivity analysis is performed by using available weights instead of relative weights in random numerical values in the AHP model. The map-based FHI and FVI using the AHP model require a sensitivity analysis to determine if the results obtained from the AHP model are consistent. The fundamental importance of the parameters of hazard and vulnerability with weightage values is analysed through this model. Sensitivity analysis determines which parameters are suitable for flooding and helps identify flood risk zones.

5.5.2 Validation of the model

After preparing the flood hazard and vulnerability model using the AHP, the flooded and non-flooded areas are separated through points in the raster map (Wubalem et al. 2020; Dash and Sar 2020; Akay 2021). With those points, the ability to predict the model based on training and testing information is assessed using various statistical parameters. The specificity, accuracy, precision and sensitivity of the estimated results obtained from FHI and FVI are evaluated mainly through receiver operating characteristic curve (ROC) analysis. Also, the area under the ROC curve (AUC) is available through the ROC, which can be used to express the effectiveness of the predicted model.

6 Results and Discussions

6.1 Spatial distribution of flood as hazard

The FHI map is available by arranging the indicators responsible for the flood hazard according to their compliance according to the comparison matrix table with spatiality in the ArcGIS environment (Fig. 5). Classes are arranged from very low to very high by preparing all the maps in 4 different classifications according to the symbology tool. The maps show that most flood hazard areas are confined to the study area's east and southeast, mainly beside the riparian zone. The elevation of the land is much lower than the area covered by the floodplain. Due to constant channel change in the meandering flow of the river, most of the old abandoned channels have remained on both sides of the river, with some oxbow lakes. Floodwaters easily inundate low-lying areas, marshy land and wetlands, causing waterlogging and submergence problems. As a result, the flood situation here quickly became catastrophic. Although the flood hazard index is shown in four parts, the basic information about the flooded areas is taken from the land area. It shows that the essential information is very similar to the classification done by the Natural Break method. From the point of view of regional hazard distribution, most of the region has been part of the moderate to very high flood hazard index. While shallow hazard distribution is not seen in the EI classification distribution, it is well seen in the other three classifications (Table 5). From the administrative point of view, flood-prone areas are observed in fig 7(a) according to the flood hazard index. Since the hazard index is mainly dependent on physical parameters, distance to river, drainage density, low elevation and slope, high rainfall, excessive sedimentation is primarily responsible for flood hazard and disaster.

6.2 Spatial distribution of flood as vulnerability

While the hazard indicator is based entirely on physical parameters, the vulnerability indicator depends on the social, economic and socio-economic status of the people living in the area. In the same way as the hazard index, the flood vulnerability index has been prepared in the ArcGIS environment by ranking the weightage factor of the indicators through comparison matrix and classification according to 4 different types according to symbology tool (Fig. 6). The vulnerability factor is entirely linked to human livelihoods, so the most populated areas, the presence and density of urban aquaculture, the location near the river and the low education rate create the right environment to build high vulnerability. The quantile classification presents a realistic picture of the four categories, with the highest density being found in the most densely populated urban areas and adjoining villages (Table 8). Many places in the south have low population and high education rates, so the goodness rate is much lower in those areas. The vulnerability rate is much higher in Bihar (Jamui Block) and Kolkata, with dense inclusions of urban and industrial patches in case of kolkata. But in case of Jamui, less number of flood shelters are present so, this area is highly vulnerable. Depending on the region according to the classification type of quantile and GI, most of the entire study area is in moderate to very high variability. Still, according to the NB and EI classification, the opposite environment is also possible. In fig 7(b) flood vulnerable blocks can be easily identified.

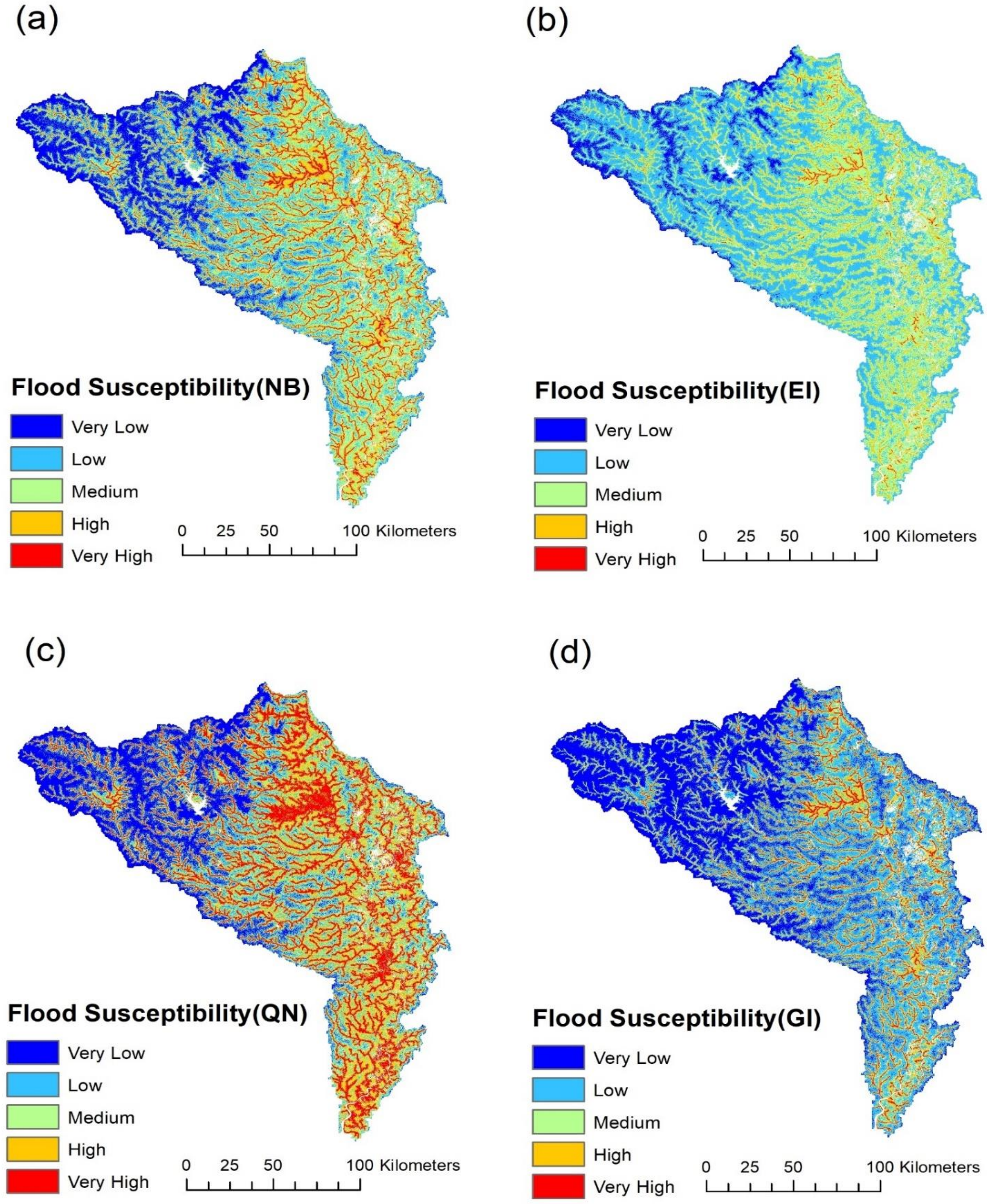


Figure 5: Spatial distribution of flood hazard intensity through different types of classification (a) Natural Break (NB), (b) Equal Interval (EI), (c) Quantile (QN), (d)

Geometric Interval

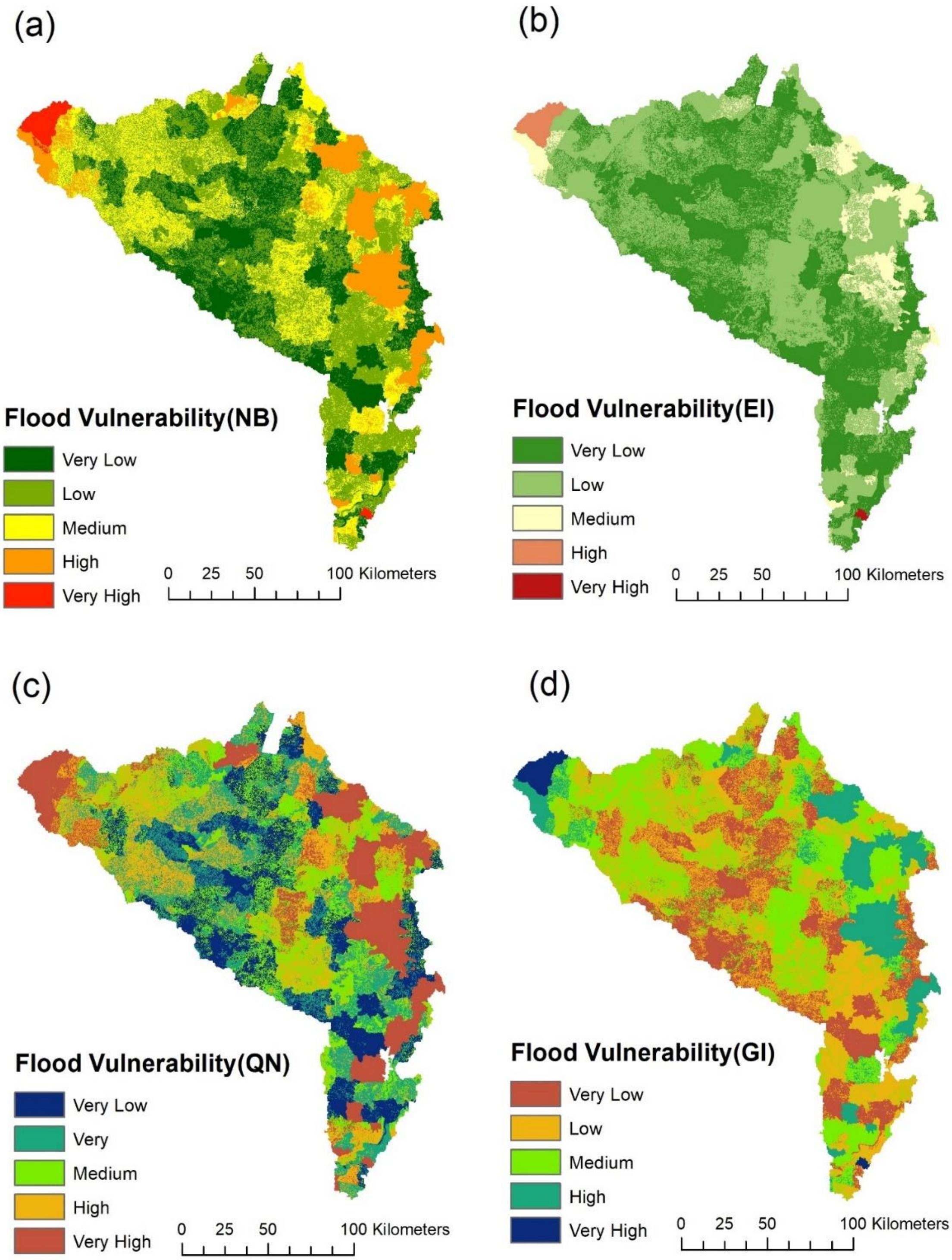


Figure 6: Spatial distribution of flood vulnerability through different types of classification

(a) Natural Break (NB), (b) Equal Interval (EI), (c) Quantile (QN), (d) Geometric Interval (GI)

	Natural Break		Equal Interval		Quantile		Geometric Interval	
FSL	**Area in sq km**	**Area in %**	**Area in sq km**	**Area in %**	**Area in sq km**	**Area in %**	**Area in sq km**	**Area in %**
Very Low	4058.38	16.40	1602.11	6.47	4882.42	19.73	8222.70	33.22
Low	7548.12	30.50	12158.74	49.12	5187.79	20.96	10189.61	41.17
Moderate	7368.20	29.77	8623.87	34.84	4894.79	19.78	2346.57	9.48
High	3892.17	15.73	2254.75	9.11	5027.42	20.31	2635.85	10.65
Very High	1884.55	7.61	111.96	0.45	4759.00	19.23	1356.69	5.48

Table 9 : Flood Susceptible Level in different classification methods

Table 10 : Flood Vulnerability Level in different classification methods

	Natural Break		Equal Interval		Quantile		Geometric Interval	
FVL	**Area in sq km**	**Area in %**	**Area in sq km**	**Area in %**	**Area in sq km**	**Area in %**	**Area in sq km**	**Area in %**
Very Low	7263.02	24.83	12839.75	43.89	5673.55	19.40	6395.19	21.86
Low	11391.08	38.94	13859.49	47.38	6122.70	20.93	9081.67	31.05
Moderate	6591.98	22.54	2141.93	7.32	6029.03	20.61	9706.67	33.18
High	3574.36	12.22	378.30	1.29	5912.41	20.21	3657.65	12.50
Very High	431.32	1.47	32.29	0.11	5514.07	18.85	410.59	1.40

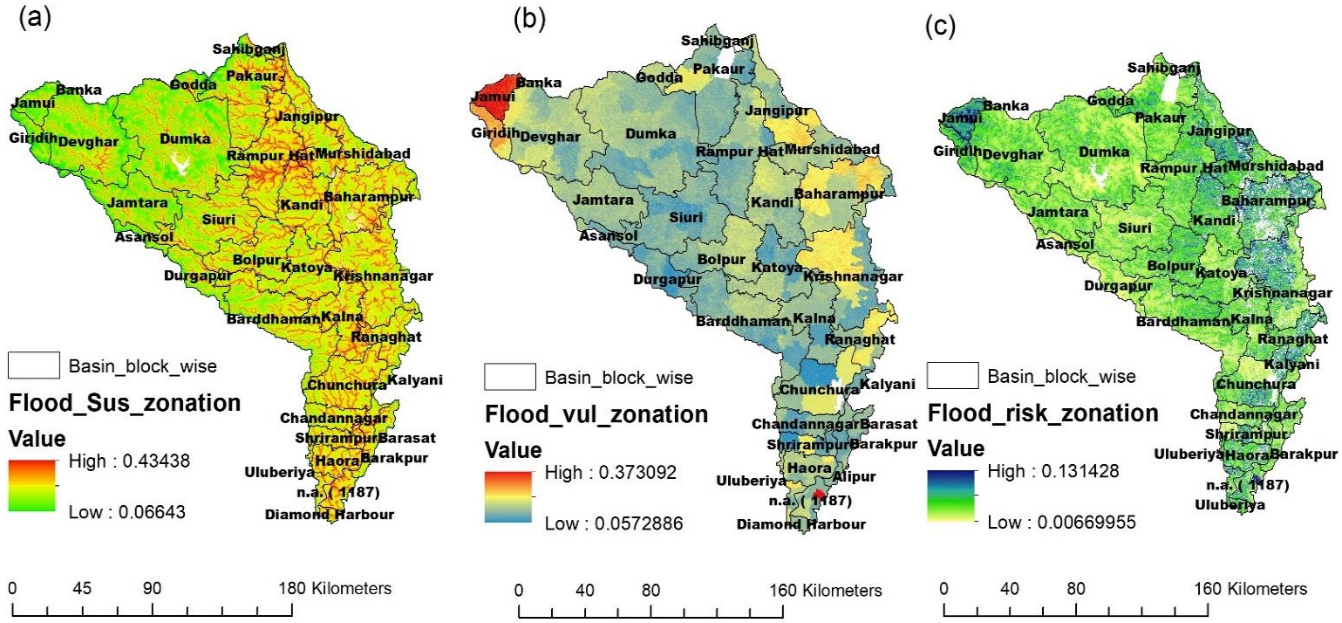


Figure 7: Block Wise Spatial distribution of (a) flood Susceptibility, (b) flood vulnerability and (c) flood risk zonation

6.3 Sensitivity analysis

A single parameter sensitivity analysis on the hazard and vulnerability indicators in the current study area shows that the results are almost identical to the theoretical results obtained from the AHP model (Table 9 a and b). According to the AHP model, distance to river is an essential food hazard indicator for flood organizations. By empirical weight, the elevation value is 26.66%, but as a result of single-parameter sensitivity analysis, the mean effective weight stands at 29.05%. Similarly, the most important of the indicators in terms of vulnerability is the total population. The value of the total population in terms of empirical weight is 30.41%, but as a result of single-parameter sensitivity analysis, the mean effective weight becomes 18.6%. According to the AHP model, the values of FHI and FVI can be determined using empirical weightage, which is 7.01 and 6.84, respectively. Similarly, the mean effective weight of single parameter sensitivity analysis is used to select the Flood Hazard Index of Sensitivity Analysis

(FHIS), and Flood Vulnerability Index of Sensitivity Analysis (FVIS) values are 7.41 and 6.52, respectively. As a result, a comparison between FHI / FVI and FHIS / FVIS shows that their values are almost the same, and statistically, these two models are validated with the above.

Table 11: Single Parameter Analysis of Flood Hazard

Thematic Layer	Empirical Weight(%)	Effective Weight(%)			
		Min	Max	Mean	SD
Distance to river	26.66	4.20	61.65	29.05	12.03
Drainage Density	19.20	3.98	54.70	24.00	6.63
Elevation	12.34	1.84	42.77	11.06	6.11
Slope	12.22	1.32	23.51	8.53	2.62
TWI	8.67	0.82	31.10	10.03	5.70
MNDWI	6.27	0.52	31.97	8.11	5.14
Roughness	4.44	0.67	23.07	3.64	2.75
Average Rainfall	2.84	1.28	18.15	4.73	2.17
MFI	2.84	0.50	13.89	1.72	0.92
NDVI	1.51	0.09	4.51	0.79	0.51
Soil	1.51	0.16	9.55	1.98	0.97
STI	1.51	0.12	5.70	1.19	0.69

Table 12 : Single Parameter Analysis of Flood Vulnerability

Thematic Layer	Empirical Weight(%)	Effective Weight(%)			
		Min	Max	Mean	SD
Total Population	30.41	2.55	102.43	18.87	9.86
Child Under 6	18.92	2.38	82.20	15.92	6.82
Female Population	15.88	2.88	94.19	22.98	9.22
Distance to Flood Shelter	10.77	1.11	70.07	13.63	11.83
LULC	7.60	0.80	25.61	4.57	4.46
Distance_Hospital	5.26	1.05	26.14	6.63	4.33
Distance from Road	3.52	0.59	19.24	4.87	3.61
Road Density	3.52	1.07	21.90	8.16	3.74
Illeterate Rate	2.40	0.29	19.70	5.40	4.29

Employment Rate	1.74	0.27	15.21	2.32	1.54

6.4 Validation of FHI through ROC curve

The accuracy, quality and predictability of the FHI models based on the AHP model are tested with the help of the ROC curve. The flood risk zone in the study area has been calculated and predicted based on the hazard index's prediction capacity. So, first of all, it is necessary to verify the validity and prediction of these two indexes based on actual and false-positive rates. FHI, this index, are validated based on their predictive ability (Fig. 8). Success rates are observed using training datasets (733 points), which depend on flood locations in 75% of the region. The prediction accuracy depends on the rest of the data set that was not used in training (245 points) and guided the flood situation in 25% of the region. Furthermore, the fact that the AUC value is close to 1 shows that the model is reliable. The prediction values of the AUC curve on hazard index is 0.799, which proves the accuracy of the model's prediction at 79.90%.

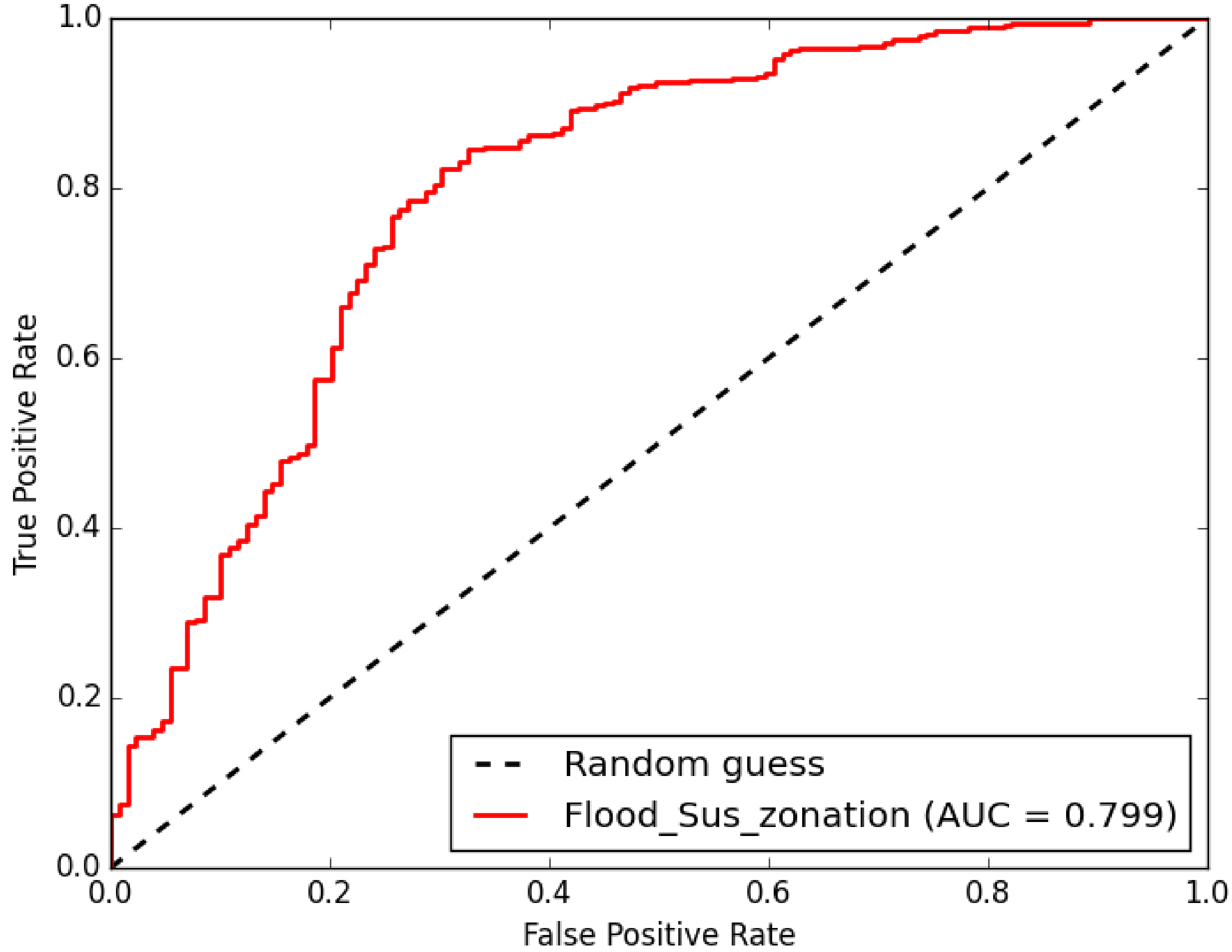


Figure 8 Validation of FHI through ROC curve

6.5 Spatial distribution of flood as risk

Flood risk indexes across the entire study area were measured using the FRI based on hazard and vulnerability's parameters. The FRI index is prepared spatially using the algebra tool in the ArcGIS environment by determining the weightage of the hazard and vulnerability indicators and ranking them according to the comparison matrix table (Fig. 9). Due to the inclusion of the low-rise floodplain system in the maximum part of study area and the continuity of channel shifting in the river meandering flow, there is a substantial risk of flooding and inundation in the region in the future. Most of the eastern, north-western and south-eastern parts of the entire study area have a high risk for future flood-prone areas. The flood risk increases in Jamui in

Bihar; Nabadwip, Krishnanagar, Ranaghat, Kolkata and Shantipur block of Nadia district, Balagarh, Chinsurah block of Hooghly district and Kalna block of East Burdwan district; Baharampur in Murshidabad District and Kolkata. According to the Geometric Interval Method method, the regional area format revealed that more than 39% of the study area is classified from moderate to very high flood risk zone (Table 10). The rest of the scenarios show the exact opposite situation of the Geometric Interval, which does not match reality. However, all the demands of human habitation are reflected in the features of this study area. With this, the amount of water in the river will increase every monsoon season, and it will cause floods and human catastrophes.

Table 13: Flood Risk Level in different classification methods

	Natural Break		Equal Interval		Quantile		Geometric Interval	
FRL	Area in sq km	Area in %	Area in sq km	Area in %	Area in sq km	Area in %	Area in sq km	Area in %
Very Low	6363.15	26.07	17527.87	71.81	4796.13	19.65	4672.68	19.14
Low	8918.99	36.54	6522.38	26.72	4930.18	20.20	5775.16	23.66
Moderate	5742.81	23.53	334.63	1.37	5128.25	21.01	9524.09	39.02
High	2824.07	11.57	21.96	0.09	4871.46	19.96	4295.98	17.60
Very High	560.27	2.30	2.44	0.01	4683.26	19.19	141.38	0.58

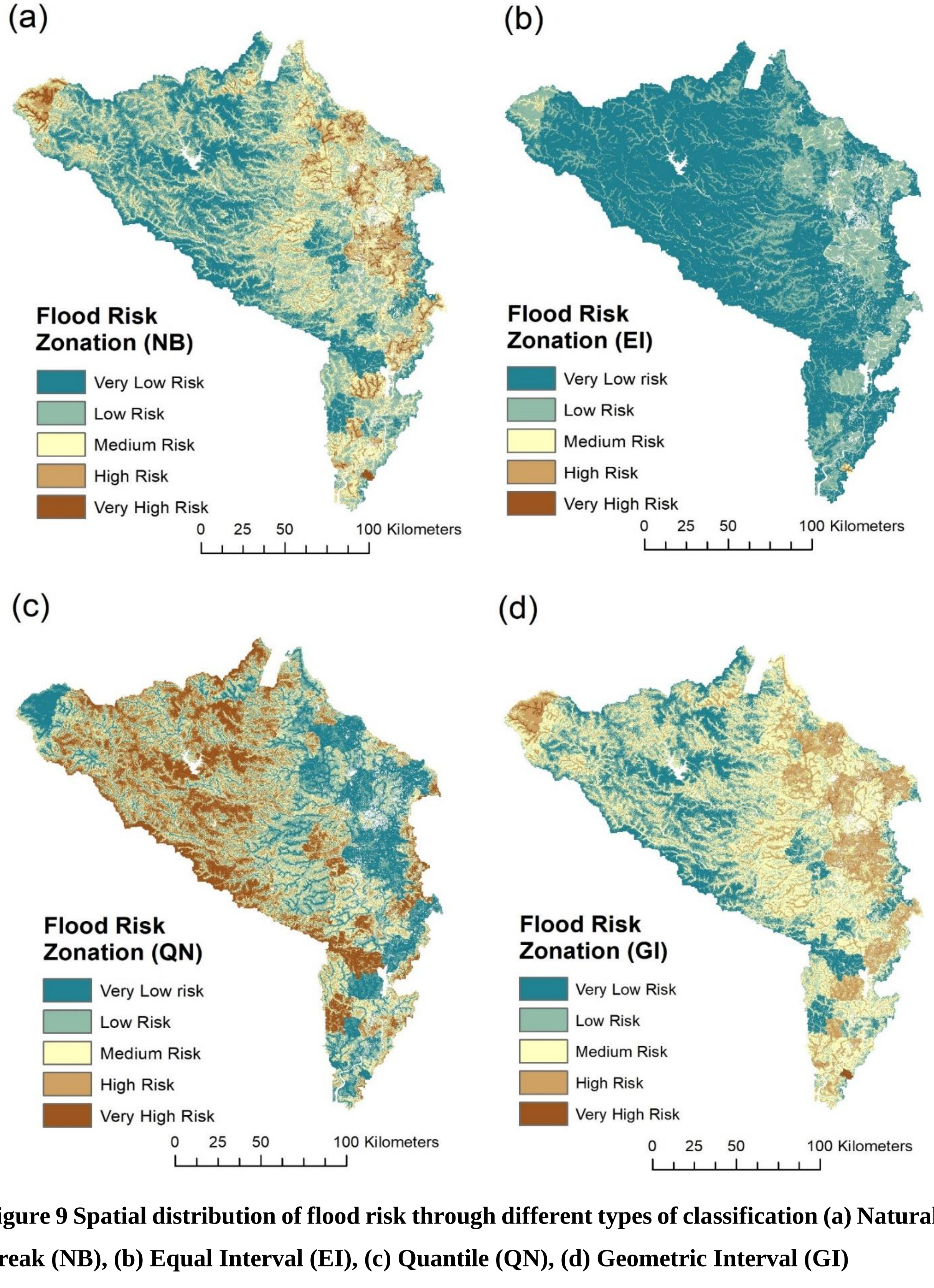


Figure 9 Spatial distribution of flood risk through different types of classification (a) Natural Break (NB), (b) Equal Interval (EI), (c) Quantile (QN), (d) Geometric Interval (GI)

7 Conclusion

Floods can occur naturally in floodplain areas, but they can sometimes be a blessing or a curse. In developing countries like India, the population is a big problem, and the idea of creating a River Regulation Zone (RRZ) to protect against floods is unimaginable. The present article discusses the flood situation in the Bhagirathi-Hooghly river basin, which has created a catastrophic environment of hazard and disaster in a region rich in agriculture and industry. The flood situation and range in this region has been measured through the weightage and ranking factor of the AHP model, as the AHP model helps to present the accurate picture very well. By spatiality in the ArcGIS environment, FHI and FVI indexes have been created by adjusting the hazard and vulnerability indicators according to their weightage and quality. The FRI map of the region has been prepared based on specific mathematical measurements on the spatial interpolation of FHI and FVI. Judging by the hazard, vulnerability and risks of floods, it observed that the flood situation is much higher in the eastern, north-eastern and south-eastern regions of the entire study area. Due to the low altitude, low slope and channel shifting by the meandering flow of the river, the flood situation is deteriorating. Also, population growth, illegal construction along the river and on the river bank, urban construction along the river bank has increased the sedimentation by reducing the navigability of the river. For all these reasons, during the monsoon season, the river swells quickly and floods its banks. Based on regionalism, more than 60% of Navadwip, Krishnanagar 1, Shantipur, Chakdaha block of Nadia district, Kandi in Murshidabad district and Purbasthali 1 block of East Burdwan district are considered as flood-prone areas. However, in all three cases, hazard, vulnerability, and risk, the classification is shown in four ways with the help of symbology tools, which have a lot in common with the actual picture of reality with the Natural Break Method. The western part of the region is much higher than the eastern part, so the risk and disaster of floods are much lower compared to the eastern part.

- ❖ The maps based on flood hazards, vulnerability and risk along the Bhagirathi-Hooghly river are expected to play a significant role in future flood management and control. Since all the work is based on mouzas, it is likely to help in shaping government policy and measures for flood victims. Since the hazard and vulnerability index is prepared based on data from each mouza, mouza basis flood situation discussed and sustainable development is expected to be possible.

- ❖ There is an urgent need to construct artificial embankment in the mouzas along the river to control the flood situation. According to the RRZ, settlements 500 meters away from the river are less likely to be damaged by floods. However, there are doubts about how widespread this policy will be amongst the riparian people in this densely populated region.
- ❖ As the navigability of the river decreases and floods occur, there is an excellent need for dredging in the river. In addition, illegal and unscientific sand mining from the river bed should be restricted. There is a need to create awareness about floods, prevent them and build more healthy flood shelters.

8 Recommendations:

Previously there was no flood risk study employed in the whole Bhagirathi basin. So, these flood susceptibility, flood vulnerability and flood risk map can be share with Government to reduce the social and economic loss in flood prone areas.

Also, flood shelter can be constructed to prevent the loss of human life.

9 Future Scopes:

Flood can not be avoided easily. So, preventive measures can not be taken to prevent this. But further study can be involved with the utilization of flood for the benefit of our society. Also, we can use Oxbow Lakes, which are situated beside the rives, to hold the flood water and its future use.

During flood, huge sedimentation deposited in river bed. As a result, depth of river reduced and makes trouble in navigation. So, the further study can involve to reduce this sedimentation.

Also, in future river bank protection during flood can be studied. Because flood water erodes river bank and breach embankments.

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