A Comparative Evaluation of GIS based Flood Susceptibility Models: A Case of Kopai River Basin, Eastern India

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A comparative evaluation of GIS based flood susceptibility models: a case of Kopai river basin, Eastern India

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Abstract

Flood is a typical natural disaster which every year causes enormous damage to the natural environment, buildings and victims worldwide. The efficiency of flooding depends upon numerous criteria: flood strength, amplitude, frequency, flow time, changes in plan and river geometry, etc. In this research, three statistical models such as the frequency ratio, Shannon's entropy, and weight of evidence have been used to identify flood susceptibility regions in the Kopai River Basin. In order to run these statistical models, flooded and non-flooded pixels were employed. The outcome of these three models demonstrates that the upper reach of the basin is characterised by non-flooded zones and the bottom reach of the basin is high flooded zones. The lower part of the basin is therefore more vulnerable than that of the upper portion. 11 thematic layers are employed to get the final output of flood susceptibility zones. e.g., soil type, normalised vegetation difference index, normalised water differential index, river lift, slope, drainage density, land usage and land cover, rainfall, soil moisture indices, surface roughness. 370 sample points have been taken as test data and finally receiver operating curves have been plotted for testing the degree of accuracy. The result of the validation reveals that the accuracy of the frequency ratio is 96.5%. Shannon entropy is 91.2% accurate and the weight of evidence is 97.1% accurate. Weight of evidence is therefore the best model for flood susceptibility zones identification for this Kopai basin.

Keywords: Weight of evidence, Shannon entropy, Frequency ratio, flood susceptibility, Receiver Operating Characteristics curve

Introduction

Every year, many natural and man-induced hazards and calamities are witnessed across the globe such floods, earthquakes, landslides, etc. (Youssef et al. 2011; Du et al. 2013; Tehrany et al. 2014a; WHO 2019). However, the trend has recently increased significantly because to numerous variables, such as climate change, deterioration of the ecosystem, fast population

1 expansion, etc. (Caruso 2017). Among these, floods are one of the most prevalent and destructive
2 natural catastrophes, resulting in substantial financial damage and the loss of lives every year all
3 over the globe. (Kowalzig 2008; Kourgialas and Karatzas 2011). Floods, in addition to these
4 factors, play a significant role in causing destruction on the environment's ecology. (Billa et al.
5 2006; Rahmati et al. 2015, 2016). Globally, 31% of economic damage is occurred due to this
6 natural disaster (Yalcin and Akyurek 2000). Floods generally occur when significant volumes of
7 water exceed the usual limits, riverside submerges and causes stagnant water during the fleeting
8 season.

9 Furthermore, floods in India are more prevalent among all other natural disasters. Around
10 the one-eighth geographic region of this nation, over 40 million hectares of land are at danger of
11 flood. (Gupta et al. 2003; Mohapatra and Singh 2003). In India, flood-prone areas have increased
12 significantly at a rate of 0.14 million hectares per year (Singh and Kumar 2013). The Ganga and
13 Brahmaputra are the most chronic flood-prone basins covering northern and north-eastern states
14 of this country. During the monsoon, most floods occur because to the seasonal and temporal
15 variations in rainfall patterns, which lead to a lot of flux from rivers during this time. (Kumar et
16 al. 2005). In addition to this, siltation on riverbeds, insufficient capacity on river banks to hold
17 high flow, change in river course, break down of dams, poor drainage condition in flood-prone
18 areas, and glacial outbursts are other responsive factors of flood occurrence. Every year, around
19 30 million people in this nation experience the flood, more than 1500 of them perish. (Gupta et
20 al. 2003). In terms of the flood, India's position is second, just after Bangladesh, due to its flat
21 topography, shallow river bed, monsoonal rainfall variation, massive sediment discharge, etc.
22 (Sarkar and Mondal 2020). Identifying flood-prone locations is thus the most important activity
23 of scientists to prevent loss of life and property. Many scientific research has been carried out in

1 order to classify and identify various kinds of floods and their immediate and long-term
2 repercussions.

3 Flood sensitivity mapping refers to the quantitative or qualitative assessment and
4 classification of the spatial distribution of floods, which may exist or potentially occur in an area.
5 Consequently, techniques for flood susceptibility mapping and flood vulnerability assessment
6 may without doubt assist policy makers and authorities involved in drawing up requirement
7 plans and policies. Although the occurrence of flood risk cannot be eliminated, flood damage
8 may be prevented or minimised greatly by recognising flood-prone locations effectively (Sahoo
9 and Sreeja 2017). Therefore, flood sensitivity assessment is a crucial work for disaster remission,
10 although this will be challenging work due to the direct and indirect involvement of many
11 conditioning factors. In recent years, researchers have suggested, so many broader models for
12 flood risk assessment incorporate remote sensing and GIS tools, which provided considerable
13 good accuracy (Pradhan 2009; Bates 2012; Wanders et al. 2014; Nikoo et al. 2016). Most of the
14 previously used models were mainly focused on the hydrodynamic model, hydrological model,
15 multi-criteria decision analysis (MCDA), statistical models (SM), and machine learning (ML)
16 techniques, which are incorporated in the geographic information system (Singh and Kumar
17 2013; Pradhan 2014; Elkhachy 2015; Vojtek and Vojteková 2016; Rosser et al. 2017; Samanta
18 et al. 2018; Tiriyaki and Karaca 2018; Liuzzo et al. 2019; Santos et al. 2019; Tehrany et al.
19 2019a; Shahabi et al. 2020). The most commonly used models and techniques concerning flood
20 susceptibility mapping include frequency ratio (FR) (Rahmati et al. 2015; Shafapour Tehrany et
21 al. 2017; Samanta et al. 2018; Tehrany et al. 2019a; Sarkar and Mondal 2020), analytical
22 hierarchy process (AHP) (Elkhachy 2015; Dahri and Abida 2017; Das 2018; Rahman et al.
23 2019; Sepehri et al. 2020a), shannon's entropy (Khosravi and Pourghasemi 2016; Haghizadeh et

al. 2017), weights of evidence (WoE) (Tehrany et al. 2014b; Rahmati et al. 2015; Shafapour
Tehrany et al. 2017; Costache 2019), artificial neural networks (ANN) (Kia et al. 2012; Ruslan et
al. 2013; Elsafi 2014; Rahman et al. 2019; Kordrostami et al. 2020), fuzzy logic (Nandalal and
Ratnayake 2011; Sahana and Patel 2019; Sepehri et al. 2020b), support vector machines
(Tehrany et al. 2014b, 2015, 2019b; Nandi et al. 2017), biogeography based optimization and
BAT algorithms (Ahmadlou et al. 2018; Wang et al. 2019), adaptive neuro-fuzzy inference
system (ANFIS) (Wang et al. 2019; Vafakhah 2020), reduced error pruning trees (Khosravi et al.
2018), multivariate adaptive regression splines (Tien et al. 2019), maximum entropy
(Haghizadeh and Rhamti 2017), random forest (Lee et al. 2017; Reza et al. 2020) etc.

The present study of flood vulnerability assessment has been done through frequency
ratio (FR), weights of evidence (WoE), and shannon's entropy (SE) models. The previously used
literature section reveals that these are the most useful statistical models for not only flood
vulnerability assessment but also landslide vulnerability mapping. In this study, several
parameters, i.e., Soil type, Normalized Difference Vegetation Index (NDVI), Normalized
Difference Water Index (NDWI), Distance to River, Elevation, Slope, Drainage Density, Land
use and Land cover, Rainfall, Soil Moisture Index (SMI), and Surface Roughness have been used
for flood vulnerability assessment. In several previous studies, these selected parameters (Table
1) have been used to identify flood vulnerable zones and susceptibility mapping by different
researchers. For this study, three models have been chosen instead of one because only one
model will not be adequate to predict susceptible flood zone. Many research works confirms that
most of these are site-specific models and each of these models has some specific advantages
and disadvantages. Therefore, the main objective of this work is to develop a unique flood risk

map of this study area and to achieve a best-fitted model considering these supreme performing models.

Table 1[Near here]

1. Materials and methods

This portion describes the data gathered and used, as well as the theoretical concept of the flood susceptibility modeling approaches. The data was prepared and evaluated to create databases for constructing and validating models, which included a flood vulnerability map and flood conditioning variables. To assess flood susceptibility, bivariate models (FR, SE, and WoE) were used, and validation methods (ROC and AUC) were chosen to check the bivariate models' effectiveness.

1.1 Location of the study area

Kopai river basin is one of the important river basin in Rarh Bengal. The source of the river is Khajuri village, Jharkhand and its confluence is Babla river, Murshidabad. The total area of the basin is about 1533 Km² and the total length of the river is about 176 Km. The latitudinal extension of the basin is from 23°26'18" North to 23°56'30" North and longitudinal extension is from 87°13'00" East to 88°09'30" East. The location of the Kopai river basin has been shown in Fig. 1

Fig.1 [Near here]

2.2 Flood Inventory Map

Floods that have existed in the past offer valuable details are provided an important initial foothold in the phase of the creation of flood inventory map. In order to forecast potential flooding, the accuracy of data from previous and current floods is important. Not only did the Desk Research, but even the field research was done. At first, the aerial photos of the region were used to prepare an inventory of the flood risk zones, and this was inspected during field verification. The study area's 274 flooded areas were identified and mapped from an aerial photo analysis of the entire region. A field experiment was used to locate and verify these coordinates. Fig. 2 depicts the site locations of 274 inundated areas. 192 (two-to-thirds) 82 (one-to-thirds) of these points were picked from the random dataset for modeling, and the remaining 82 (one-to-thirds) points acted as reference points for the model's accuracy.

Fig. 2[Near here]

2.3 Modeling of Flood Susceptibility

2.3.1 Frequency Ratio Model

The Frequency Ratio (FR) is an observation-based model since it has a clear and intuitive description, as well as it is precise, and is used in a large variety of research applications, making it a good tool for planning flood susceptible maps. The FR approach is based on observed correlations between the distribution of flood incidence locations and each of the variables that influence floods, and it is used to uncover the association between them. The FR model is interpreted mathematically as follows:

$$FR = \frac{N_{Pix(Fi)} / N_{Pix(Ni)}}{\sum N_{Pix(Fi)} / \sum N_{Pix(Ni)}} \dots \dots \dots (1)$$

Where, The number of pixels containing flood in class i is represented by $N_{pix(Fi)}$, and $N_{pix(Ni)}$ is used to reflect the total number of pixels in class i. The degree of association between flood and the concerned class of conditioning variables is expressed by the measured value of FR. A value greater than 1 indicates a good and favorable association as well as high flood susceptibility, while a value less than 1 indicates a detrimental interaction as well as low flood susceptibility. The FR of each class was subsequently summarized using the given formula equation to determine the Flood Susceptibility Index (FSI):

$$FSI = \sum FR \dots \dots \dots (2)$$

2.3.2 Shannon's Entropy Model

Entropy is a methodological approach that is used in a framework to avoid abnormality, instability, disruption, and uncertainty. In 1948, Shannon developed the entropy model, which Stephan Boltzmann introduced to quantify the disorderliness of thermodynamic systems, and this concept has since been used to measure inhomogeneity in the distribution of variable values. This approach can also be used in the flood susceptibility analysis using the concept of entropy. Using the following equations, Shannon's Entropy Model has been structured:

$$P_{ij} = \frac{FR}{\sum_{j=1}^{Nj} FR} \dots \dots \dots (3)$$

Where FR depicts Frequency ratio values, and P_{ij} represents the probability density.

$$H_j = - \sum_{i=1}^{Nj} P_{ij} \log_2 P_{ij}, \quad j = 1, \dots, n \dots \dots \dots (4)$$

$$H_{jmax} = \log_2 Nj$$

$$I_j = \left(\frac{H_{jmax} - H_j}{H_{jmax}} \right), I = (0,1), j = 1, \dots, n \dots \dots (5)$$

$$W_j = I_j FR \dots \dots \dots (6)$$

H_j and H_{jmax} represent entropy values, I_j depicts information coefficient, and W_j refers to resultant weight values for each parameter.

Now the W_j of each class was subsequently summarized using the given formula equation to determine the Flood Susceptibility Index (FSI):

$$FSI = \sum W_j P_{ij} \dots \dots \dots (7)$$

2.3.3 Weight of Evidence Model

It is a quantitative “data-driven” approach for predicting the frequency of incidents based on the Bayes theorem (Rahmati et al. 2015). Recently several scholars are using this model to prepare a flood susceptibility map (Tehrany et al. 2014b; Rahmati et al. 2015; Shafapour Tehrany et al. 2017; Costache 2019). The statistical association between flood locations and each conditioning factor can be calculated by overlaying flood locations with each influencing factor and determining if and how significantly the effective factor is responsible for previous floods. This model is built on the concept of determining positive and negative weights. In this method, positive and negative weights have been calculated based on the weight for each flood conditioning factor (A) based on the presence or absence of the floods (B) within the specific area as follows:

$$W_i^+ = \ln \frac{P\{B|A\}}{P\{B|\bar{A}\}} \dots \dots \dots (8)$$

$$W_i^- = \ln \frac{P\{\bar{B}|A\}}{P\{\bar{B}|\bar{A}\}} \dots \dots \dots (9)$$

Where the probability is P, and the natural log is $\ln$. B and $\bar{B}$ are both the existence and absence of the influencing variables. Furthermore, the presence of the flood is demarcated by A

and absence by $\bar{B}$. A positive weight (W_i^+) demonstrates that the influencing factor is prevalent in flooded areas and that it is a representation that the existence of the conditioning factor and floods are correlated in a positive way. On the other hand, the non-existence of the influencing factors represented by negative weight (W_i^-).

$$C = W^+ + W^- \dots \dots \dots (10)$$

Where C reflects all positive and negative spatial relationships dependent on positive and negative values in this statistical equation. Now, $S(c)$, which is the standard deviation of positive and negative weights, is calculated as follows:

$$S(C) = \sqrt{S^2(W^+) + S^2(W^-)} \dots \dots \dots (11)$$

The variance of the positive and negative weights is described by $S^2(W^+)$ and $S^2(W^-)$, respectively. The following equation may be used to measure the weights' variance (Bonham-Carter 1994).

$$S^2(W^+) = \frac{1}{N\{B \cap A\}} + \frac{1}{B \cap \bar{A}} \dots \dots \dots (12)$$

$$S^2(W^-) = \frac{1}{\{\bar{B} \cap A\}} + \frac{1}{\bar{B} \cap \bar{A}} \dots \dots \dots (13)$$

The final weight is represented by the studentized constant, which is described as the ratio between contrasts and standard deviation.

$$W_{final} = \left(\frac{C}{S(C)} \right) \dots \dots \dots (14)$$

After calculating the model's final weights, a flood susceptibility map can be produced using FSI values. FSI values have been calculated using the following formula:

$$FSI = \sum W_{final} \dots \dots \dots (15)$$

2.4 Flood susceptibility influencing factors

Numbers of thematic maps have been developed to produce the flood susceptibility map. For this purpose, Soil type, Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Distance to River, Elevation, Slope, Drainage Density, Land use and Land cover, Rainfall, Soil Moisture Index (SMI), and Surface Roughness has been used for flood vulnerability assessment. Each factor has individual importance over the preparation of the final output.

a. Rainfall: It is one of the main influencing parameters to accelerate flood phenomena (Rahman et al. 2019). Heavy rainfall occurrences can be observed in the upper reach of the basin, where >1400 mm rainfall has been recorded annually. Contrary, the lowest rainfall occurs along the lower reach of the basin where annually <1200 mm rainfall has been recorded (Fig. 3i). Thus, though the highest rainfall was recorded in the upper reach, the highest flood has been recorded in the lower reach. So, here slope plays a vital role in the accelerating flood.

b. Elevation and Slope: Land elevation and slope are the second most crucial flood susceptibility influencing factors as they control runoff of a river basin (Rahman et al. 2021). Runoff generally occurs from highland to lowland; thus, flood probability is highest in the lower reach of a basin. The highest elevation of the test region ranges between 110-160 meters in the western part of the basin, but the basin experiences 16-38 meters as the lowest elevation in the eastern part (Fig. 3a).

If we consult the degree of slope, it can be observed that the western part has been experienced by 2.64-27.94% of the slope, but the eastern part where the elevation is lowest has been characterized by 0.98% of slope (Fig. 3b).

- c. Land use and Land cover:** The land use pattern for an area shows the kind of land use by living populations and natural processes (Ajin et al. 2013; Kaur et al. 2017). Land use and land cover maps are critical in determining flood risk, as vegetated areas are less vulnerable to flooding events due to the negative association between a flooding event and vegetation density (Mojaddadi et al. 2017). LULC directly affects When combined, these characteristics provide details about the hydrological response and the degree of flood threat (Islam and Sado 2000).
- d. Soil type:** Different types of soil influence the degree of flood susceptibility (Costache 2019; Dano et al. 2019; Das 2019; Rahman et al. 2021) as the soil form affects an area's ability to retain water (Asare-Kyei et al. 2015; El Morjani et al. 2017). Fig. 3g depicts that the name of the soil classes has been given as per their location, and based on locational nomenclature, Ghoshgram-Gourbazar soil is predominant here.
- e. Distance to the river:** Flooding is a common phenomenon along the stream in the research region. Distance to the river was also considered another element relevant to geomorphology. A distance from the river map was subsequently created as the rivers would disturb the stability of the slopes either by cutting the toes or by saturating the pieces of material lying within the river (Mojaddadi et al. 2017; Shafapour Tehrany et al. 2017; Rahman et al. 2019). Distance from the river or proximity map has been prepared in ArcGIS 10.5 software (evaluation version) using the Euclidean distance method. Fig. 3e reveals five proximity zones or five buffer zones from the mainstream. There is an inverse relationship between distance from mainstream and flood occurrences; increasing the distance from the river, flood susceptibility becomes decreased and vice-versa.

f. Drainage Density: Increased flooding probability is closely correlated with increased drainage density, as it implies increased surface runoff. It has been indicated that areas with a higher drainage level produce more surface runoff than areas with a low drainage density (Kumar et al. 2007). Thus, the extent to which flood risk increases can be dependent on drainage density, a key factor in runoff production (Ogden et al. 2011). A drainage density map has been prepared in ArcGIS 10.5 (evaluation version) using the grid method. Fig. 3d shows that higher drainage density present in the upper reach of the basin but lower drainage density in the lower reach of the basin. Due to the slope factor, flood susceptibility is high in the lower reach despite lower drainage density.

g. Normalized Difference Vegetation Index (NDVI): Intensity of flood and flood susceptibility has been associated with vegetation cover (Ajin et al. 2013; Kaur et al. 2017; Rahman et al. 2021). Normalized Difference Vegetation Index or NDVI has been derived from LANDSAT-8 imagery in Arc GIS 10.5 software (evaluation version) using the raster calculator tool. To get the final output of NDVI from Landsat-8 imagery following formula has been used.

$$NDVI = \frac{(NIR\ band - R\ band)}{(NIR\ band + R\ band)} \quad (16)$$

Fig.3J shows that the upper reach has been characterized by dense vegetation due to a high degree of the slope, but the lower reach has sparse vegetation cover.

h. Normalized Difference Water Index (NDWI): Normalized Difference Water Index or NDWI refers to the data of liquid water derived from the satellite images. It locates all the water bodies present on the surface, directly affecting the inundation period and frequency of flood (Memon et al. 2015; Khalifeh Soltanian et al. 2019; Sivanpillai et al. 2020). NDWI has been derived from Landsat-8 satellite imagery in ArcGIS 10.5 software

(evaluation version) using the raster calculator tool. The following formula has been used to calculate NDWI.

$$NDWI = \frac{(Green\ band - NIR\ band)}{(Green\ band + NIR\ band)} \quad (17)$$

NDWI values range from -1 to 1. The NDWI value for water bodies is more significant than 0.5, while lower values, such as negative values, equate to plants, making it simple to differentiate water bodies from vegetation. Fig. 3K reveals the spatial pattern of NDWI.

- i. **Soil Moisture Index (SMI):** Soil moisture plays an important role in the regulation of the water cycle and flood inundation period (Saha et al. 2018). If soil contains high moisture and even it receives further rainfall, soil cannot hold more water. As a result, overflow occurs around the land areas, ultimately converting to flood (Beran and Sutcliffe 1972; Ahlmer et al. 2018). The soil moisture index of SMI has been derived from LANDSAT 8 satellite imagery using the following formula in ArcGIS software.

$$SMI = \frac{(LST\ Max - LST)}{(LST\ Max - LST\ Min)} \quad (18)$$

Where LST Max means Maximum land Surface Temperature

LST Min means Minimum land Surface Temperature

Fig. 3h depicts maximum soil moisture is present in the lower reach of the river basin; that's why flood intensity is maximum in the lower reach.

1
2 **j. Surface Roughness:** It is another factor that affects flood susceptibility differently. More
3 the roughness in the surface, flood susceptibility becomes reduced and vice-versa. This
4 parameter is a Digital elevation model or DEM derived factor, and this map has been
5 prepared using ArcGIS 10.5 software (evaluation version)

6 Fig. 3c displays that surface of the basin is rough in the upper reach of the basin,
7 and it is smooth in the lower reach.

8
9
10 Fig. 3 [Near here]

11 The entire methodology from data collection to application of statistical model has been
12 in detail in Fig.4

13
14
15 Fig. 4 [Near here]

16 **3. Result and discussion:**

17 *3.1 Frequency ratio and flood susceptibility zones*

18 Eleven parameters have been taken to run the frequency model. Table 3 shows the
19 frequency ratio value for all parameters and associated feature classes. Here higher the values of
20 frequency ratio, the higher will be flood susceptibility and vice-versa. Therefore, a strong
21 positive relationship prevails between FR values and flood intensity (Liuzzo et al. 2019). The
22 outcome of FR model is strongly related to elevation and drainage density (Fig...5a, 3a, and 3d).
23 So, it can be easily explained that the number of flood occurrences as per the frequency model

depends on the elevation and drainage density factor. Fig.5a reveals, as per the FR model, high flood susceptibility zones present in the lower reach of the basin and low to very low flood susceptibility exists in the upper reach of the Kopai river basin. Moreover, soil moisture index is also an important influencing parameter for flood occurrence as per the FR model. If we observed Fig. (3h) and Fig. (5a), both resemble at the lower reach where river basin holds excessive moisture, and it accelerates high flood susceptibility. In this model, high and very high flood susceptible zones acquire 362.403 and 191.184 Km² area (Table2)

3.2 Shannon's Entropy and flood susceptibility zones

Shannon's entropy is another statistical model has been applied here to extract the flood susceptibility zones of Kopai river basin. Detail methodology of this model has been discussed in the methodology section. The result of Shannon's entropy has been depicted in Fig. 5b. This figure has been clearly shown that the area high flood susceptibility zones are much larger than FR model, and also this model reveals the larger absence of very low susceptibility, e.g., in Shanno's model high and very high flood susceptible zones contain 522.757 and 314.266 Km² area in respect to FR model (Table2). So, this model gives a different result than FR model.

3.3 Weight of Evidence and flood susceptibility zones

Fig. 5c explains that this model more or less similar to the FR model. Both FR and WOE show the same areal coverage of flood susceptibility zones (Table2). This model shows the lower reach of the Kopai river basin is more susceptible to flood than the upper reach.

There is a similarity of these three models, i.e., for each model highest value indicates high flood susceptibility and vice-versa.

Fig. 5 [Near here]

3.4 Validation of models

For the validation of these three models, the receiver operating curve or ROC has been applied. The AUROC curve was utilized in this work to depict and evaluate the predictive capability of standalone models. The AUROC diagram is constructed by graphing the sensitivity on the x-axis against the 1-specificity on the y-axis. The AUROC curve quantitatively illustrates model prediction capability and map accuracy. The AUROC and prediction accuracy connection fluctuates between 0 and 1, and was divided into five categories (Wang et al. 2011) viz. >0.9 to 1 perfectly applicable, 0.8 to 0.9 highly applicable 0.7 to 0.8 moderately applicable 0.6 to 0.7 Poorly applicable 0.5 to 0.6 very poorly applicable. For ROC drawing, more than 300 sample points have been taken as test files, and the test points have been selected to identify where the susceptible zones are really flooded or not. With the help of these 300 selected ground points, we have tried to judge the reality of flood and non-flooded zones in the concerning test area. If we look at Fig. 6, it depicts three ROC curves for three respective models like FR model, Shannon's entropy, the weight of evidence. Three models give three different results: AUC of FR, Shannon's entropy, and WOE are 0.965, 0.912, and 0.971, respectively (Fig.6).

Fig. 6 [Near here]

Therefore, validation of the model emphasizes that the FR model and WOE are more applicable statistical models in this region than Shannon's entropy. If we observed the output of flood susceptibility zones, it would be clear that Shannon's entropy gives more flooded regions than the other two models, but in reality, the Kopai river basin holds flooded areas only in the lower reach. As the ROC curve has been depicted based on field data, the validation result of Shannon's entropy failed for the proper explanation of flood susceptibility than FR and WOE model. Here WOE gives a more accurate result than the other two models, and it provides 97% accuracy. So, we accept the weight of evidence as a valid model to identify the flood susceptibility zones for this particular river basin.

2. Conclusion

This study proposed flood susceptibility zones based on three statistical models. To run the three models, 10 flood influencer parameters have been taken into consideration. For each model same parameters have been selected to get the comparative result. Three models give uniform results in the sense that in all models upper reach of the basin displayed lower flood susceptible zones, and the lower reach give higher susceptible zones. These five zones have been identified to show the intensity of flood susceptibility viz. very high susceptible, high susceptible, moderately susceptible, low susceptible, and very low susceptible.

In terms of validation of the model, we can observe that the weight of evidence gives more accuracy than the other two models, e.g., frequency ratio and Shannon's entropy. ROC has been plotted here to identify the curve and accuracy of the model, where WOE method depicts more than 97% accuracy compared to other consecutive methods.

For preventing floods in the Kopai river basin, the flood susceptibility map described in this research could be a valuable resource for engineers, policymakers, planners, and administrative organizations. Another notable difference is that the methodologies used in this study bridge the gap of comprehending catastrophic floods and their effectiveness. This methodology is advised for providing a greater understanding of the magnitude and frequency of floods as well as the area where people are at risk for floods.

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Figures

Figure 1

Location of the study area: a. India b. West Bengal c. Kopai river basin

Figure 2

Flood inventory map

Figure 3

Input data: a. Elevation b. Slope c. Surface roughness d. Drainage density e. Distance from river f. Landuse/landcover g. Soil h. Soil moisture index i. Rainfall j. NDVI k. NDWI

Figure 4

Figure 5

Flood susceptibility map based on (a) Frequency ratio (b) Shannon's entropy (c) Weight of evidence

ROC Curve

Figure 6

ROC for model validation

Supplementary Files

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