



Flood Susceptibility Analysis in Chennai Corporation Using Frequency Ratio Model

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Abstract

Natural disasters like flood are causing massive damages to natural and human resources, especially in coastal areas. In respect to social, economic and environmental perspective, flood is one of the most devastating disasters in Chennai for the recent days. Flood susceptibility mapping using frequency ratio model was done for the 88 micro watersheds of Adyar, Cooum and Kosasthalaiyar watersheds of Chennai Corporation area. Flood Susceptibility map was generated using frequency ratio model by considering ten different independent variables (landuse/land cover, elevation, slope, topographic wetness index, surface runoff, landform, lithology, distance from the main river, soil texture and soil drainage) through weighted-based bivariate probability values. In total, 123 historic flood reported locations were taken for this study from which 100 locations were used for susceptibility mapping and 23 locations were used for validation. Both the independent variables and historic flood locations were combined together to generate frequency ratio database for flood susceptibility mapping. The developed frequency ratio was varied from 0 to 27.11 and reclassified into five flood vulnerability zones namely, very low (less than 5.0), low (5.0–7.5), moderate (7.5–10.0), high (10.0–12.5) and very high susceptibility (more than 12.5). The result revealed that 10.48 and 38.93 percentage of the land have very high and high vulnerable class, respectively. The frequency ratio model validated using 23 flood locations, where 22 locations are presented in high and very high susceptibility class. This analysis exemplified that prediction was with success rate of 95.6%. The flood susceptibility analysis using this model will be very useful and efficient tool to the local government administrators, researchers and planners for devising flood mitigation plans.

Keywords Flood Susceptibility · Watersheds · Chennai Corporation · Frequency Ratio

Abbreviations

FR	Frequency Ratio	MCDA	Multi-Criteria Decision support Approach
RS	Remote Sensing	WofE	Weights of Evidence
GIS	Geographic Information System	ANN	Artificial Neural Networks
TWI	Topographic Wetness Index	NRSC	National Remote Sensing Centre
NRSC	National Remote Sensing Centre	SRTM	Shuttle Rader Topographic mission
SCS	Soil Conservation Service		
AMC	Antecedent soil Moisture Condition		
AHP	Analytical Hierarchy Process		

Introduction

Globally, most of the people are exposed to various natural disaster. Among them, floods are one of the significant natural disasters in the world (Faiz Ahmed & Natraj Kranthi, 2018). The instantaneous widespread and continuous rainfall leads to waterlogging and flood. In particular, in the region of south India due to the depression over southwest Bay of Bengal and owing to a strong El Nino (Bhatt & Ashish Mishra 2016). McGranahan et al. (2007) said that 13% of Asia population live in low elevation

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coastal area which is severely exposed to weather events like flood and 140 million people are affected by flood event in every year as per WHO 2003 report. The Chennai is the important coastal low-lying city in south India. The past flood events of Chennai in 1976, 1985, 1996, 1998, 2005, 2008 and 2010 are caused several damages to property, human health and infrastructures (Lavanya, 2012). The reasons for these flood events are failure of major rivers and drainage management system (Bisht et al., 2016). To controlling of flood and suggesting preventive measures are necessary to reduce the probable damages to agriculture, infrastructure and other natural resources (Billa et al., 2006; Huang et al., 2008; Samanta et al., 2018). Therefore the flood susceptibility study is significant for early warning system and mitigation of upcoming flood episodes (Tehrany et al., 2015).

Many comprehensive tools used by many researchers for flood susceptibility mapping includes Analytical Hierarchy Process (AHP) (Billa et al., 2006; Chen et al., 2011; Yalcin, 2008), Multi-Criteria Decision support Approach (MCDA) (Samanta et al., 2016), Weights of Evidence (WofE) (Rahmati et al., 2016), adaptive neuro-fuzzy interface system (Sezer et al., 2011), Artificial Neural Networks (ANN) (Tiwari & Chatterjee, 2010) and Frequency Ratio (FR) model (Lee et al. 2012; Liao & Carin, 2009). Even though AHP is most popular and widely used method, it is constrained to be weak as it provides uncertainty due to its enslavement of information provided by the researchers (Chen et al., 2011). Likewise, MCDA could be useful in flood mapping for no data region, but it is successfully approached only by the local planners (Samanta et al., 2018). ANN method was also attempted to show relationship between conditioning parameters and the outcome (Pradhan & Buchroithner, 2010). This method accepts all inputs which produces uncertainty in obtaining meaningful information (Lohani et al., 2012). WofE and FR model are new for flood susceptibility analysis, but it was widely used for other natural hazards like landslide mapping (Rahmati et al., 2016). Both the models yield similar results for flood susceptibility mapping. However, flood susceptible zones obtained through FR model found useful in programmes to reduce flood and its damages (Lee et al., 2012). The Remote Sensing (RS) and Geographic Information System (GIS) is an efficient method to provide the opportunity to analyses, capture, store, combine, manipulate, retrieve and display the potential hazard areas (Samanta et al., 2018).

The main aim of the present study is to identify and map out flood risk zones in the Chennai Municipal Corporation. The objectives of the research are to generate the wall-to-wall data sets that are considered as input into the FR model to identify the flood vulnerable areas and mapping of flood susceptible zones using Frequency Ratio model

with the combination of Remote Sensing and Geographic Information System in Chennai Corporation which can be helpful for researchers, local government and planners for devising flood mitigation plans.

Study Area

Chennai Municipal Corporation is located at north eastern part of Tamilnadu in South eastern coast of India and confined within latitude of 12°50'00'' to 13°15'00''N and longitude of 80°05'00'' to 80°20'00''E.

It encloses an area of 595.81 sq.km (Fig. 1) and accounts for high population density with 17,000 per square kilometre. The Chennai Corporation consists of approximately 88 micro watersheds of Adyar, Cooum and Kosasthalaiyar rivers. The average elevation of the area is 6.7 m. The average annual rainfall is about 140 cm and the maximum temperature is around 35–40 °C and the minimum temperature is around 19–25 °C. In the study area, most of the places are categorized under clayey and gravelly clayey soil. At about 60% of the area was occupied by recently developed urban infrastructures. Lithologically, the coastal stretch comprises marine sediments and inland area characterized by fluvial sediments and charnockite. The study area experiences heavy rainfall associated with depressions and cyclones which lead to frequently occurring floods (Lavanya, 2012). Figure 1 shows the location map of the study area.

Material and Methods

The flood susceptibility analysis was carried out using ten individual parameters, namely landforms, landuse/land cover, slope, elevation, soil texture, soil drainage, lithology, Topographic Wetness Index (TWI), distance from the river and surface runoff. Table 1 shows the data products used for this entire study. Preparation of geo database and the integration of this layers were done using Arc GIS software (Sahoo et al., 2020). The landform and landuse/land cover (Lu/Lc) maps prepared by visual interpretation method using Google earth imagery (2018) and National Remote Sensing Centre (NRSC) classification (level 2 classification for Lu/Lc) were adopted for this Interpretation. The elevation and slope are key parameters for flood susceptibility mapping, and variations of elevation have influences on climate characteristics (Samanta et al., 2012). Slope of the area can control the surface runoff (Adiat et al., 2012) and also vertical percolation (Youssef et al., 2011). The elevation and slope map were prepared using globally available Shuttle Rader Topographic mission (SRTM) Digital Elevation data (Jena et al. 2016) in Arc

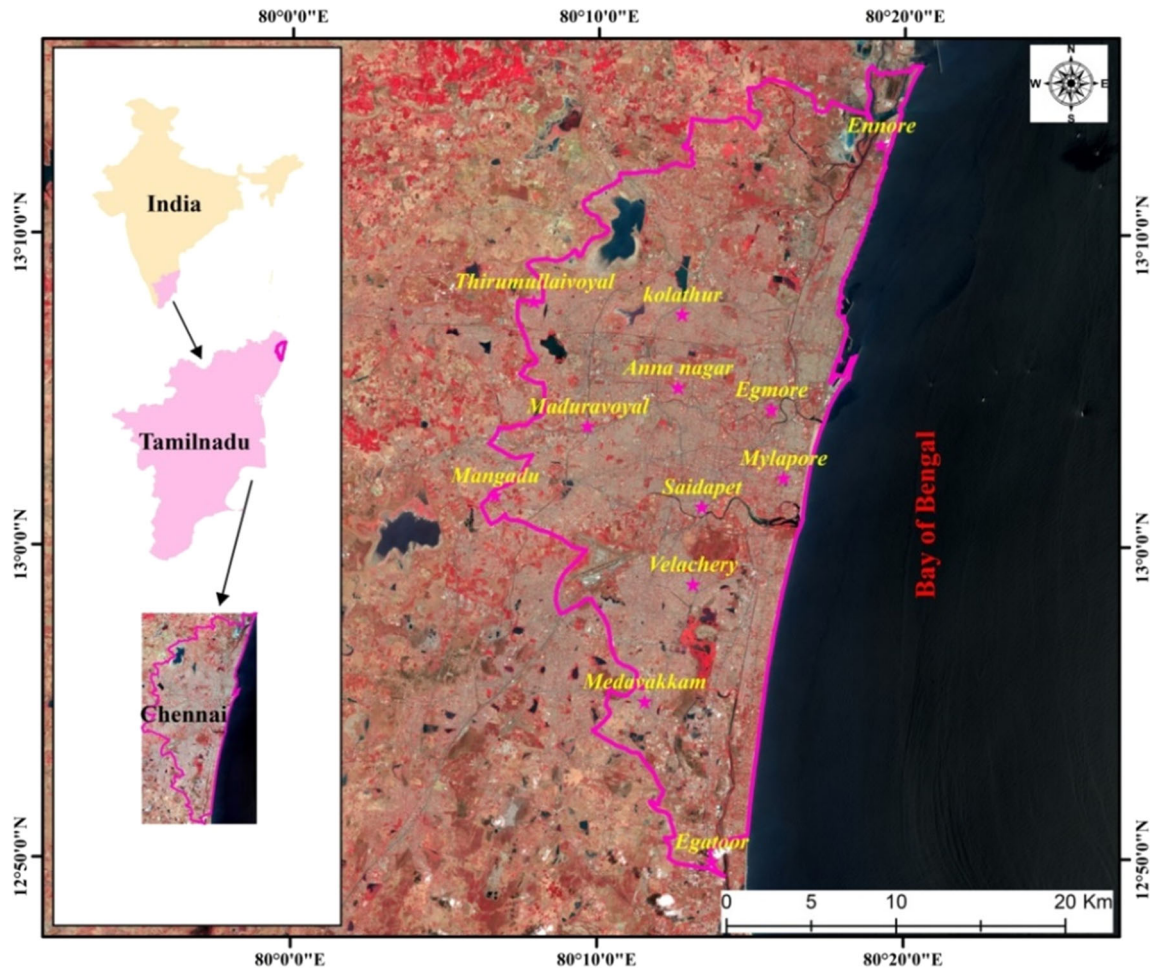


Fig. 1 Study area location map

Table 1 Data sets used for flood susceptibility mapping

S. no.	Data description	Purpose	Year	Source	Resolution/Scale
1	Google earth imagery	Landform and Lu/Lc	2018	Q-GIS software	0.3 m
2	SRTM DEM	Elevation, slope, TWI	2014	USGS (Earth Explorer)	30 m
3	Rainfall	Surface runoff	2004–2018	Public works Department (PWD)	–
4	Soil	Soil texture	1996	National Bureau of Soil Survey and Landuse Planning	1:500,000
5	Lithology	Lithology	1995	Geological Survey of India (GSI)	1:500,000
6	Historic flood locations	Frequency Ratio Model	Before 2018	News reports and satellite imagery of pre and post flood event	–

GIS spatial analysis tool (Fig. 2 d, c). The flood generally happens near to the river. So, distance from the river was important for flood susceptibility mapping. It is prepared by buffering of river digitized from google earth imagery using proximity analysis tool in Arc GIS (Fig. 3a).

Topographic Wetness Index (TWI) is the spatial distribution of wetness, and it controls the overland flow of

water. So, the TWI contributes an important role in flood mapping. Equation 1 (Beven and Kirkby, 1979; Regmi et al., 2010; Cheng-Zhi Qin, 2011; Samanta et al., 2018) helps to calculate the TWI.

$$TWI = \text{Ln} \left(\frac{a}{\tan B} \right) \tag{1}$$

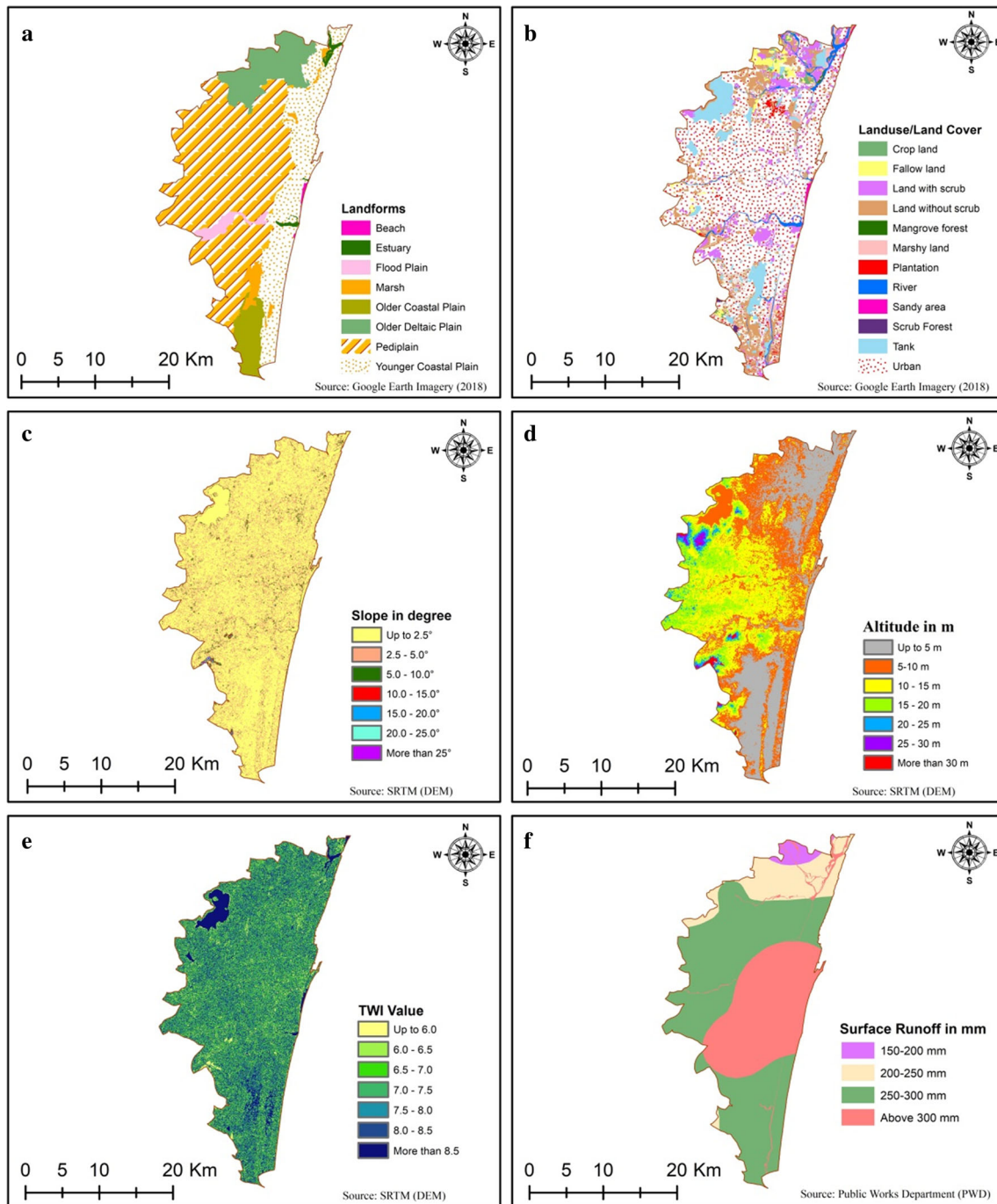


Fig. 2 Parameters used for Frequency Ration modelling: **a** Landform, **b** Landuse/land cover, **c** Slope, **d** Elevation, **e** Topographic wetness index, **f** Surface runoff

where a is the catchment area [$a = A/L$, total area (A) divided by length of contour (L)], and B is mentioned to slope in degree. (A catchment is an area wherever water is collected by the natural landscape like creek, river and lake.)

Prediction of sudden, flashy and short durational floods is made easier with significant surface runoff due to storm

rainfall (Pal & Samanta, 2011). Surface runoff map was created based on Soil Conservation Service (SCS) model (Amutha & Porchelvan, 2009; Samanta et al., 2018) (Eq. 2).

$$Q = (P - Ia)^2 / (P - Ia + S) \quad (2)$$

where Q is actual surface runoff in mm (The surface runoff is the flow of water occur on the ground surface when

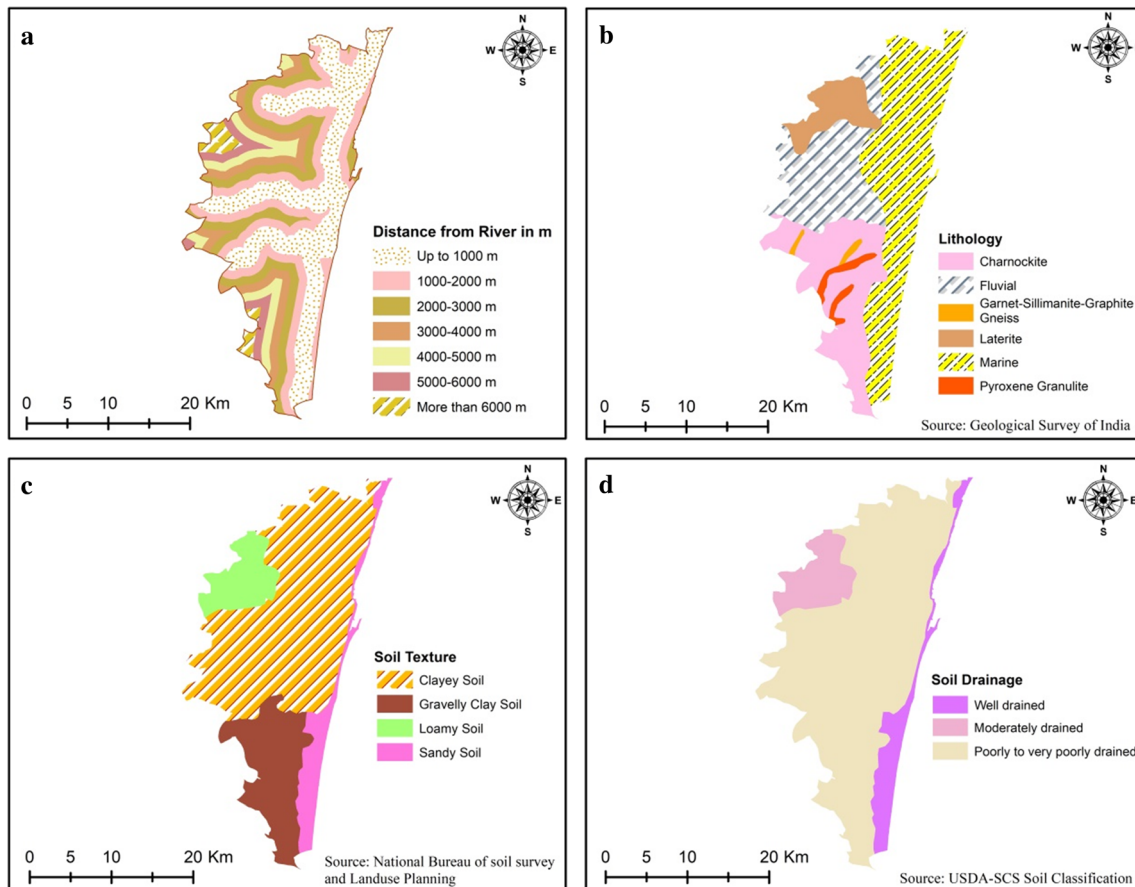


Fig. 3 Parameters used for Frequency Ration modelling: **a** Distance from the river, **b** Lithology, **c** Soil texture, **d** Soil Drainage

excess of rain water, storm water or other sources and when there is more water than land can be absorb); P is storm rainfall in mm (The storm rainfall is a heavy rainfall occurring continuously for more than five days along with the severe wind action); S is the potential maximum retention in mm (The potential maximum retention represents infiltration occurring after the runoff has started), and I_a is $0.2S$ [Initial abstraction (mm)].

In Eq. 2, the rate of potential maximum retention (S) was calculated based on Eq. 3.

$$S = (25400/CN) - 254 \quad (3)$$

where CN is the curve number of hydrologic soil cover complex and function of the ability of soil to allow infiltration of water with respect to Lu/Lc and Antecedent soil Moisture Condition (AMC) (Amutha & Porchelvan, 2009; Kumar et al., 1991; Rao et al., 1996; Samanta et al., 2018; SCS, 1972).

The lithology and soil texture map were prepared by using Geological survey of India (1:500,000) and National Bureau of Soil Survey & Landuse planning (1:500,000), respectively. Soil drainage of the study area was mapped

with the help of USDA-SCS soil classification data sets (SCS, 1972).

Mapping of historic or past flood records is essential to identify the future flood events (Manandhar, 2010; Samanta et al., 2018). Totally, 123 historic flood locations were collected from news reports and satellite data of pre- and post-flood event. Among 123 flood locations, 100 were used for model building and 23 were used for validation. Frequency Ratio (FR) model was adopted for this study. This model establishes a quantitative relationship between the occurrence of flood episodes and various flood determining parameters. The FR index values were calculated using Eq. 4.

$$FSI = \sum FR \quad (4)$$

where FSI and FR are the Flood Susceptibility Index and Frequency Ratio for each factor, respectively.

The FR is the ratio of flooded area to the total study area that delineates flooded area from non-flooded area (Bonham-Carter, 1994; Samanta et al., 2018). Equation 5 was used to calculate the FR value.

$$FR = (E/F)/(M/L) \quad (5)$$

where E is the number of flood events for each factor; F is the total number of flood events; M is the areal coverage (histogram) of the each factor; L is the total areal coverage (histogram) of the study area.

The FR value indicates the types of correlation between factors and floods. FR value higher than 1 indicates strong flood correlation; on the other hand, a value lower than 1 indicates weak flood correlation. Table 2 shows the FR value for each parameter.

Finally, all the parameters are converted into raster format and spatial resolution of each raster layer was set to 15 m × 15 m cell size and it is integrated in Arc GIS based on database. And this integrated database was reclassified into four flood susceptibility class (Samanta et al. 2018), namely very low (Up to 5.0), low (5.0 to 7.5), medium (7.5–10.0), high (10.0–12.5) and very high (more than 12.5).

Results and Discussion

The 10 flood identifying parameters, namely landforms, landuse/land cover, slope, elevation, soil texture, soil drainage, lithology, Topographic Wetness Index (TWI), distance from the river and surface runoff, are consisted their subcategories (Figs. 2, 3 and Table 2). The landform has eight subclass, namely beach, estuary, flood plain, marsh, older deltaic plain, pediplain, younger coastal plain and older coastal plain (Fig. 2a). The flood plain, pediplain and younger coastal plain have consisted highly correlated flood FR value of 1.49, 1.20 and 1.10, respectively (Table 2). The landuse/land cover is categorized as crop land, fallow land, land with scrub, land without scrub, mangrove forest, marshy land, plantation, river, sandy area, scrub forest, tank and urban (Fig. 2b). In this, the urban category covers 61.4% of the study area which has a FR value of 1.17 (Table 2).

The elevation of the area has ranged from 0 to 149 m. The prepared elevation map was reclassified into 7 classes (up to 5, 5–10, 10–15, 15–20, 20–25, 25–30 and more than 30 m) (Fig. 2d). Up to 5 m, 5–10 m and 10–15 m classes are predominant categories and it covers 27.3, 30.9 and 27.1% of the study area, respectively. The highest calculated FR value is 1.43 for the category of 10–15 m (Table 2). The generated slope map also reclassified into seven classes (up to 2.5°, 2.5–5°, 5–10°, 10–15°, 15–20°, 20–25° and more than 25°). Figure 2c shows the slope map of the study area. The highest slope class (> 25°) indicated the FR value of 0. On the other hand, the lowest class (< 2.5°) have FR value of 0.88 (Table 1). The soil texture and soil drainage are the important parameters for flood susceptibility mapping. Four soil texture classes are

presented within the study area as follows: clayey soil, gravelly clayey soil, loamy soil and sandy soil. Clay soil presented 61.6% of the study area and having a highest rate of (1.31) FR value. The soil drainage is classified into three category based on USDA-SCS soil classification, and the classes are well drained, moderately drained and poorly to very poorly drained. The predominant class is poorly to very poorly drained, covering 81.08% of the study area. The highest flood correlation FR (1.14) value is calculated for poorly to very poorly drained soil. Figure 3c and d shows the soil texture and soil drainage of the study area, respectively.

The TWI was calculated using Arc GIS, and it is reclassified into seven classes (Samanta et al., 2018) viz., up to 6.0, 6.0–6.5, 6.5–7.0, 7.0–7.5, 7.5–8.0, 8.0–8.5 and more than 8.5 (Fig. 2e). The high value of TWI is represented in blue colour, and the low value is represented in yellow colour. High TWI values have higher chances of flooding (Rahmati et al., 2016). The lithology map was classified into six classes, namely charnockite, fluvial, garnet–sillimanite–graphite gneiss, laterite, marine and pyroxene granulite (Fig. 3b). In this, marine area covers 41.86% and the FR value is 1.19. Lithology has a direct influence on land permeability and thus surface runoff. So, it is an important conditioning parameter for flood susceptibility mapping (Haghizadeh et al., 2017; Samanta et al., 2018).

The surface runoff map is generated using storm rainfall data and soil conservation service model. The minimum and maximum surface runoff of the study area is 159 mm and 332 mm, respectively. This surface runoff is reclassified into four classes (Up to 200 mm, 200–250 mm, 250–300 mm and above 300 mm). Figure 2f reveals the surface runoff of the study area. Above 300 mm, surface runoff area has the highest FR value of 2.02. The flood intensity was higher in those locations which is closer to the river bank. So, distance from the river is an important parameter for flood mapping. The distance from the river ranges is up to 1000 m, 1000–2000 m, 2000–3000 m, 3000–4000 m, 4000–5000 m, 5000–6000 m and more than 6000 m (Fig. 3a). The FR value of up to 1000 m and 1000–2000 m is higher (1.11 and 1.53, respectively).

The calculated FR value for every parameter was varied from 0 to 14.85 in the study area (Table 2). FR value less than 1 is indicated as weak correlation and greater than 1 is indicated as strong correlation with flood occurrence (Lee et al., 2012). Finally, the flood susceptibility database was developed using FR model equation (Eq. 4). This generated final FR value database was varied from 0 to 27.11. The high FR value-presented area is indicated as high flood risk, and low value is low flood risk. The created database was reclassified into four flood susceptibility class (Samanta et al., 2018) viz., very low (up to 5.0), low (5.0 to

Table 2 Parameters used for flood susceptibility mapping through FR model

Class name	Subclass name	Histogram	% of Histogram	Flood numbers	Frequency ratio
Landuse/land cover	Crop land	317	0.5884	2	3.3988
	Fallow land	1215	2.2554	2	0.8868
	Land with scrub	4573	8.4888	4	0.4712
	Land without scrub	7498	13.9184	7	0.5029
	Mangrove forest	54	0.1002	0	0.0000
	Marshy land	494	0.9170	1	1.0905
	Plantation	538	0.9987	4	4.0053
	River	1268	2.3538	3	1.2746
	Sandy area	236	0.4381	0	0.0000
	Scrub Forest	67	0.1244	0	0.0000
	Tank	4493	8.3403	5	0.5995
Distance from the river	Urban	33,118	61.4765	72	1.1712
	Up to 1000 m	18,811	36.0371	40	1.1100
	2000 m	12,270	23.5062	36	1.5315
	3000 m	8298	15.8969	11	0.6920
	4000 m	5358	10.2646	6	0.5845
	5000 m	3714	7.1151	4	0.5622
	6000 m	2097	4.0173	1	0.2489
Elevation	more than 6000 m	1651	3.1629	2	0.6323
	Up to 5 m	174,554	27.3308	13	0.4757
	5–10 m	197,797	30.9701	32	1.0333
	10–15 m	173,431	27.1550	39	1.4362
	15–20 m	77,183	12.0849	14	1.1585
	20–25 m	13,820	2.1639	2	0.9243
	25–30 m	4431	0.6938	0	0.0000
Slope	More than 30 m	2108	0.3301	0	0.0000
	Up to 2.5°	460,910	72.1670	64	0.8868
	2.5–5.0°	160,003	25.0525	24	0.9580
	5.0–10.0°	15,948	2.4971	9	3.6042
	10.0–15.0°	1096	0.1716	2	11.654
	15.0–20.0°	430	0.0673	1	14.852
	20.0–25.0°	175	0.0274	0	0.0000
Landform	More than 25°	109	0.0171	0	0.0000
	Marsh	1234	2.2907	0	0.0000
	Beach	156	0.2896	0	0.0000
	Younger Coastal Plain	12,721	23.6138	26	1.1011
	Older Coastal Plain	2801	5.1995	3	0.5770
	Older Deltaic Plain	5813	10.7906	2	0.1853
	Estuary	455	0.8446	0	0.0000
Lithology	Pediplain	29,613	54.9702	66	1.2007
	Flood Plain	1078	2.0011	3	1.4992
	Charnockite	14,155	23.7552	24	1.0103
	Marine	24,944	41.8615	50	1.1944
	Fluvial	13,798	23.1561	22	0.9501
	Laterite	4978	8.3542	0	0.0000
	Garnet–sillimanite–graphite gneiss	456	0.7653	1	1.3067
Pyroxene Granulite	1256	2.1078	3	1.4233	

Table 2 (continued)

Class name	Subclass name	Histogram	% of Histogram	Flood numbers	Frequency ratio
Surface runoff	Up to 200 mm	1116	2.0716	0	0.0000
	200–250 mm	6662	12.3666	4	0.3235
	250–300 mm	28,553	53.0025	30	0.5660
	Above 300 mm	17,540	32.5593	66	2.0271
Soil drainage	Well drained	4941	9.1719	6	0.6542
	Moderately drained	5250	9.7455	1	0.1026
	Poorly to very poorly drained	43,680	81.0826	93	1.1470
Soil	Clayey Soil	33,204	61.6281	81	1.3143
	Loamy Soil	5249	9.7424	1	0.1026
	Sandy Soil	4965	9.2153	5	0.5426
	Gravelly Clay Soil	10,460	19.4142	13	0.6696
Topographic wetness index	Up to 6.0	12,820	2.0073	1	0.4982
	6.0–6.5	65,647	10.2787	19	1.8485
	6.5–7.0	130,116	20.3729	13	0.6381
	7.0–7.5	122,588	19.1942	9	0.4689
	7.5–8.0	91,471	14.3221	28	1.9550
	8.0–8.5	53,495	8.3760	22	2.6266
	More than 8.5	162,534	25.4488	8	0.3144

7.5), medium (7.5–10.0), high (10.0–12.5) and very high (more than 12.5). Figure 4 explains the flood susceptibility classes. Flood susceptibility analysis indicates that 10.48, 38.93, 37.45 and 13.11 percentage of area is demarcated as very high, high, medium and low flood vulnerable class, respectively (Table 3).

The very high and high class presented areas are high chances for flood. It is characterized with lower slope and elevation, higher runoff, higher TWI, closer to the main river, poorly to very poorly drained soil, braided flood plain and urban like concreted terrain land use, which are the important conditioning points for flood mapping using FR model. Based on flood susceptibility analysis, the high and very high flood prone areas are covering the part of Mylapur, Adyar, Mandaveli, Alandur, Vadapalani, Egmore, Saidapet and Anna nagar. The success rate and prediction accuracy are needed to validate the FR model. The success rate was calculated by using 100 training flood locations, and the predication of accuracy was calculated by using remaining 23 flood locations which were not used while the time of model building. The future flood event might occur in the area of high and very high susceptibility zones (Samanta et al., 2018). The calculated success and prediction accuracy rates are 0.96 and 0.956, respectively (Table 4). The 95.6% prediction accuracy is validates the FR model suitable for flood susceptibility analysis.

Flood Management Plans

Mitigation measures are greatly involved in reducing the impacts or overcoming of hazards, especially like flood. This could be achieved through structural and non-structural measures (Faiz Ahmed & Natraj Kranthi 2018). The former one includes periodical de-silting of rivers, namely Adyar, Cooum and Kosasthalaiyar that drains across the study area. Lakes, namely Chembarapakkam, Poondi and Puzhal, should be checked at regular intervals in the sense of water-holding capacity and quality of enclosing concretionary structure. No infrastructures should be permitted in high flood plain, whereas buildings with elevated platforms shall be allowed to construct along medium and low flood plain areas. The later one, i.e. non-structural measures, suggests relocation of residence from high flood plain area to non-vulnerable area. People residing in low flood plain areas should be readily provided with community infrastructures during the time of flood. Reforestation of river banks will play a vital role in reducing the impact of flood and increasing the retention capacity.

It is recommended to create awareness for the people in moderate, high flood plain and flood vulnerable areas about necessary precautions to be taken before the flood event. Concerned government authorities (Water Resource Department, Corporation of Chennai-Storm Water Drainage Department-SWDD, Corporation of Chennai (Zonal Office), Chennai Metropolitan Development Authority-

Fig. 4 Flood susceptibility of the study area

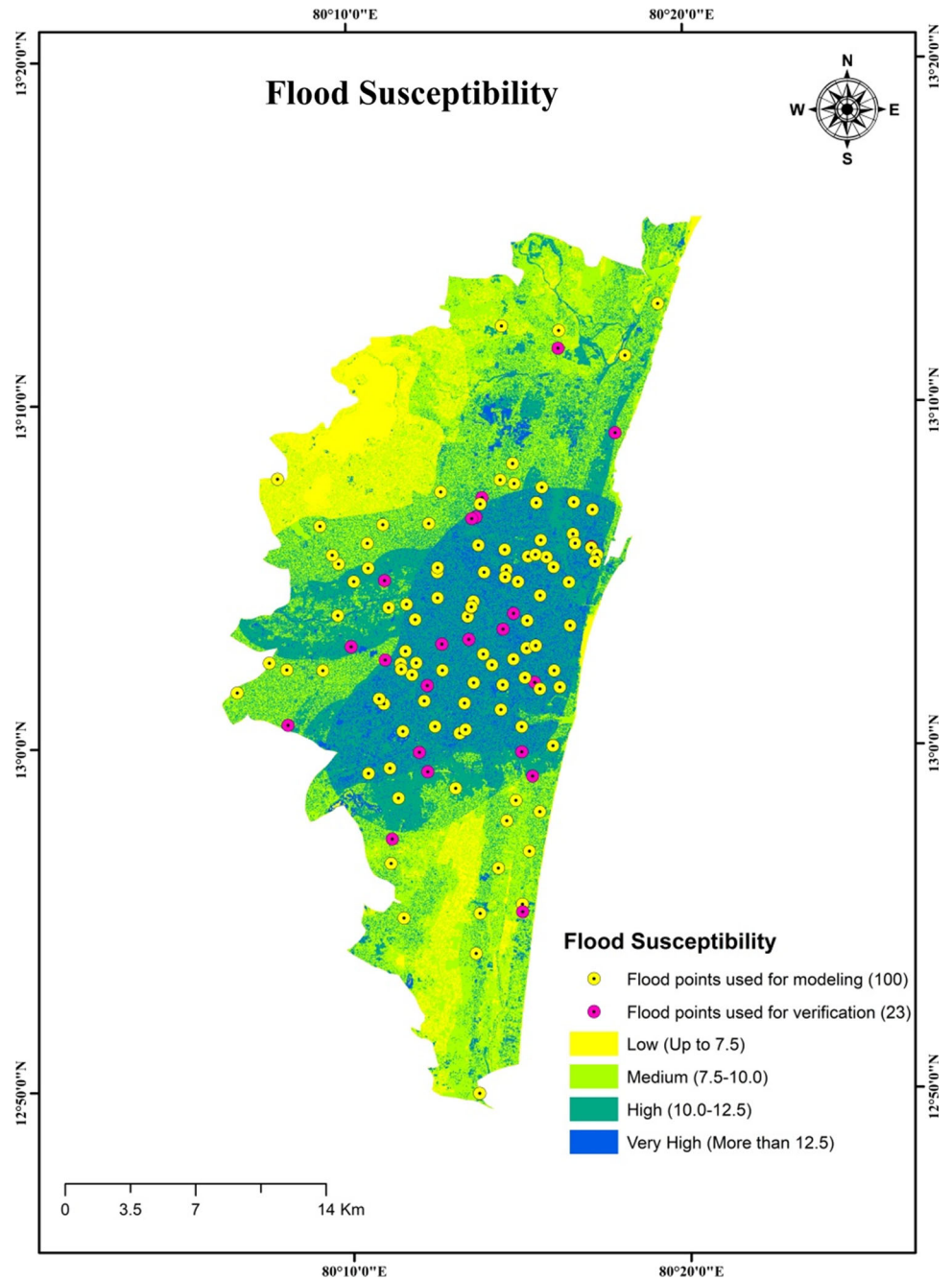


Table 3 Spatial distribution of flood susceptibility class in the study area

S.No	Flood susceptibility class	Range of FR value	Area in Sq.km	% area
1	Very high	More than 12.5	62.51	10.48
2	High	10.0–12.5	232.17	38.93
3	Medium	7.5–10.0	223.36	37.45
4	Low	5.0–7.5	78.23	13.11

CMDA, Chennai Metropolitan Sewerage and Water Supply Board-CMWSSB (Jameson & Baud, 2016)) involved in rescue services should be skilled with flood map reading

and kept ready well in advance as a response during emergency situations. As recommended by National Disaster Management Plan (NDMP, 2016) immediate,

Table 4 Success rate and prediction accuracy of flood susceptibility analysis

S.No	Flood susceptibility class	Training (100 flood locations)	Success rate (high to very high)	Validation (23 flood location)	Prediction accuracy (high to very high)
1	Very high	59	0.96 or 96%	12	0.956 or 95.6%
2	High	37		10	
3	Medium	4		1	
4	Low	0		0	
Total		100		23	

medium term and short term measures should be prepared. Disaster management plan combined with geo-spatial technology would facilitate local communities and government officials in decision making before and after the flood to minimize the loss of life and property.

Conclusion

The study intended to analyse the flood susceptibility zones of Chennai Municipal Corporation by using FR model. Ten independent parameters, namely landforms, landuse/land cover, slope, elevation, soil texture, soil drainage, lithology, Topographic Wetness Index (TWI), distance from the river and surface runoff, were used as an input of FR model for flood susceptibility mapping. It is known fact that the higher the input, the greater would be the accuracy of the result. So, mapping of flood susceptible zones through FR model could be done only to the areas where the required flood locations are minimum 100 points. In total, 123 flooded locations were collected from news reports and satellite data of pre- and post-flood event. From this, 100 flood locations were used for model building and 23 were used for validating the result. The created flood susceptibility zone using FR model was classified into four (Very high, high, medium and low). The high (38.93%) and very high (10.48%) classes are highly vulnerable for flood. The success rate of the flood susceptibility analysis is 0.96 or 96%, and the prediction accuracy is 0.956 (95.6%). The flood susceptibility mapping was carried out for Markham river basin using MCDA (Samanta et al., 2016) and FR model (Samanta et al., 2018) in which the latter one produces the better results. Hence, the FR model is well suitable for predicting the flood susceptibility zone. The result of this analysis will be helpful for decision makers to execute appropriate flood management in future.

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