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Flood Susceptibility Accuracy Assessment of Panchganga River Basin (PRB), Kolhapur, Maharashtra (India) using Frequency Ratio and Weight of Evidence Model

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ABSTRACT

In the past few decades, the world has experienced some of devastating and frequent. flood events. The Panchganga River basin (PRB) of Maharashtra state, India had been selected for flood susceptibility mapping using the frequency ratio (FR) model and weight of evidence (WoE) model. In the present study, a flood inventory with 224 historic flood locations was prepared. 75% of flood locations were randomly selected for training and 25% for testing purposes. The flood susceptibility map prepared using FR and WoE model was classified into five zones such as very high, high, moderate, low, and safe zone using ArcGIS software. The receiver operating characteristics (ROC) curves were plotted with an area under the curve (AUC) values of 88.78% and 89.27% for the FR model and 85.84% and 87.34% for the WoE model for success rate and prediction rate respectively. The present study will help people near the Panchganga River to move to a safer place during flooding. The farmers can minimize their losses of different kind due to flood disasters in the PRB.

KEYWORDS

Flood Susceptibility Mapping (FSM), Digital Elevation Model (DEM), Frequency Ratio (FR), Weight of Evidence (WoE), Remote Sensing (RS)

1. INTRODUCTION

Floods are the most devastating and recurrent natural calamity all over the world. Flood creates a negative impact on society in terms of loss of life, property, and agriculture damages [1]. From the available literature, it is found that the changes in land-use land cover pattern with an increased impervious surface increase flow velocity [2].

India is a land with diversified natural features such as mountains, oceans, rivers, and valleys which made the country among the most disaster-prone countries in the world [3]. This research paper mainly focuses on the flood susceptibility mapping of the PRB in the Kolhapur district of Maharashtra, India using FR and WoE models. The various rivers flowing through the Kolhapur district receive a very high rainfall in their upper catchment. During the monsoon period, the upper catchment of the Panchganga river receives very high rainfall from June to September which turns the region into floods. In the past, many flood events had triggered the region in the years 2005, 2006, 2010, 2019, 2020, 2021, and 2022. History reveals that tehsils like Hathkangale, Shirol, and Karveer are frequently affected by floods [4].

Satellite imagery through remote sensing (RS) with an advanced geographic information system (GIS) provides spatial information that is used for determining flood hazard areas very quickly and efficiently with minimal cost [5, 6, 7].

Various methods have been investigated and applied so far for flood susceptibility mapping and risk assessment but FR model is the easiest method to implement [8]. The machine learning model requires a huge amount of training data for higher accuracy as compared to FR and WoE models [9]. FR and WoE method provides a better correlation between flood conditioning factors and dependent factors. The FR method assigns value to every single class of the classified flood factor (elevation, slope, land use, etc) and evaluates its impact on flood occurrencee [10]. The WoE method derives the relationship and the contrast value (C) between the flood locations and flood conditioning factors [25].

2. MATERIALS AND METHODS

2.1 Study Location:

The PRB is located in the upper region of Kolhapur district of Maharashtra state, India situated in the south-western part of Maharashtra with latitudes of 16^0 31'N to 16^0 92' N and longitudes of 73^0 63' E to 73^0 72' E (Fig. 1). The study area covers 33% (2580.86 km^2) of the total area of the Kolhapur district. The elevation in the region varies between 526 to 1030 meters. The hilly area lies towards the west whereas low lying area is located in the eastern part of the study region. The study area had recently encountered major flood events therefore this area has been selected for flood susceptibility mapping (FSM).

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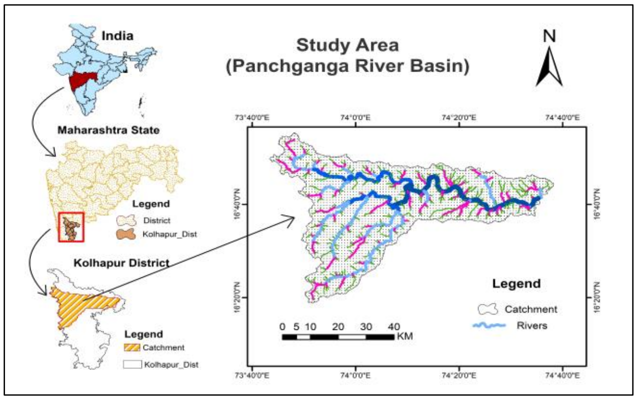

Fig. 1 Location of Study Area

2.2 Data:

For the present study, several spatial data layers were used as flood causative factors like elevation, slope, drainage density, topographic wetness index (TWI), land use land cover (LULC),

2.3 Data Preparation:

The topographic factors derived from the DEM have a direct effect on flow size and runoff velocity [11]. In the present study, different raster layers like elevation, slope angle, distance to a river, and drainage distance were produced in ArcGIS 10.8 environment using SRTM DEM of 30 m resolution downloaded from USGS Earth Explorer [29]. The Using the spatial analyst tool of ArcGIS, distance to river map was generated. The normalized difference vegetation index (NDVI) layer is derived from near-infrared and red band from Sentinel-2. The curvature tool from the surface toolset of spatial analyst tool was used to generate the profile curvature layer. The topographic wetness index (TWI) layer is derived from DEM. The inverse distance weighted (IDW) method was used to map the rainfall distribution in the study area. The spatial layers thus produced are finally converted into five classes to check its impact on flooding.

2.4 Flood Inventory Mapping:

Accuracy of the past flood events has a very high influence on the accuracy of flood susceptibility map [30]. One of the important steps in flood susceptibility mapping was to create a flood inventory of historic flood locations. Total 224 ground truth points were randomly chosen from Google Earth. 75% points were selected for training the model and 25% for testing purpose.

3. FLOOD SUSCEPTIBILITY MODELLING

3.1 Frequency Ratio Model (FR)

In this paper, the FR model which is a bivariate statistical analysis method based on the spatial distribution of flood conditioning factors and the flood locations [21]. FR determines correlation between flood conditioning factors and flood locations [14]. FR is the ratio of a flooded area to the total area or the ratio of the probability of flood occurrence to non-occurrence of that phenomenon [2]. It is expressed by (1) as:

$$FR = \frac{E/F}{M/L} \quad (1)$$

where, E is total flood pixels in each class; F is total flood pixels in study area; M is total pixels in each class of a factor; L is total pixels in the study area [5]. The FR value greater than 1 indicates a strong correlation between the flood location and a given factor. The correlation is weak if the ratio is less than 1 [20].

3.2 Weight of Evidence Model (WoE):

Another model used here for flood susceptibility mapping was the WoE model which is also a bivariate statistical approach based on the Bayesian method that uses prior and conditional probability [26]. In this method, the historic flood locations were overlayed with each of the flood conditioning factors, and a statistical relationship is obtained between them to determine how effectively the factor is contributing to floods. The calculation of weights in the WoE model requires positive (W+) and negative (W-) weights based on the contribution of each flood factor to flood occurrence [53]. The W+ and W- is calculated using (2) and (3) as:

$$W+= ln\frac{P\,\{B|A\}}{P\,\{B|\bar{A}\}} \quad (2)$$

$$W-= ln\frac{P\,\{\bar{B}|A\}}{P\,\{\bar{B}|\bar{A}\}} \quad (3)$$

where, P is the probability; B and $\bar{B}$ are the presence and absence of flood conditioning factors. A and $\bar{A}$ are the presence and absence of flood respectively [26]. The weight of contrast (C) is the difference of W+ and W- and gives the spatial association between flood factors and flood occurrences. S(C) is the standard deviation of W and calculated using (4) as:

$$\mathrm{S(C)} = \sqrt{S^2(W^+) + S^2(W^-)} \quad (4)$$

where, $S^2(W^+)$ and $S^2(W^-)$ are the variances of W^+ and W^- respectively [27]. The final weight is the measure of confidence and is calculated as C/S(C), (Table I).

4. FLOOD CAUSATIVE FACTORS

The flood susceptibility modelling using RS and GIS requires different spatial layers derived from the DEM. In this paper, we used elevation, slope, drainage density, distance to streams, TWI, NDVI, soil texture, rainfall, LULC, and curvature as the spatial data layers [11]. These layers are considered as the most important spatial data for flood related studies [15]. All these layers are then converted to a raster grid of 30 x 30 m^2 using ArcGIS 10.8 as shown in Fig. 2a – 2j.

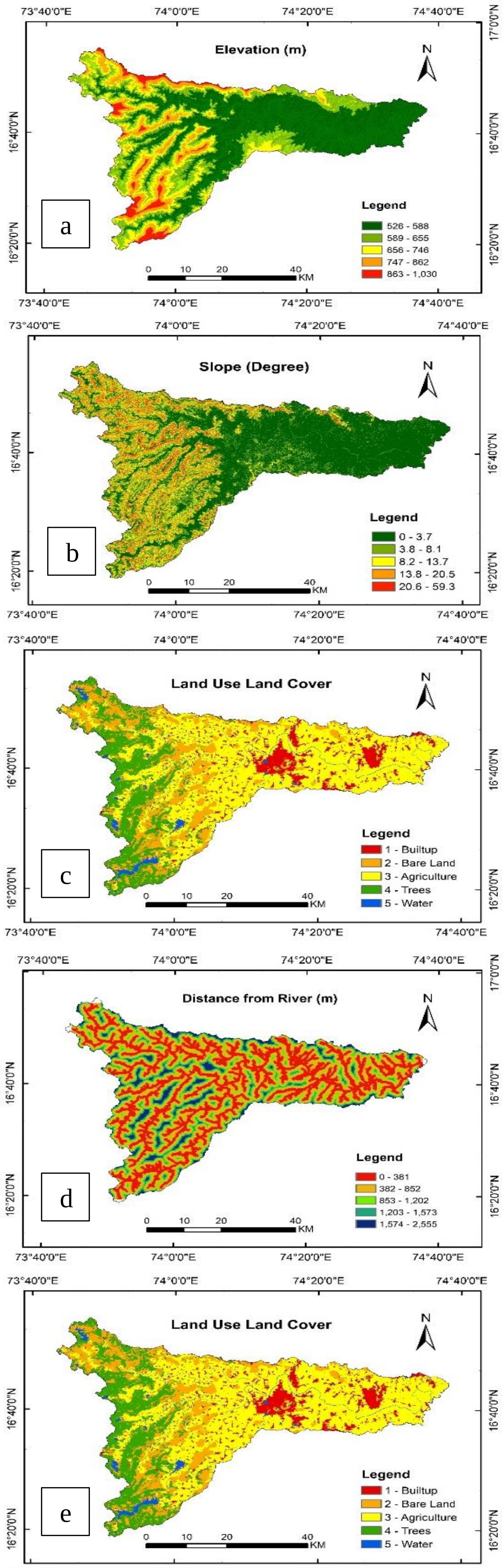

Fig. 2a – 2e Flood conditioning factors for study area

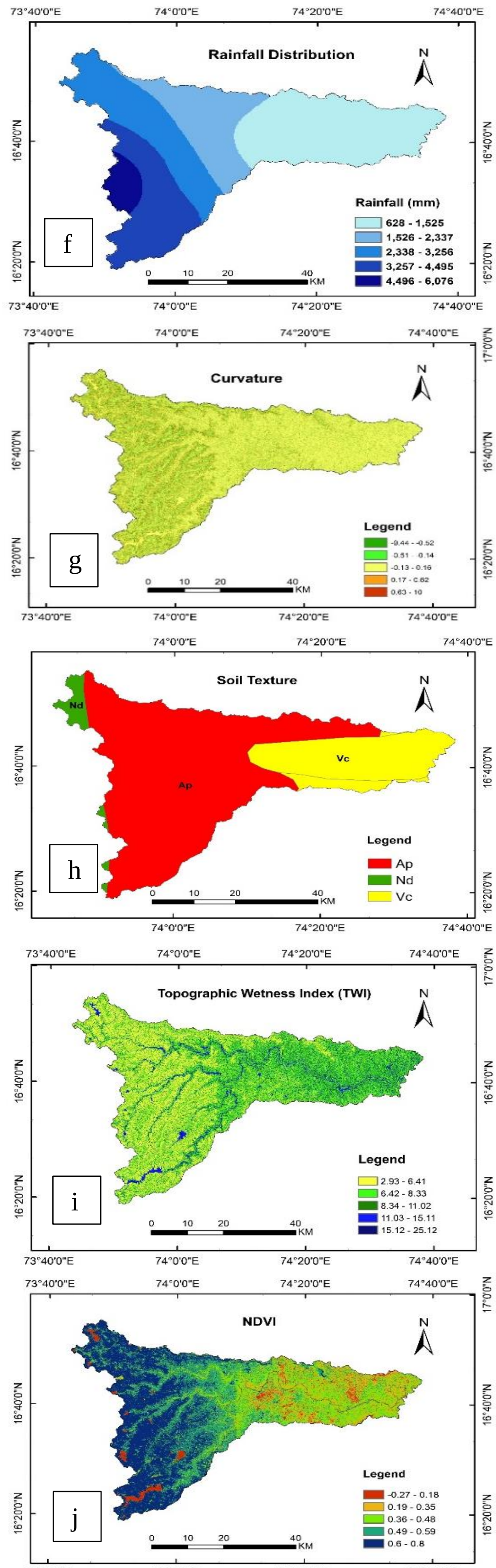

Fig. 2f – 2j Flood conditioning factors for study area

Table. 1 Spatial relationship between flood conditioning factor and historic flood locations using FR and WoE models

Factor	Factor Class	FR	W^+	W^-	C/S(C)
Elevation (m)	526- 588	2.15	0.71	-3.76	6.29
	589- 655	0.05	-3.09	0.29	-4.75
	656- 746	0.00	0	0.17	0
	747- 862	0.00	0	0.12	0
	863- 1030	0.00	0	0.04	0
Slope (Degree)	0- 3.7	1.93	0.61	-1.86	8.54
	3.8- 8.1	0.24	-1.48	0.21	-4.94
	8.2- 13.7	0.11	-2.22	0.16	-4.10
	13.8- 20.5	0.00	0	0.11	0
	29.5- 59.3	0.15	-1.93	0.04	-1.96
LULC	Built-Up	1.33	0.23	-0.01	0.52
	Bare Land	0.03	-3.56	0.23	-3.78
	Agriculture land	1.71	0.48	-1.20	7.62
	Trees	0.06	-2.81	0.21	-4.25
	Water	1.03	-0.02	0.00	-0.09
Distance to River (m)	0 - 381	1.46	0.33	-0.25	3.71
	382 - 852	1.25	0.16	-0.11	1.73
	853- 1202	0.31	-1.23	0.17	-4.30
	1203- 1573	0.21	-1.60	0.07	-2.87
	1574- 2555	0.00	0	0.05	0
TWI	2.93- 6.41	0.16	-1.90	0.39	-6.66
	6.42- 8.33	1.27	0.19	-0.16	2.25
	8.34- 11.02	1.41	0.30	-0.07	1.97
	11.03- 15.11	2.21	0.74	-0.12	4.44
	15.12- 25.12	1.45	0.32	-0.01	0.65
NDVI	-0.27- 0.18	0.77	-0.32	0.01	-0.81
	0.19- 0.35	2.01	0.65	-0.14	4.33
	0.36- 0.48	2.41	0.83	-0.46	8.35
	0.49- 0.59	0.74	-0.36	0.10	-2.27
	0.6- 0.8	0.09	-2.42	0.48	-6.97
Drainage Density	0 - 52.34	0.06	-2.93	0.39	-5.68
	52.35- 107.86	0.28	-1.33	0.22	-4.98
	107.87- 69.72	0.75	-0.35	0.09	-2.13
	169.73- 42.68	2.37	0.81	-0.26	6.55
	242.7-404.46	5.43	1.64	-0.43	13.10
Rainfall (mm)	628- 1525	2.12	0.69	-0.86	8.93
	1526- 2337	1.42	0.29	-0.09	2.20
	2338- 3256	0.00	0	0.27	0
	3257- 4495	0.00	0	0.23	0
	4496- 6076	0.00	0	0.05	0
Soil Texture	Chromic Vertisols	2.54	0.88	-0.64	9.67
	Distric Nitosols	0.00	0	0.03	0
	Plinthic Acrisols	0.54	-0.67	0.95	-10.24
Curvature	-9.44- -0.52	0.00	0	0.04	0
	-0.51- -0.14	0.82	-0.25	0.05	-1.42
	-0.13- 0.16	1.36	0.25	-0.52	4.31
	0.17- 0.62	0.43	-0.90	0.14	-3.75
	0.63- 10	0.25	-1.44	0.02	-1.46

5. RESULTS AND DISCUSSION

For this paper, FR & WoE models were used to determine the level of correlation between historic flood locations and flood factors for the PRB [16].

5.1 Results of FR Model

From Table 1 it is found that the region with lower elevation gets flooded easily. The subclass with lowest elevation of 526-588 has highest FR value of 2.15 than the remaining subclasses. Thus, lower elevation regions are highly prone to flood (Fig. 2a). The result reveals that around 46% flood occurred in low laying area [17]. The slope map was classified into 5 sub-classes as shown in Table I. The lowest slope with slope angle between 00 to 3.70 has highest FR value of 1.93 and this region is very much prone to flood as shown in Fig. 2b [9]. The western part of the study area with steep slopes is very less prone to flood. Figure 2c shows distance from river map which is classified to 5-subclasses. The regions nearby stream within 0–381m with FR of 1.46 are highly susceptible to flooding [18]. Figure 2d shows a drainage density map with subclass of 242.69 – 404.46 having highest FR of 5.43 which reveals the accumulation of a large quantity of water [11]. So, these regions are highly prone to flooding due to reduced infiltration [8].

The LULC map is classified as built-up, barren land, agriculture, trees, and water body as shown in Fig. 2e. The result showed that built-up and agriculture land are more responsible for flooding [19]. Increase in built-up area generates surface runoff due to increase in impervious surface and hence the flood intensity [8].

The rainfall data layer is shown in Fig. 2f which was divided into 5 classes. FR for the class 628-1525 mm and 1526-2337 mm which is on the eastern side of PRB, is 2.12 and 1.42 respectively, and is less than 1 for the remaining classes on the west. The western part of the PRB is least vulnerable to flood (Fig. 3) in spite of highest rainfall as all the water flows down the east due to hilly area. The eastern part in contrast is highly flood-prone due to the flat surface in spite of minimum rainfall. Figure 2g shows the curvature layer with 5 subclasses in the range -9.44 to -0.52, -0.51 to -0.14, -0.13 to 0.16, 0.17 to 0.62, and 0.63 to 10.0. The highest FR value of 1.36 is found for the range of -0.13 to 0.16 which governs the flat portion of the study area and is more prone to flooding. Hillsides (FR<1) towards the west is less prone to flood as it promotes water flow to lower and flat regions towards east, leading to flooding [9]. A curvature map was prepared using SRTM-DEM [23]. The soil map of the Panchganga River basin mainly consist of Distric Nitosols found to the west, Plinthic Acrisols in the middle, and Chromic Vertisols to the east (Fig. 2h). FR value for Chromic Vertisols with high water holding capacity of found highest among all and thus reveals the area to be more prone to floods [12].

TWI spatial layer is derived from the DEM of the catchment using ArcGIS. Figure 2i shows the TWI layer with 5 classes that can be used to predict a region with potential flood hazard [13]. The highest values of FR for TWI classes were found for the eastern region of the study area with range of 11.03 – 15.11 (FR = 2,21) and 15.12 - 25.12 (FR = 1.45). It therefore confirms that TWI had a strong correlation with chances of flooding [6].

From the literature, the lower values of NDVI influenced flooding as the land is forbidden of vegetation. The NDVI map was classified into 5-classes as shown in Fig 2j. The class with NDVI higher than 0.48 is located towards the western side of the study area that is full of hills with minimal flooding whereas the eastern region with NDVI less than 0.48 corresponding to built-up, barren land, cropland is found more prone to flooding [9]. The flood susceptibility map using FR model is shown in Figure 3.

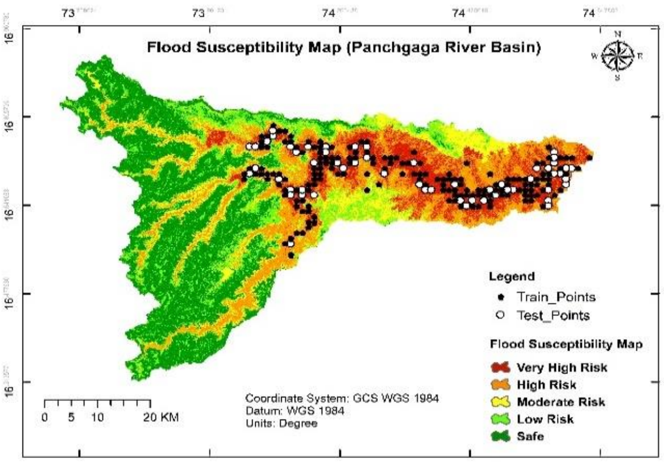

Fig. 3 Flood Susceptibility map using FR model

5.2 Results of WoE Model

For the present paper, all the WoE parameters were calculated as shown in Table 1 for each of the flood factors. The final weight calculated as C/S(C) decides the dependence of flood occurrence on a particular factor class.

The elevation subclass of 526 - 588 m had the highest C/S(C) of 6.29. So, this region is highly susceptible to flood. Similarly, it is found that for slope, the C/S(C) value of 8.54 is the highest for a subclass of 00 to 3.70. Among different LULC classes, agricultural land is highly prone to flooding. The distance from the river in the range of 0 – 381 m had the highest C/S(C) of 3.7 with the highest flood susceptibility. The TWI in the range of 11.03- 15.11 is highly prone to flood with C/S(C) of 4.43. The NDVI in the range of 0.36- 0.48 is highly prone to flood with C/S(C) of 8.35. The drainage density subclass with range 242.69-404.46 had the highest C/S(C) value of 13.09 which is highly prone to flooding.

The eastern region of the study area with minimum rainfall in the range of 628- 1525 mm had the highest flood susceptibility as all the water flows down to this region from hilly area on the west. The C/S(C) value of 9.66 for Chromic Vertisols (Vc) as soil subclass towards the east is the highest among other subclasses. This showed positive influence on flooding. Lastly, the curvature profile in the range of -0.13- 0.16 showed highest C/S(C) value of 4.31 with positive influence. The flood susceptibility map using WoE model is shown in Figure 4.

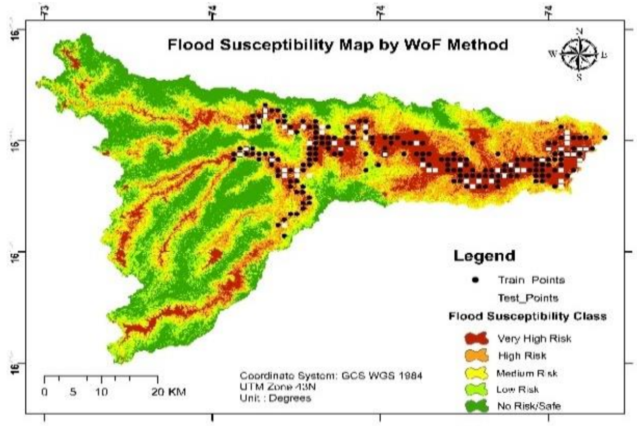

Fig. 4 Flood Susceptibility map using WoE model

Table 1 shows all the results using FR model that indicates a correlation between different flood conditioning factors and flood occurrence in the study area. The FR >1 indicates a high correlation and FR <1 shows a lower correlation between the flood location and flood factors [20]. Also, the results for WoE model are summarized in Table 1. The flood conditioning factors used to derive WoE parameters are shown in Fig. 2a-2j.

6. RESULTS AND DISCUSSION

The accuracy of the results obtained in Table I for flood susceptibility mapping using FR and WoE models need to be validated by some means. In this paper, we used the receiver operating characteristics (ROC) method to evaluate the performance of the model in terms of its accuracy and reliability [10, 22]. The ROC method was used to evaluate the success and prediction rate of the flood susceptibility model [6] as shown in Fig.5. The success rate was plotted using training and prediction rate using the testing dataset. The AUC values of 88.78% and 89.27% were found for the FR model and 85.84% and 87.34% for the WoE model for success and prediction rate respectively. Thus, both the models were proved to be quite accurate and suitable to predict the flood-prone areas in the PRB [24]. Table 2 shows the comparison of AUC values from the literature with present study.

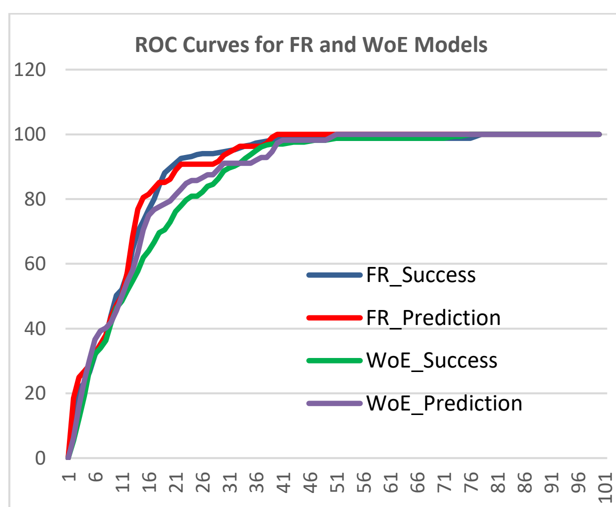

Fig. 5 ROC Curves for FR and WoE model for PRB

Table. 2 Comparison of AUC for different papers

AUC (Success)		AUC(Prediction)		Ref No.
FR	WoE	FR	WoE	
62.17%	88.73%	60.05%	88.07%	[9]
--	--	76.47%	74.74%	[8]
82.04	--	84.74%	--	[2]
84.80%	--	81.20%	--	[28]
88.78%	85.84%	89.27%	87.34%	Present paper

7. CONCLUSION

This research paper has used the FR and WoE models to prepare the flood susceptibility map of Panchganga River basin, Kolhapur, Maharashtra. The floodplain of Panchganga River basin has been classified into 5 classes as very high, high, moderate, low and no flood risk zones which is not been done previouslyfor the same syudy area. Also, the accuracy assessment of flood risk in PRB has been carried out using statistical approach and AUC values for both success and prediction rate were enhanced as compared to previous studies using Ranking, Rating and AHP models [31]. Different flood conditioning factors were taken into consideration to map the correlation with historic flood locations. The elevation had maximum influence to flooding phenomena followed by soil texture, slope, and drainage density. The rainfall, curvature, distance to a river, LULC have a medium impact on flood occurrence whereas the TWI and NDVI have the least influence on flooding (Table 1). Approximately, 40% of the total area in PRB was found in high to very high-risk flood zone, 12.3% is in a medium, 13.3% is in low and 33.7% is in safe or no flood zone. The present study will help people, town planners, farmers minimize their losses of different kind due to flood disasters in the PRB.

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