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Integrating Remote Sensing and Geographical Information Systems for Urban Flash Flood Susceptibility Mapping in Rawalpindi and Islamabad, Pakistan

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Abstract
The most devastating type of flood is urban flash floods, which combine lightning-fast speed with the destructive force of a flood. They occur when there is not enough ground storage for more precipitation.
The main objective of this study is to produce flash flood maps using GIS techniques. Mapping urban flash flood vulnerability is essential to managing and mitigating flood risks. This study maps and evaluates Rawalpindi and Islamabad, vulnerability to urban flash floods using remote sensing (RS), and geographic information systems (GIS). A total of seven 07 factors elevation, slope, LULC, rainfall, drainage density, NDVI, and soil map were examined using high-resolution satellite data and GIS techniques. A total 110 flood points were used to create the flood inventory map and random points were used to ensure proper algorithmic analysis. To create accurate susceptibility maps, the dataset was split into 30% testing and 70% training sets. Flood zones were divided into five (05) categories very low (23%), low (13%), moderate (15%), high (22%), and very high (27%). The results showed that the research area's western, southern, and central parts had high susceptibility, which changed to reduced susceptibility zones. Significant insights for urban planning and disaster management techniques were obtained from the effective identification of high-risk regions through the integration of RS and GIS. This approach highlights the importance of accurate flood event documentation and multi-factorial analysis in enhancing urban flood protection.

Introduction:

Urban flash flooding is a type of natural disaster that profoundly affects the lives of a large number of people (Salvati et al., 2010). In the past, flash floods have caused greater devastation to human lives and infrastructure worldwide (Tariq et al., 2022). The world's changing climate circumstances continue to make some countries increasingly vulnerable to the dangers of flash floods (Tariq et al., 2023). During these catastrophes, people are lost and the built environment might be demolished. It is very challenging to quantify the extent and spread of flooding-related damage (Tehrany et al., 2015). Floods might happen more frequently and for longer periods. As a result, it is imperative to evaluate and mitigate flash floods. It is challenging to forecast flash flooding with any degree of accuracy due to its complexity. Landslides, sinkholes, and erosion are common secondary disasters that coexist with flash floods (Grimaldi et al., 2013) One of the world's most dangerous natural calamities is flooding. In the Global South, the frequency of floods has increased during the last few decades. Between 1980 and 2009, floods are projected to have caused about 2.8 billion people to be impacted, 539,811 deaths, and 361,974 injuries. There was a rise in damages of USD 1.6 trillion between 1980 and 2016. More than half of all global fatalities occur in South Asia, which is also the world's most affected area (Sharifi et al., 2021, Eckstein et al., 2019). In Pakistan's northern rivers, there has been a significant rise in the frequency and intensity of floods in recent decades, due to climate change (Moazzam et al., 2018). Since United India's split, Pakistan has seen horrific floods throughout its history. Ten billion (USD) in losses were attributed to the 2010 flood (Tariq et al., 2021a). Based on thirty years of disaster data, floods are almost always reported in Pakistan (Waqas et al., 2021). The country's large latitudinal breadth, geographic location, three mountain systems, a wide range of temperature fluctuations, and earth form are the reasons it has turned into a hazardous country (Chen et al., 2020). In addition to physiographic factors, other factors contribute to susceptibility: the population's phenomenal growth rate; the vast majority of underprivileged individuals; the lack of national and local disaster management initiatives (such as accurate flood mapping); the nation's low rate of economic growth; and the lack of pre- and post-disaster management education (Yin et al., 2022). The effects of disasters are not evenly dispersed and come in many forms. Disasters and susceptibility are intimately correlated; greater exposure will cause disasters to have a greater impact. The poorest people are the most harmed because they lack strength, coming in behind women, youth, and the crippled (Thomas et al., 2017). The people of Islamabad and Rawalpindi have seen a variety of natural calamities and disasters in the past several years due to current global climate changes. The most recent one occurred in August 2020 and was caused by an unexpected cloud that resulted in severe monsoon rainfall throughout the Study region. Urban flash floods have caused periodic disasters and emergencies throughout the last 10 years, killing people, injuring animals, and partially or destroying infrastructure (Costache et al., 2021). Significant parts of this infrastructure suffered damage that is beyond communities' capacity to repair. Heavy rains that discharge more water than rivers, dams, and canals can hold back and result in flooding (Ullah et al., 2022). Modeling flood risks is an essential strategy for managing and reducing floods. Furthermore, modifications to land use, alteration of channels, construction of bridges and barrages, riverbank farming, and deforestation are changes in land use, channel manipulation, building of bridges and barrages, agricultural practices on riverbeds, and deforestation are other human causes that contribute to repeated floods. Thus, the first steps should be taken to reduce the harm caused by flood hazards. Such a susceptibility analysis must be carried out, and risk analysis ought to be done as soon as feasible (Relief et al., 2013). Because of its widespread application in reducing the risk of flooding, Hazard and susceptibility maps are crucial for risk reduction initiatives. It may also integrate, arrange, geo-visualize, and process data from various sources, both spatial and non-spatial (Khatoon et al., 2017). Since the moment they set foot on the earth's surface, humans have been the primary agents of ecosystem manipulation. With recent challenges of climate change, it has been proven that the major drivers have been human beings through anthropogenic activities (Bhatti, Iftakhar, 2023). Transformation of land built forms and their impacts of unplanned human settlements have negatively impacted the human growth and raised concerns associated with safety, security and risks mitigation based on climate change phenomena's (Bhatti et al., 2024). Agricultural practices and deforestation are two examples of land modification and use practices that are man-made and contribute to repeated flooding (Bera et al., 2022). Therefore, conducting risk analysis is essential and required, susceptibility analysis, and awareness of human manipulations earlier on (Jalayer et al., 2022). Geographic Information Systems (GIS) and remote sensing (RS) are the most commonly utilized methods to gather the information needed for flood modeling and learn about the ecological and physical features of the land (Wahla et al., 2022). GIS and RS methods are becoming essential instruments for creating multi-criteria zoning decision analyses (Tariq et al., 2022b). One of the latest approaches for handling flood disasters is modeling flood susceptibility. Floods are a regular occurrence in the study area; they destroy standing crops, harm infrastructure, and sometimes even result in fatalities. Assessment and mapping of flood susceptibility are lacking. Flood modeling is another option for developing floodwater routing by taking into account the interplay of physical elements (Dewan et al., 2015). By integrating all of the criteria, the Multi-Criteria Analysis (MCA) and FR model can be utilized to identify very high to very low susceptibility zones. This study aimed to predict the zonation and risk susceptibility in the floodplains of Islamabad and Rawalpindi districts. The FR model has been used to evaluate flood susceptibility with the integration of GIS. A key component of flood risk reduction is flood modeling, which seeks to lessen the vulnerability of components that are at risk (Ouma et al., 2014). This study highlights attention to the risks associated with flooding and provides data for flood risk management plans to decision-makers. The main goal of this analysis was to estimate the areas at risk and create and apply quantitative analysis methodologies with the integration of GIS and remote sensing for flood-susceptible assessment in the Islamabad and Rawalpindi districts. The research area's flood risk areas were identified and spatially mapped using the GIS, FR, and analytical results. Models and FR were employed to assess potential flood-prone locations. These findings will help researchers, planners, and local government with impact assessments so they can identify potential flood zones and create various plans to reduce the risk of flooding.

Methodology

Study Area

Islamabad and Rawalpindi

In Pakistan's Islamabad District, Rawalpindi District of Punjab, and Abbottabad District of North-West Frontier Province, the metropolitan region of Islamabad-Rawalpindi is located between longitudes 72°45' and 73°30' E. and latitudes 33°30' and 33°50' N. Rawalpindi is a considerably larger, older city that serves as the focus of military, commercial, and industrial activity; Islamabad serves as the capital and seat of all governmental activities.

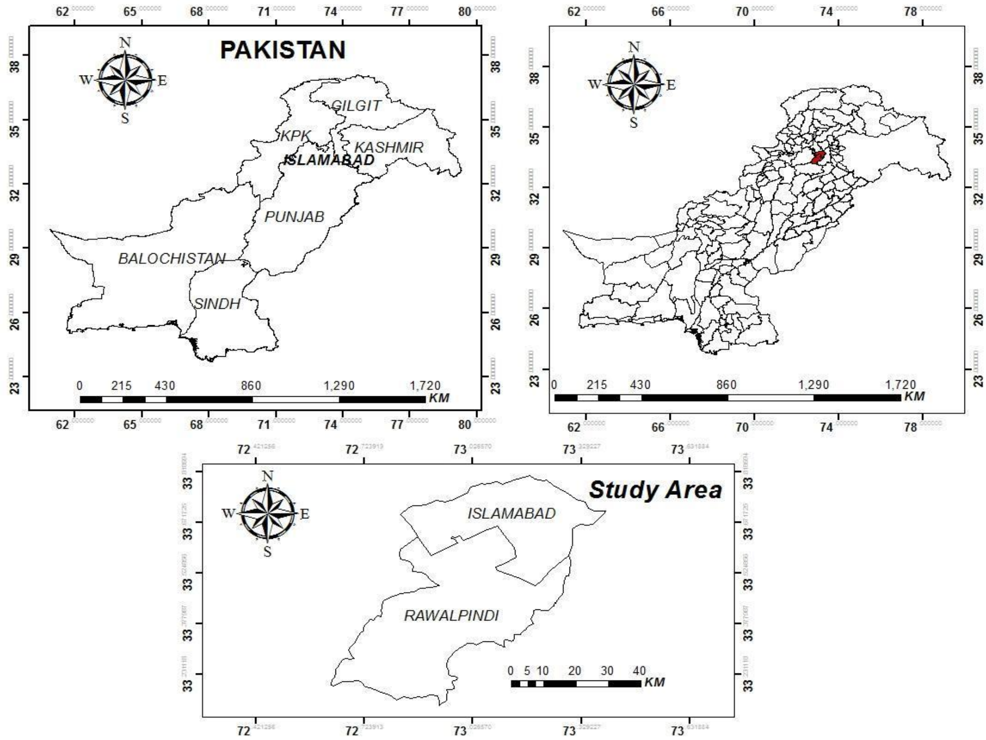


Fig 1: Location of the Study area

Collection and Preparation of Data

Collection of Historical Flash Flood Data

It is essential to gather exact data on the places that have already experienced flooding to create an accurate visualization of the areas vulnerable to flooding (Martinis et al., 2009). An accurate forecast of likely flash floods in that location can be made if records of past flash flood events have been preserved. Land use activities, rainfall frequency, drainage, slope, elevation, NDVI, and soil map are some of the important characteristics that affect The likelihood of flash floods and the damage that they might trigger (Chen et al., 2022). All these factors must be taken into consideration when planning, inventorying flash floods, and ultimately altering the prediction. Data from 110 distinct zones some of which were not affected as well as some that were previously affected, were used in this investigation. Fig 2 shows how the area is categorized according to various potential risk categories.

Flash Flood Inventory

Mapping flood risk and susceptibility is heavily impacted by the accuracy of flood event data. In this study, a total of 110 location points were selected for the flood inventory. The analysis was made easier by using random points instead of a polygon pattern, which presents difficulties for the program. Natural hazard modeling often uses this inventory data type. The map was split 70% to 30% into training and testing sets to produce dependent results. Specifically, 110 training locations were randomly chosen, with dependent results coded as 1 for the presence of flooding and 0 for its absence, and 33 points were designated as non-flooding locations fig 2.

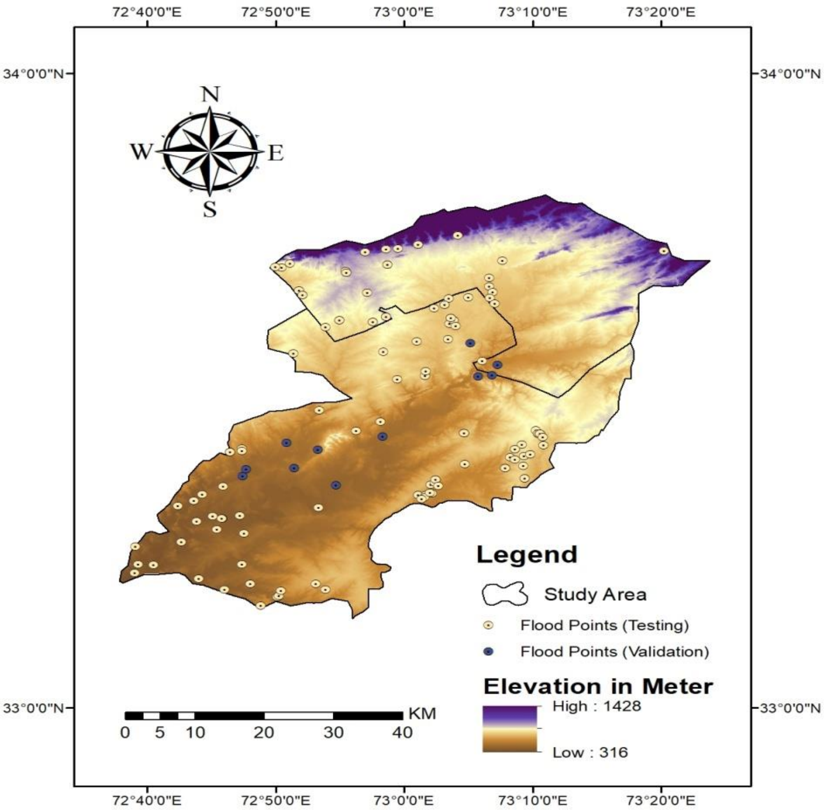


Fig 2: Showing the study area's Flood Inventory map

Flood Conditioning Factors

Choosing the appropriate parameters or criteria for decision-making is the most crucial phase in any risk assessment and zonation process to obtain the most accurate and suitable results. Only then can acceptable and optimal outcomes be achieved. There are several variables in every flood-risk area, and some of those variables only affect certain zones (Sajjad et al., 2019). Therefore, a thorough field survey was carried out in several locations throughout the research region to establish a trustworthy image of the risk of urban flash floods. The initial step in mapping flood-affected zones in any catchment area is to pick effective variables. Problems arise while researchers are making susceptibility maps (Majeed et al., 2021b).

Consequently, to determine the probable flood-triggering variables, we carried out a field survey. After visiting the most damaged locations, information was gathered based on the individuals' viewpoints. In the end, we used seven different parameters: soil type, LULC, NDVI, elevation, slope, drainage density, and rainfall. It's critical to remember that topographic data significantly influences modeling outcomes and that a dearth of precise topographic data restricts a great deal of study (Pimentel et al 2011). Topography and derivative factors are important in determining vulnerability to and susceptibility to flooding (Ouma et al., 2014). Data on mean annual rainfall for the preceding 15 years, from 2008 to 2023, was obtained from the Pakistan Metrological Department (PMD). One of the best methods for predicting floods is to utilize a digital elevation model (DEM), which offers a three-dimensional representation of the topography below the surface.

S. No	**Primary Data**	**Spatial Resolution**	**Format**	**Source of Data**	**Derived Map**
1	Sentinel-2	10 m	Raster	(https://earthexplorer.usgs.gov)	Land Use Land Cover Map (LULC) NDVI
2	SRTM (DEM)	30m	Raster	https://opentopography.org/	Elevation Slope Drainage Density
3	Soil Data	1:100,000	Vector	https://soil.punjab.gov.pk/	Soil Map
4	Rainfall Data	1:100,000	Raster	https://www.pmd.gov.pk/en/	Rainfall Map

Table 1: Source of Data Collection

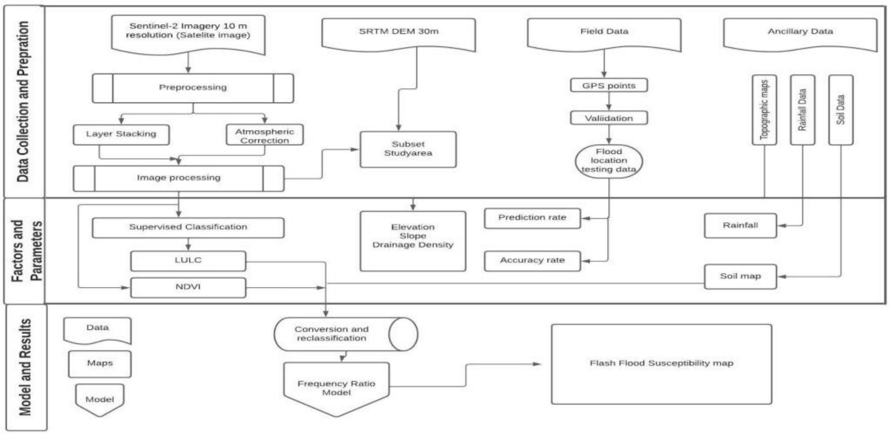
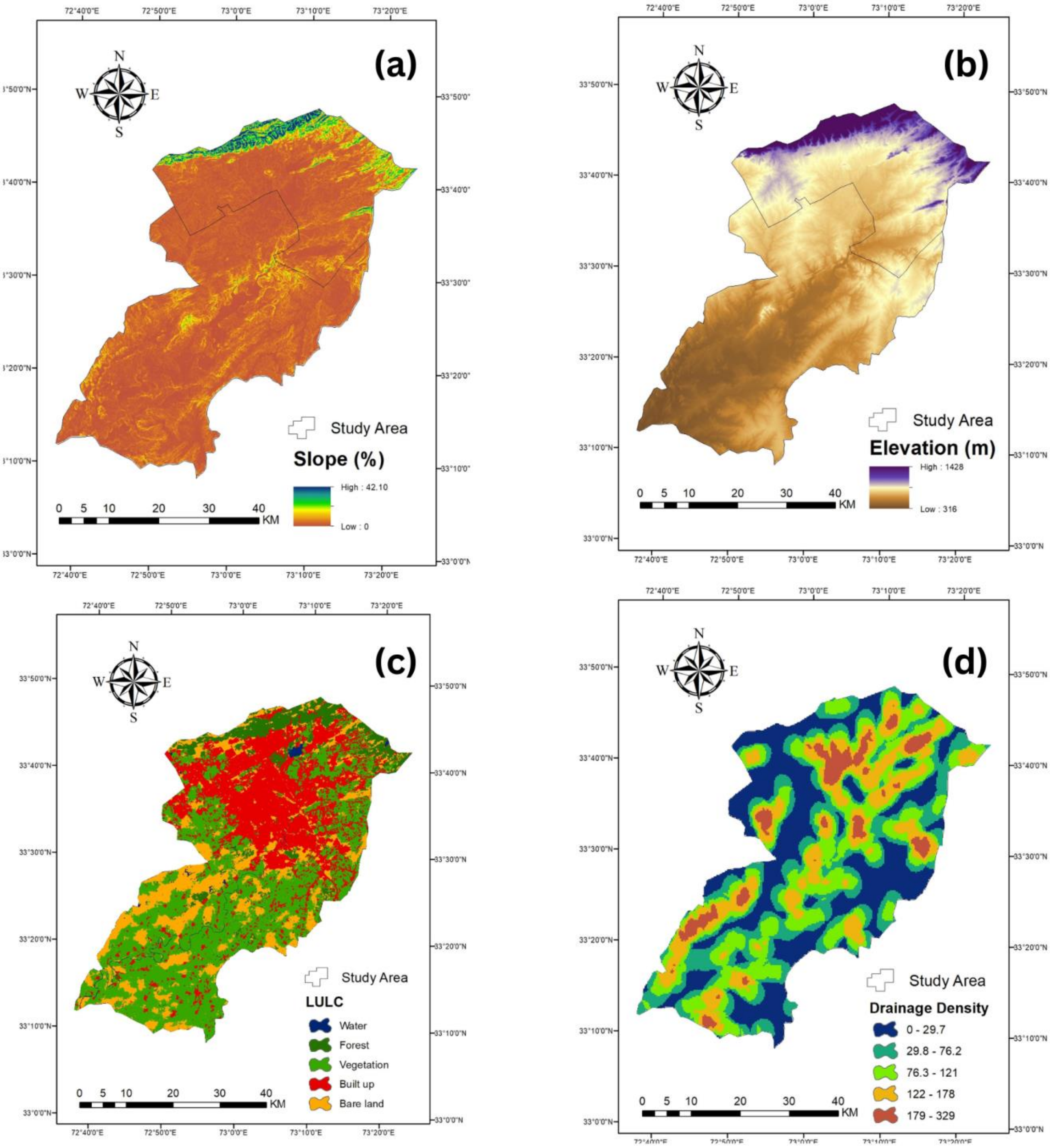


Fig.3 Flow chart of the methodology for preparing flood susceptibility map.

NASA's Shuttle Radar Topography Mission SRTM was utilized to obtain the DEM at a resolution of 30 meters for the study districts from Earth's Atmosphere. Using DEM data, a slope map was produced in degrees. Using DEM satellite imagery and a raster calculator in the spatial analyst tool, the drainage density data map was produced. Land use land cover data was acquired from sentinel 2 imagery data and supervised classification was done using the Erdas imagine tool. Soil data was acquired from www.soil.punjab.com, and further analysis through a spatial analyst tool. USGS Earth Explorer was used to calculate the NDVI and obtain Landsat 8 satellite imagary (https://earthexplorer.usgs.gov/).

$$NDVI = \frac{Band5 - Band7}{Band5 + Band4} \quad (1)$$


(a)
Study Area
Slope (%)
High : 42.10
Low : 0
(b)
Study Area
Elevation (m)
High : 1428
Low : 316
(c)
Study Area
LULC
Water
Forest
Vegetation
Built up
Bare land
(d)
Study Area
Drainage Density
0 - 29.7
29.8 - 76.2
76.3 - 121
122 - 178
179 - 329
0 5 10 20 30 40 KM

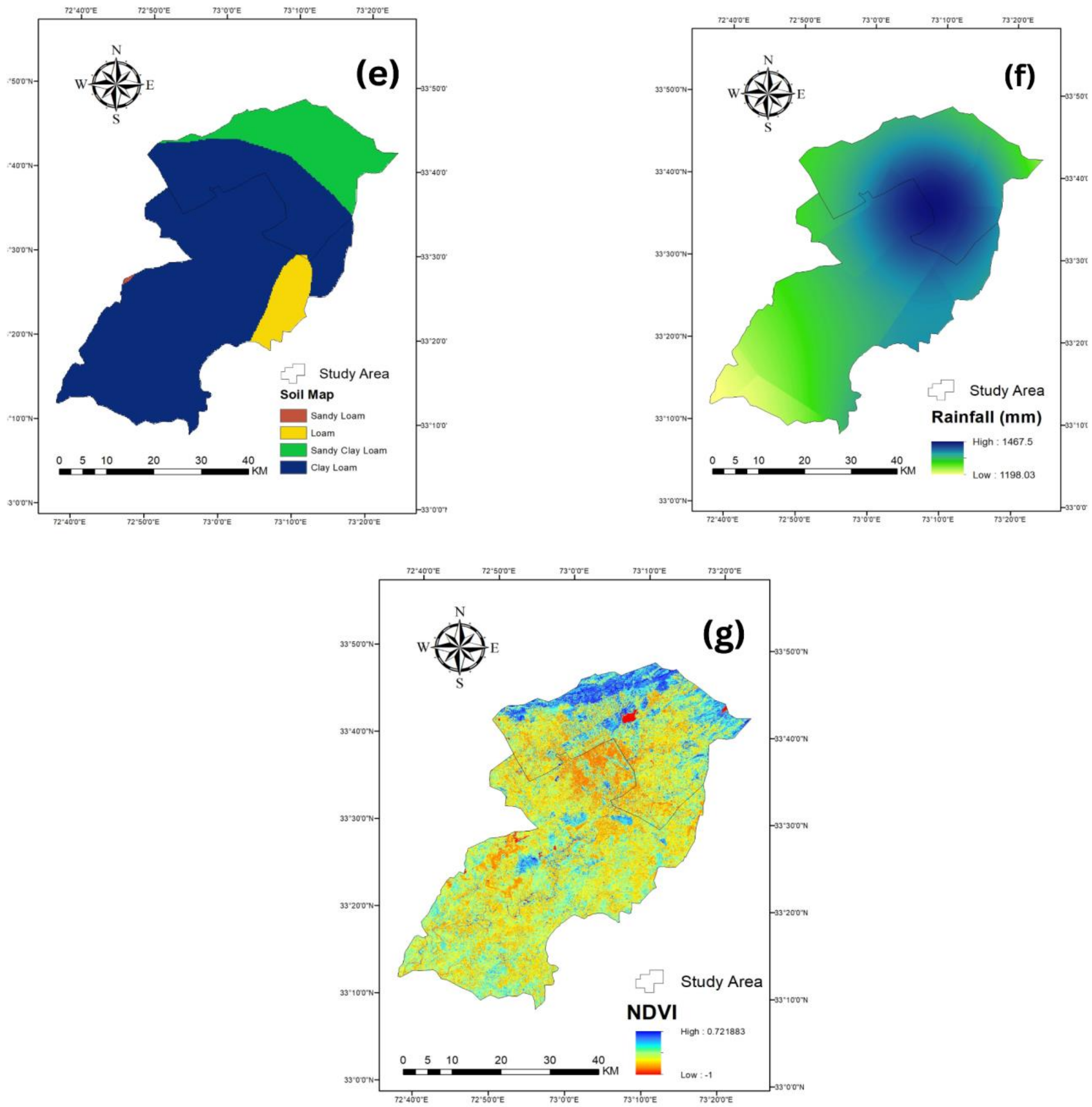


Fig 4: Parameters used for FR modeling (a) Slope (b) Elevation (c) LULC (d) Drainage Density (e) Rainfall (f) NDVI (g) Soil Map

Bivariate Statistical Analysis (BSA)

Frequency Ratio Model (FR):

One of the primary bivariate analysis methods that is widely used in flood susceptibility studies is FR. Based on the geographical relationship between the independent and dependent variables, FR is a bivariate statistical analysis. The training locations chosen Considering the components that cause flooding, like geography, climate, and local characteristics, which were presented as separate variables investigated in this research, determined the spatial correlations between the dependent components. The research has made effective use of the frequency ratio model on flood susceptibility and insecurity in several flood-prone areas across the globe (Khosravi et al., 2016).

$$FR = \frac{\text{Flood points in factor class/Total flood points}}{\text{Factor class area/Total area}} \quad (2)$$

The final map of flood susceptibility was generated by combining all of the data from each controlling factor after the FR values for each class were calculated. The following formula is used to create a map of flood risk:

The relative frequency (RF) over a range of probability levels [0, 1] is then calculated by normalizing the FR using Eq 3.

$$RF = \frac{Factor\ class\ FR}{\sum Factor\ class\ FR} \quad (3)$$

Another disadvantage of the RF is that, after normalization, it assigns the same weight to each causal element. Equation 4 was utilized to assess each flood causative component and create a prediction rate with a shortened PR or weight to solve this issue and determine the reciprocal link between them.

$$PR = (RF_{max} - RF_{min})/(RF_{max} - RF_{min}) \quad (4)$$

Parameters	Class	Class Pixels	% Class Pixels	Flood Pixels	% Flood Pixels	FR	RF
Slope	< 2.8	1689576	60.2	41782	65.8	0.02	0.3
	2.8 - 7.6	794006	28.3	15812	24.9	0.02	0.241
	7.6 - 16.25	203238	7.2	4912	7.7	0.02	0.293
	16.25 - 29.15	76284	2.7	965	1.5	0.01	0.153
	29.15 - 60.94	43584	1.6	47	0.1	0.00	0.013
Elevation	< 434	816306	29	40464	63.7	0.050	0.571
	434-524	1074038	38.1	5924	9.3	0.006	0.064
	524-651	748647	26.6	15907	25	0.021	0.245
	651-883	121996	24.3	1271	2	0.010	0.12
	883-1428	56299	2	0	0	0	0
LULC	Water	26876	1	12073	19	0.449	0.865
	Forest	220589	7.8	1556	2.4	0.007	0.014
	Vegetation	1186463	42.1	21365	33.6	0.018	0.035
	Built up	832826	29.6	11402	17.9	0.014	0.026
	Bare land	550593	19.5	17167	27	0.031	0.06
Drainage Density	< 0.21	835063	29.6	6427	10.1	0.008	0.06
	0.21 - 0.57	648133	23	15524	24.4	0.024	0.187
	0.57 - 1.05	687468	24.4	18479	29.1	0.027	0.21
	1.05 - 1.71	477754	17	17597	27.7	0.037	0.288
	1.71 - 3.26	168815	6	5506	8.7	0.033	0.255
Rainfall	< 1264.60	275049	12	33521	61	0.122	0.79
	1264.60- 1316.38	521676	22.7	5643	10.3	0.011	0.07
	1316.38 - 1359.71	691283	30.1	9923	18.1	0.014	0.093
	1359.71 - 1408.32	811488	35.3	5877	10.7	0.007	0.047
	1408.32 - 1467.49	517884	22.5	8603	15.7	0.017	0.108
NDVI	-1.08	483344	17.2	19880	31.3	0.041	0.363
	0.08 - 0.17	797662	28.3	12373	19.5	0.016	0.137
	0.17- 0.26	685218	24.3	15871	25	0.023	0.204
	0.26 - 0.38	557245	19.8	11767	18.5	0.021	0.186
	0.38 - 0.72	293890	10.4	3675	5.8	0.013	0.11
Soil Map	Sandy Loam	2081	0.1	345	0.5	0.166	0.49
	Loam	153060	5.4	7035	11.1	0.046	0.136
	Sandy Clay loam	443371	15.7	56139	88.3	0.127	0.374
	Clay loam	2218064	78.8	76	0.1	0.000	0

Table 2: Calculation results for FR and RF for all classes for factors

Finally, by adding the PR of every issue or element and the RF of each class, Equation No. 5 is utilized to determine the flood vulnerability index.

$$FVI = \sum_{j=1}^{n} FR \quad (5)$$

Model Validation:

Using the Area Under the Curve (AUC) approach, the flood susceptibility map of the Islamabad and Rawalpindi study areas was validated. This straightforward approach, supported by science, enables the accuracy of the FR model to be confirmed. It is based on the confirmation of historical events. It is regarded as the most suitable technique to validate the FR model and has previously been applied in multiple research (Rahman et al., 2021).

$$AUC = \sum_{i=1}^{n=100} \frac{(X_1 + X_2)}{2(Y_2 + Y_1)} \quad (6)$$

In the AUC value range of 0.00 to 1.00, poor accuracy is denoted by values of 0.50–0.60, moderate accuracy by values of 0.61–0.70, high accuracy by values of 0.71–0.80, very good accuracy by values of 0.81–0.90, and excellent accuracy by values of 0.91–1.00 (Yesilnacar et al., 2005).

Result & Discussion

A significant amount of independent variables, known as conditioning factors, are specifically involved in flood susceptibility mapping (Kia et al. 2012). The statistical databases and spatial distribution for each of the seven (07) conditioning factors are as, Slope, Elevation, LULC, Rainfall, NDVI, Drainage Density, and Soil map were constructed with their subclasses (Table 2). Low-lying land regions are closely related to the flood scenario during rainy spells since the slope determines the frequency of floods. The likelihood of floods and flood events increases with decreasing slope gradients (Rahmati et al. 2016a). The slope's gradient frequently affects the infiltration technique. An increasing gradient causes surface runoff to grow while penetration decreases. As a result, places with abrupt gradient descents experience floods because a substantial amount of water becomes inactive (Muhammad Ishaq et al 2020). Using DEM data, the slope (in degree) was computed and classed into five (5) groups. The results indicate that the maximum FR values of 0.02 are found to be for the anticipated two lower side slope gradients with stated grades i.e. < 2.8° and 2.8° - 7.6°, respectively. While the other side has the lowest FR value of 0.000, the slope gradient is above 29.1° (fig a). Elevation plays a significant part in the frequency of floods because water frequently moves from higher elevations to lower land areas. Flooding is more likely to occur in lowland areas and less likely in higher-elevation locations, according to a previous study. In general, as the area's height rises, the FR value will decrease According to Table 2, hence there is a comparatively higher probability & chances of flooding in these explored low elevated locations and areas since the 1 lower elevated class in the study zone < 434m has high-frequency Ratio values of 0.050, respectively. In regions with explored as a low FR value for the overall area and a high altitude as compared to the allied context, flooding is less likely. (Das et al., 2018). Humans and nature cycles are depicted in land use patterns. Due to the less amount of vegetation and plantation to help regulate and act as a hindrance to the rapid outflow or outflux of water onto the exposed soil and top earth surface, runoff is higher in fallow farmland and greater in metropolitan areas due to the wide impermeable soil. These places are the most sensitive to flooding and run the risk of both soil erosion and flooding. Built-up regions along rivers are particularly vulnerable to flooding because of their high population density, housing stock, and economic prosperity (Nandi et al., 2016). Table 2 shows that in the explored study area and its vicinity, the higher FR based and calculated values observed in bare land as open land and water bodies as allied context based water resources are 0.031 and 0.449, respectively, showing that these highly unprotected areas have been highlighted and can be concluded that these are very vulnerable to floods in existing conditions. Rainfall continues to be a crucial factor in the research of flood vulnerability in terms of climate. Since rainfall deviation is seen to be the best indicator of flood zones, rainfall variance was taken into account when determining the risk of flooding (Das et al., 2018). In this study area, It is observed that in regions with considerable rainfall, the FR value of 0.12 is high (< 1264.60). An increased risk of flash floods is typically indicated by high drainage densities. This is because regions with a large number of streams and rivers can swiftly channel rainfall, which can create abrupt flooding and sharp increases in water flow. On the other hand, regions with low drainage densities typically absorb more water and result in delayed, less severe runoff (Lazarević et al., 2023). In the study area results show that class 1.05 - 1.71 and 1.71 - 3.26 with higher FR values of 0.037 and 0.033 respectively. These results indicate that these ranges of drainage density are more prone to flash floods. Another important flooding conditioning factor is the NDVI. The values in the index's -1 to +1 range. Khosravi asserts that negative values imply water, whereas positive (+ve) values suggest vegetation; as a result, Flooding and the NDVI are correlated negatively (-ve). Higher calculated and gathered NDVI values clearly indicate that a lower or even smaller scale flood risk can be anticipated, whereas lower NDVI levels suggest a greater risk of flooding (Paul et al., 2019). This sample's NDVI values range from -1.08 to 0.17–0.26, which corresponds to high FR values of 0.041 and 0.023, respectively. The risk of flash floods increases when there is less vegetation because less infiltration and more runoff occur. The structure and texture (sand, silt, clay) of soils are depicted on soil maps, and these factors influence the soils' ability to absorb water. Clayey soils have low infiltration rates, which increase runoff and the risk of flooding, whereas sandy soils often have high infiltration rates, which decrease surface runoff (Lazarević et al., 2023). The high FR values for Sandy Loam (0.166) and Sandy Clay Loam (0.127) indicate these soil types because of their varying infiltration rates, erosion sensitivity, and moderate to high runoff potential, they significantly contribute to flood susceptibility. Accurately analyzing and controlling flood hazards is made easier with an understanding of these qualities.

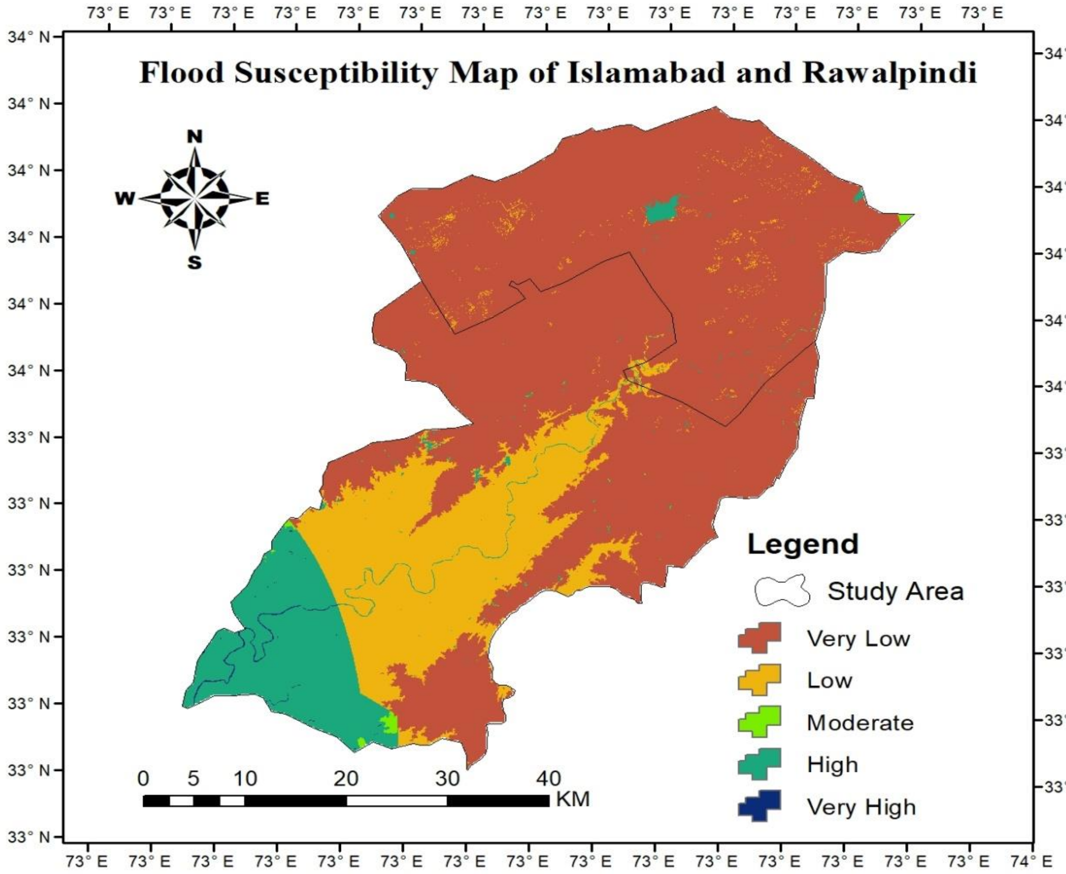


Fig 5: Showing FR model of the Study area

As evident based on the ratings gathered for each subclass mentioned and stated of all conditioning based defined parameters are determined clearly by the Frequency based Ratio values as have been already indicated in Table 2. The research area shows a gradient in flood sensitivity, with zones of moderate to low susceptibility transitioning from regions with extreme to high vulnerability, which is primarily found in the center and western regions of the study area (Fig. 5). Areas with a high to very high risk of flooding are characterized by alluvial deposits, braided flood plains, from approximately poor to extremely poorly drained slope based soil, lower elevation levels, lower slope based gradient values, and greater extent of proximity to the main river body and water resource. When utilizing the Frequency Ratio (FR) approach to map flood vulnerability and susceptibility, these attributes are crucial conditioning factors. Several models have been proposed and recommended by many academics, however, it is crucial to assess the accuracy and success rate of a model in perspective and order to enable better validation of it for the purpose of flood susceptibility as well as vulnerability based assessments towards defining any conclusion. With reference to the success rate as anticipated, forecast and prediction based accuracy as well as mentioned forecast accuracy, the proposed and evaluated FR model performs admirably (Munir et al., 2022) The model's highest accuracy of 1.0 suggests that it was impartially able to anticipate natural risks with precision (Paradhan et al.,

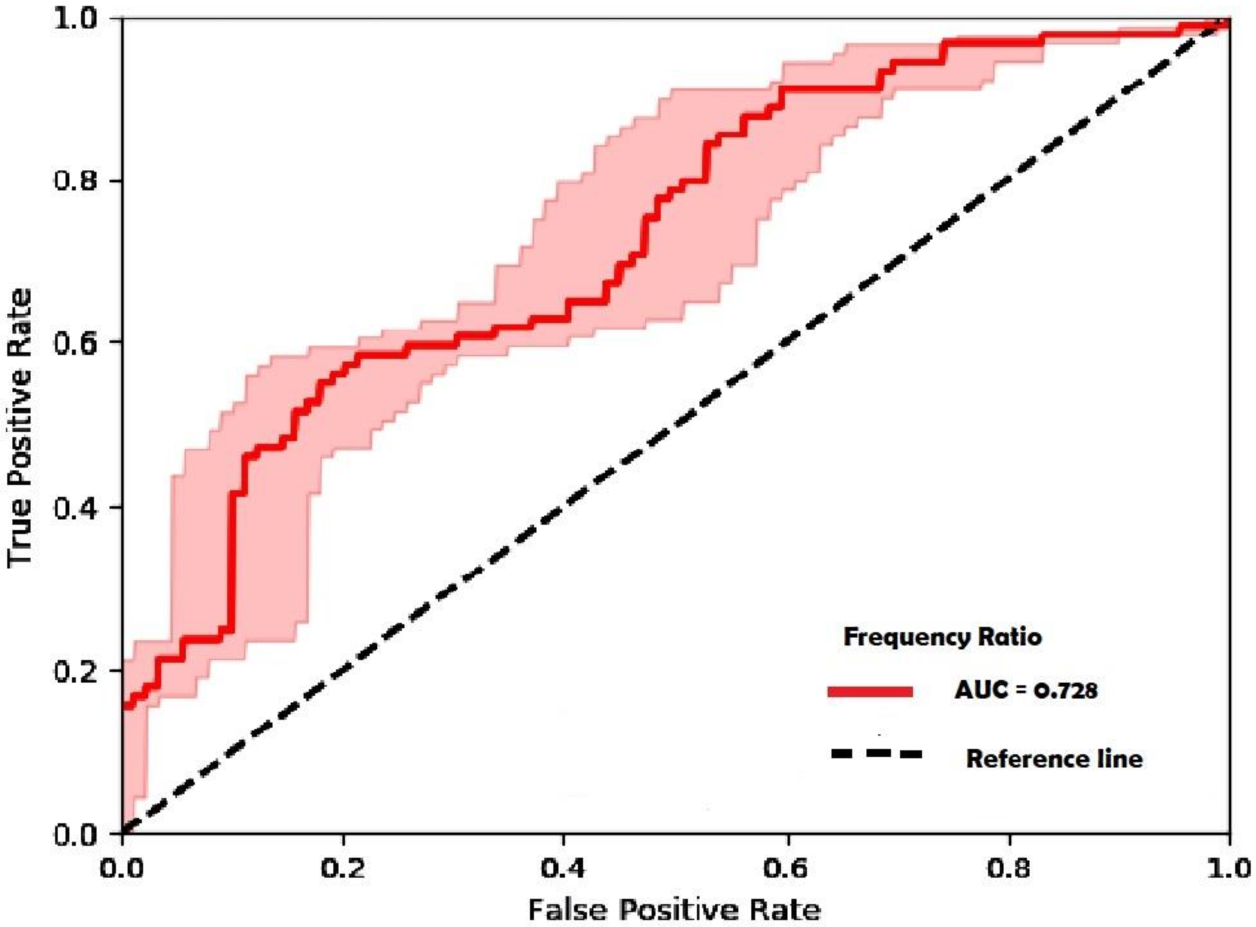


Fig 6: Showing AUC graph of the FR model

2018). With reference to the calculation related to the accuracy was based on using the remaining 33 flood areas that have not been considered in the model's creation, and hence the 77 training flood points were used to calculate the success rate. Floods with susceptibility in the future, values between "moderate" and "very high" are anticipated to be likely. The anticipated flood based forecast rate or frequency is determined by using the Area under the Curve (AUC) to validate the modeling. It must be assessed as a crucial outcome and result (Fig. 6) AUC has been the major source for the model's performance as well as for the model based validation. The AUC parameter with the intention of calculation and validation with reference to the current explored model was calculated based on the mentioned equation (6) for the stated prupose. On the y-axis of the model, the true positive rate is compared to the false positive rate on the x-axis. where P is the total integer of floods, N is the total integer of non-floods, and TP and TN indicate the number of pixels correctly identified. (Tien et al., 2018). In the validation phase, 30 percent of the total flood points were used. The model's AUC was 0.72 after assessment, indicating that 0.72 percent of the efforts were successful. Despite the limitations and imprecision of the input data, this percentage was considered good. It also clarifies how effectively the research region's components and frequency ratio model worked or predicted floods.

Conclusion

Analysis of flood susceptibility mapping is crucial to reducing destructive floods through the implementation of practical solutions. Planners can gain significant advantages by using flood susceptibility data to execute suitable land use in flood-prone places. This study successfully integrates geographic information systems (GIS) with remote sensing (RS) using a BSA-based FR model to build an extensive urban flash flood susceptibility map for Rawalpindi and Islamabad. A total of seven conditioning elements were considered, including soil map, LULC, NDVI, rainfall, drainage density, slope, elevation, and soil map. Based on the flood inventory map, individual layers were constructed with a resolution of 30 meters. The layers were created by randomly selecting (77) 70% of the total flood point and (33) 30% for validation. The validation of flood-prone mapping depends critically about the precision with which factor layers develop. The five zones on the final flood vulnerability map are very low (23%), low (13%), moderate (15%), high (22%), and very high (27%) respectively. As compared to other areas western-southern part of the area is highly susceptible area for floods. This area has inadequate capacity for adaptation and is extremely sensitive. South-Western, central part towards northern areas are showing very high to high and moderate respectively. Higher runoff potentiality, alluvial deposits, poor to extremely poorly drained soil, braided food plain, lower elevation, lower slope, and proximity to the main river are characteristics of these areas with moderate to very high flood susceptibility. These variables are important in conditioning flood vulnerability. Susceptibility has been recognized as a potential future flood and ranges from "high" to "very high." Using the ROC curve, the importance of the present Frequency Ratio model for vulnerability mapping was assessed. The graph, which shows a performance rate of 72%, indicates that the methodology used in this research produces reliable and consistent results. Therefore, it can be concluded that the accuracy of the model increases as the normal level of parameters increases, indicating that the accuracy of the conditioning factors significantly affects the mapping of flood susceptibility. For Islamabad and Rawalpindi District's flood-prone zones, the most important factors and PR are LULC (3.7), rainfall (3.7), and elevation (2.5). It is crucial to recognize climatic extreme events particularly floods for future occurrences, coupled with the realization and adoption of the future strategies on the reported science adapted extreme risks. Through this model representation of images of the plane and elevation outlining the areas that are most prone to flood disasters, this will help involve the lawmakers, the planners, the decision makers, and even the government officials in ensuring that they apply the right administrative measures for development in the research area and also help curb the development process.

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