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Assessing Flood Vulnerability in the Flood-Prone Imphal River Valley Using a GIS-Based AHP Model

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Abstract

Flood poses significant threat to people, infrastructure and economy in densely populated river basins of Monsoon Asia. Accurate assessment of flood-vulnerable areas is essential to effectively prevent and reduce impacts. The central valley of Manipur has witnessed floods of different magnitudes, with increasing frequency in recent years. This study uses Multi-Criteria Decision Making (MCDM) techniques to combine multisource data in order to create a flood vulnerability zonation map. The quality-controlled datasets used encompassed variables from socio-demographic, economic, and infrastructural dimensions for their observed influence on vulnerability. The weight for the selected flood vulnerability variables were determined based on Analytic Hierarchy Process (AHP) by experienced local flood experts. The composite flood vulnerability map (FVM) of the study area was then prepared in the GIS environment. The consistency of the AHP derived weights were checked using Consistency Index (CI), whereas importance of each variable on the model output was examined through single parameter sensitivity analysis. The results of the model show that about two-thirds of the study area (66.36 per cent) is under very low to low vulnerability zones, while 17.81 per cent are categorised within moderate vulnerability zone. Interestingly, although only a relatively small fraction of the valley (15.83%) is under high to very high flood vulnerability zones, these areas are also the most densely populated making them priority areas for future flood mitigation planning. By employing a well-established geospatial technique to process multisource data, this study produced a policy relevant flood vulnerability map to aid planners in formulating scientifically robust flood mitigation strategies.

Keywords: Flood Vulnerability Zonation, GIS, MCDM, AHP, Imphal Valley.

Introduction

Floods represent a major global natural disaster that causes loss of life and significant damage to property, infrastructure, and livelihoods (Swain et.al., 2020). Floods account for 44 per cent of all natural disasters worldwide between 2000 and

2019, with Southeast Asian countries facing the most frequent and intense flooding (CRED, 2019). In recent decades, the frequency and intensity of flooding have increased due to uneven distribution of rainfall, river overflows, rapid snowmelt, deforestation, uncontrolled urbanisation, and unplanned settlements in the low-lying flood-prone areas near the coasts and riverbanks (Gupta and Dixit, 2022).

While floods are natural events within river systems and not inherently catastrophic, they become hazardous when they threaten human lives and property. The intensity of floods varies over time and space, making it impossible to completely prevent their occurrence and negative impacts. Heavy and erratic monsoon rains now fall on landscapes altered by urbanisation and deforestation, yielding greater and faster runoff. Rapid and uncontrolled urban growth with impermeable surfaces and encroachments of natural waterways has been shown to reduce infiltration and sharply increase flood frequency and severity (Ouma and Tateishi, 2014). Climate change also alters precipitation patterns, heavy convective storms are becoming more frequent, and the duration of wet and dry spells is changing (Caretta et.al., 2022). However, effective management and mitigation strategies such as early warning systems, zoning, community-based flood management, and understanding flood risk zones can significantly reduce the severity of flood impacts (Singh and Sharma, 2023; Mulu et.al., 2025). Therefore, accurately identifying areas most likely to be affected by floods is crucial for developing effective disaster mitigation strategies (Das and Gupta, 2021; Ahmed et.al., 2022; Shrestha et.al., 2025).

Even in the data-scarce regions, researchers can produce a detailed flood risk map using Remote Sensing (RS) data and other secondary sources, such as the census data, with the help of AHP weighting in the GIS environment. For example, Ramkar and Yadav (2021) show how RS and GIS can be used to produce flood risk indices at the basin level. Leikangbam et.al. (2019) put forward that flood risk is the product of hazard and vulnerability; therefore, hazard analysis and exposure reduction are the prerequisites for flood mitigation. Many other studies emphasised flood hazard and flood vulnerability mapping for flood risk assessment (Selvam and Antony, 2023; Zhran et.al., 2024). A typical food risk map is produced from a combination multiple criteria indication physical (elevation, slope, drainage proximity, rainfall), environmental (land cover, soil moisture, vegetation), socio-economic (population density, literacy, housing quality) and infrastructural (road density, distance to roads, building density) factors that determine exposure and coping capacity (Ahmed et.al., 2022; Chakrabortty et.al., 2022; Das and Gupta, 2021; Mann and Gupta, 2023). For example, Mitra et.al (2022) used MCDM-AHP framework integrated with GIS and RS to produce the flood risk map of the Uttar Dinajpur district of West Bengal using physical, infrastructural, hydrogeological, and demographical indices. Flood hazard zonation is thus a first step, but equally important is flood vulnerability zonation (FVZ) (Mourato et.al., 2023). FVZ map identifies areas most likely to be affected by flooding and categorises these areas into different vulnerability classes (Mourato et.al. 2023).

The Imphal Valley of Manipur bears the sorrow of frequent flooding of various intensities (MASTEC Report). The increasing frequency of severe floods has become a serious problem in this region, exacerbated by unchecked deforestation due to everincreasing market demand and illegal, unsustainable destruction of the natural ecosystems, particularly in the upper catchment areas, leading to siltation of riverbeds, reducing the water-holding capacity of the rivers flowing through the valley. Consequently, multiple flood events hit this region in 2017, 2024 and 2025 that damaged infrastructure, disrupted livelihood and threatened human lives (Hindustan Times, 2024; India Today, 2025; Laikangbam et.al., 2019; Singh, 2022). Therefore, this region needs a comprehensive FVZ map to reduce flood losses. A few studies have been conducted to map the flood hazard zones in Manipur (Laikangbam et.al., 2019; Khundrakpam and Devi, 2024). However, these studies primarily focus on the basin level of some specific rivers.

Objective

The objective of this study is to develop FVZ map of the entire Imphal Valley by applying the MCDM-AHP method and GIS and RS technology to facilitate effective flood management strategies and mitigate flood losses.

Study Area

The present study is conducted in the Imphal Valley, the central plain of Manipur. This region is drained by the Imphal River and its tributaries, including the Iril, Thoubal, Khuga (Singh, 2022), and some minor rivers. The Loktak Lake, the largest fresh-water lake in the northeast India, is located in the southern part of the study area. This lake is famous for its floating vegetation locally known as *Phumdis* (Randhir et.al., 2000). Initially, the central plain had only 4 districts, but after the split of Kakching district from the Thoubal district on 9 December 2016, the plain now has 5 districts, viz: Imphal East, Imphal West, Thoubal, Kakching and Bishnupur. This study area covers 1961 sq km, nearly the entire valley districts. It extends from 24°11′N to 25° 3′ N and 93°41′E to 94° 8′E. The land is generally flat, with a few hills and hillocks standing. The elevation ranges from 753m to 1573m, with a mean of 795m. This region is gently sloping from north to south, with most part of the valley having a slope of <8 per cent. Geographically, the study area is a part of the Purvanchal region of the Himalayas. Subtropical monsoon climate (Cwg) prevails in this region (Singh, 2021), experiencing an average annual rainfall of 1473.44 mm (1985-2020). In summer, the average high temperature is about 32–34°C, while in the winter, temperatures can drop to as low as about 1–2 °C. According to the Census 2011, the Imphal valley is home to nearly 60 per cent of the state's population (Census, 2011), relying primarily on agriculture, with rice and vegetables being major crops. With poor irrigation system, the fate of agriculture largely depends on the unpredictable nature of the monsoon. The map of the Imphal valley is shown in Fig 1.

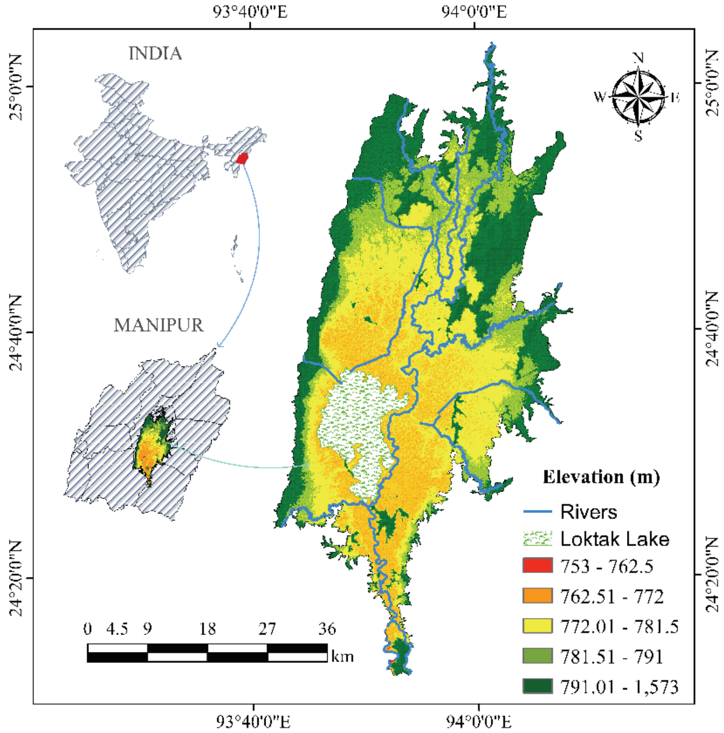


Fig 1. Map of study area.

Regarding natural disasters, hailstorms, particularly during the pre-monsoon season, and monsoon floods frequently lead to significant devastation in the region. The state has had major floods in 1929, 1941, 1953, 1965, 1966, 1989, 1992, 1997, 1998, 1999, 2001, 2015, 2017, 2019, and 2020 (Thiyam, 2023). Recently, in 2024 and 2025, devastating floods hit many areas in this region. According to news reports from various sources, the recent flood that occurred on 31 May 2025 destroyed around 115.59 hectares of crop land, affected more than 1,65,000 individuals, and damaged 35,354 households till 5 June.

Materials and Methods

Data Sources and Thematic Layers Preparation

The study used nine flood vulnerability conditioning parameters based on availability and relevance criteria. These are the total population (TP), female population (FP), child population under 6 years of age (CP), population density (PD), illiteracy rate (IR), unemployment rate (UR), distance to hospital (DH), road density (RD) and distance to road (DR). Sources and the description of the selected vulnerability factors are given in the table (Table 1). In many studies, only the vulnerable population, such as child population, female population or the aged population have been used (Pathan et.al., 2022; Gupta and Dixit, 2022). In many other studies, total population is considered an important vulnerability parameter as higher population triggers a higher exposure to flood (Mitra et.al., 2022). Roy et.al. (2021) observed that the higher the population density, the higher the vulnerability to flooding and vice versa. Access to medical facilities significantly reduces the individual's vulnerability to flooding. The road network development allows people to move faster and more easily when a disaster hits a region. Therefore, road density and distance to road are considered important conditioning parameter. Education is considered an important parameter in disaster studies. Literate people can adopt strategies to cope with flood disasters more effectively, and vice versa. Therefore, the illiteracy rate is considered an important parameter in this study. Lastly, the unemployment rate is taken as it directly affects the coping capacity of an individual. Fig 2 shows the detailed methodological flow chart of the study to delineate flood vulnerability zonation.

Table 1. Data sources

Parameters	Description	Source
Total Population, Female Population, Child Population under 6 years, Population Density, Illiteracy Rate and Unemployment Rate	Demographic and socio-economic data were extracted from the 2011 Census of India Primary Census Abstract	Primary Census Abstract 2011 Retrievedfrom: https://censusindia.gov.in/
Distance to Hospital, Road Density and Distance to Road	Hospital point locations and road vector data were downloaded from OpenStreetMap	OpenStreetMap (OSM) Retrievedfrom: https://www.openstreetmap.org/

The village boundary shapefile with which the primary census abstract 2011 data are to be linked does not accurately fit the ground reality. Therefore, the areal extent of the towns has to be compromised to a significant level. However, flood vulnerability zonation requires a degree of accuracy; otherwise, the result would not yield valuable findings. To produce maximum accuracy, village points are taken from Google Earth Pro, and the population parameters are interpolated using inverse distance weighting (IDW) from these points in GIS. In the same way, the raster layers of each of the 9 vulnerability parameters are also prepared in GIS environment. The illiteracy and unemployment rates are expressed as percentage, whereas population density is calculated using the point density tool. Distance to river and distance to hospital are prepared using Euclidean distance, and road density spatial layer map is obtained by means of line distance from the data of OpenStreetMap. All the parameters are resampled into an equal spatial resolution of 30m x 30m (Fig 3)

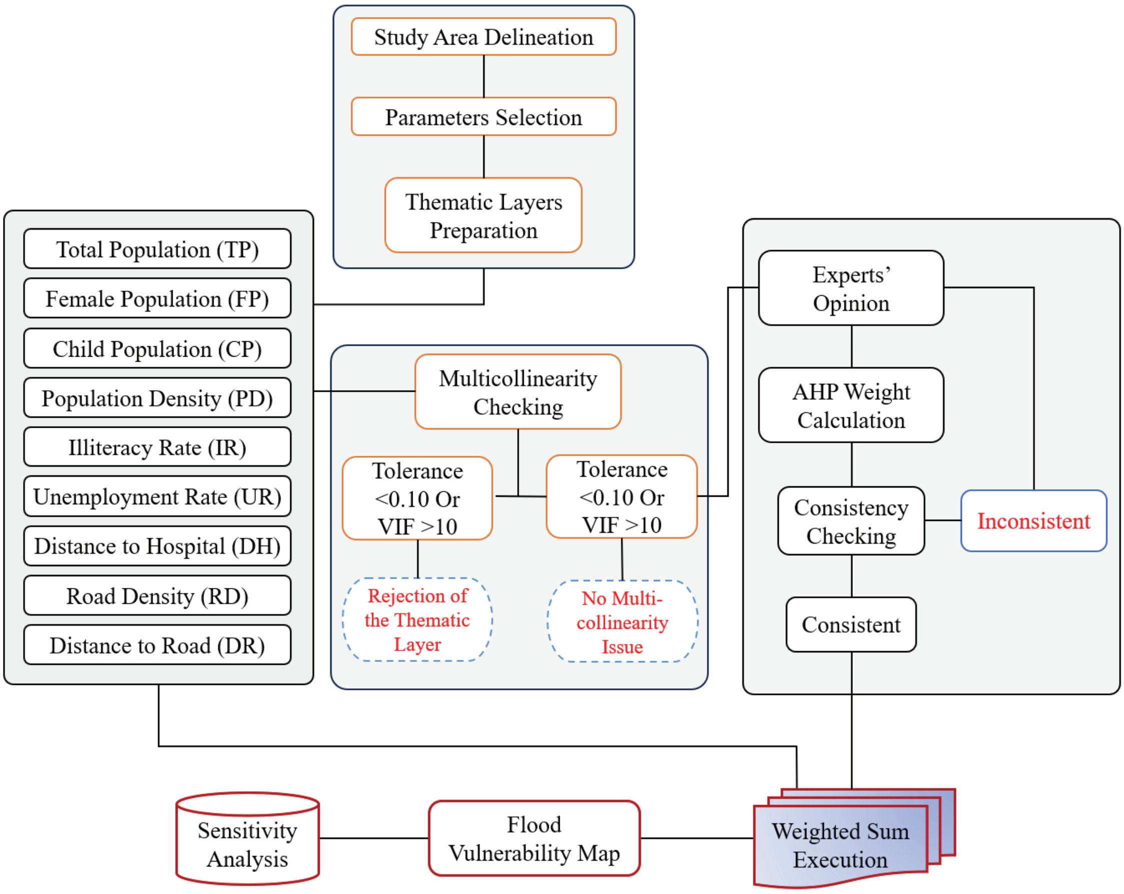


Fig 2. Methodological flow chart

Multicollinearity

Multicollinearity tests the presence of a linear interdependence among some or all independent variables in a regression model. It is an essential step in flood vulnerability mapping. Multicollinearity between two independent variables means that one variable can be linearly predicted from the other with a significant degree of accuracy (Mukherjee and Singh, 2020). However, it does not affect the reliability of the model and its predictability; it impacts only the estimations of individual parameters (Al-Juaidi et.al., 2018). Variance inflation factor (VIF) is one of the important methods to analyse multicollinearity (Mitra et.al., 2022). The following formulae in equations (i) and (ii) are used to test multicollinearity (Myers et.al., 2010):

$$\text{Tolerance of } i^{th} \text{ predictor variable } (Ti) = 1 - (Ri)^2 \quad \text{(i)}$$

$$\text{VIF for } i^{th} \text{ predictor variable } (VIFi) = 1/Ti \quad \text{(ii)}$$

where Ri^2 is the coefficient of determination of the regression equation. According to Saha (2017), a tolerance level of less than 0.10 or a VIF value of 10 or more indicates issues with multicollinearity. Thematic layers having a tolerance level < 0.10 or a VIF value of ≥10 are reduced to a few representative layers for the analysis.

To evaluate multicollinearity among the nine thematic layers, 1000 points (N = 1000) were randomly selected from the study area utilising the 'Create Random

Points' tool (Data Management Tools package; Feature Class toolset). Data for these points were extracted from each thematic layer using the 'Extract Multi Values to Points' tool (Spatial Analyst Tools package; Extraction toolset) within the GIS platform. The assessment was conducted using SPSS software, version 21.

Weighting and ranking by AHP

Thomas L. Saaty developed the Analytic Hierarchy Process (AHP) in the 1970s (Saaty, 1987). It is a qualitative, expert-based, structured technique for analysing and organising complex decisions (Saaty, 1990). AHP is widely used in ranking decision alternatives in several MCDA models (Aziz, 2016). This technique can be effectively applied in addressing complex problems (Souissi et.al., 2020). Having significant relevance to address contemporary flood issues, this MCDA technique is applied worldwide in flood zonation mapping (Das and Gupta, 2021; Mann and Gupta, 2023). Therefore, the current research study adopts the AHP technique and integrates the selected flood vulnerability conditioning thematic layers in the GIS environment. Using the pair-wise comparison matrix, the relative weight of all the selected parameters and their sub-classes are compared (Fenta et.al., 2015). Thus, based on Saaty's preference scale ranging from 1 to 9 (Table 2) and informed by literature reviews, studies in similar geographical settings, and expert knowledge, the relative weights of each layer are determined. This step is fundamental to the technique and is called the knowledge-driven approach (Mukherjee and Singh, 2020). The steps for AHP calculation are given below.

Step 1. Break down the complex, unstructured problem into a hierarchy that includes goals, criteria, and indicators.

Step 2. Create an n × n matrix where the diagonal elements are set to 1. Compare the indicators against each other using a qualitative scale to determine their relative importance.

Step 3. Compare each indicator in the first column with every indicator in the same row. If an indicator in the i^{th} row is more important than the indicator in the j^{th} column, assign a value greater than 1 to (i,j); reciprocate this value for (j,i).

Step 4. Use the eigenvector method, detailed in equations (6) to (7), to normalise the weights derived from pair-wise comparisons. This method ensures that the weights effectively reflect each indicator's relative importance.

$$X_{ij} = \frac{P_{ij}}{\sum_{i=1}^{n} P_{ij}}$$

(iii)

$$W_{ij} = \frac{\sum_{j=1}^{n} X_{ij}}{n}$$

(iv)

Where P_{ij} is the preference value in the pair-wise comparison matrix, X_{ij} is the normalised score of each criterion, W_{ij} is the priority vector representing the AHP weight of each criterion, and n is the number of selected criteria.

Consistency Check

The assigned AHP weights are to be tested for consistency. For this, the consistency ratio (CR) is calculated using the following equation (Eq.8):

$$CR = \frac{CI}{RI}$$

(v)

Where CI is the consistency index, and RI is the random index. The value of RI is constant for a specific number of criteria, as described by Saaty (Table 3), and CI is calculated as follows:

$$CI = \frac{\lambda max - n}{n-1}$$

(vi)

Where λmax and n are the principal or the largest eigenvalue and the number of criteria, respectively, of the pair-wise comparison matrix.

If the *CR* value is 0.1 (10 %) or below, the AHP result is considered acceptable. However, if it exceeds 0.1, the result is inconsistent and requires a revision.

Table 2. Saaty's scale of preference (Saaty, 2008).

Degree of Preference	Scale
Equal importance	1
Equal to moderate importance	2
Moderate importance	3
Moderate to strong importance	4
Strong importance	5
Strong to very strong importance	6
Very strong importance	7
Very strong to extreme importance	8
Extreme importance	9

Table 3. The random index (RI) value is used to check consistency (Saaty, 1994).

n	1	2	3	4	5	6	7	8	9	10	11	12
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48

Mapping of Vulnerability Zones

The aim of this study is to develop the final FVZ map of the entire Imphal valley. The weighted sum technique is performed in the GIS environment using the AHP weights and the ratings of the respective vulnerability parameters. The equation for computing the FVZ map is given below in equation (v) (Mitra et.al., 2022):

$$FVZ = \sum_{i=0}^{n} W_i \times V_i \quad \text{(v)}$$

where *FVZ* is the flood vulnerability zonation, W_i is the AHP weight of the vulnerability parameter, and V_i is the AHP rating of each sub-parameter.

Based on the priority of the criteria, AHP weights are assigned. Using these weights, flood vulnerability parameters are integrated by the 'weighted sum' technique in the GIS platform to produce a flood vulnerability map of Imphal Valley.

The produced FVZ map is classified into five vulnerability zones using natural breaks method.

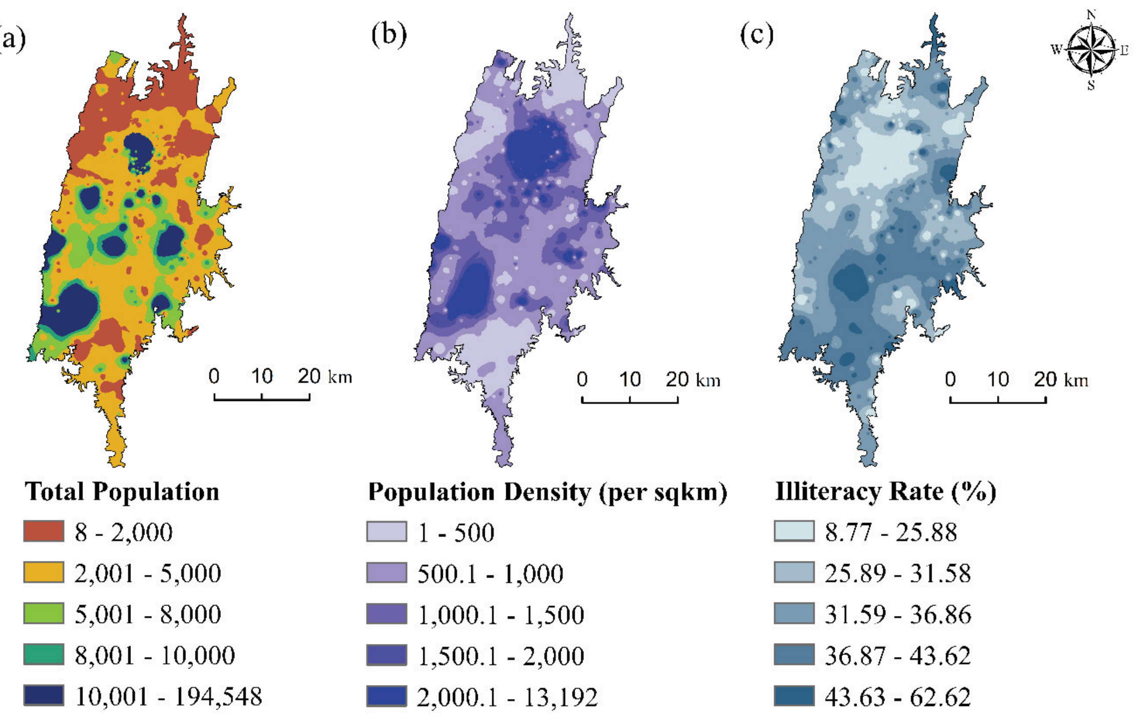
Results and Discussion

Multicollinearity results

The collinearity statistics for the selected flood vulnerability parameters have been calculated. The statistical results show that the tolerance value for DR, RD, DH, UR, IR and PD is more than 0.10, and the VIF values were less than 5 (Table 4). However, in the case of parameters CP, FP and TP, the values of tolerance are less than 0.10, and that of the VIF is more than 5. Therefore, these three parameters, TP, CP and FP are highly correlated, and therefore any one of these three parameters can be used as the representative of the other two. For this study, the parameter TP has been chosen.

Table 4. Collinearity statistics of flood vulnerability parameters

Tolerance	DR	RD	DH	UR	IR	PD	CP	FP	TP
VIF	0.740	0.446	0.829	0.809	0.724	0.521	0.011	0.000	0.000
	1.352	2.244	1.206	1.236	1.382	1.919	88.586	2627.261	2941.089



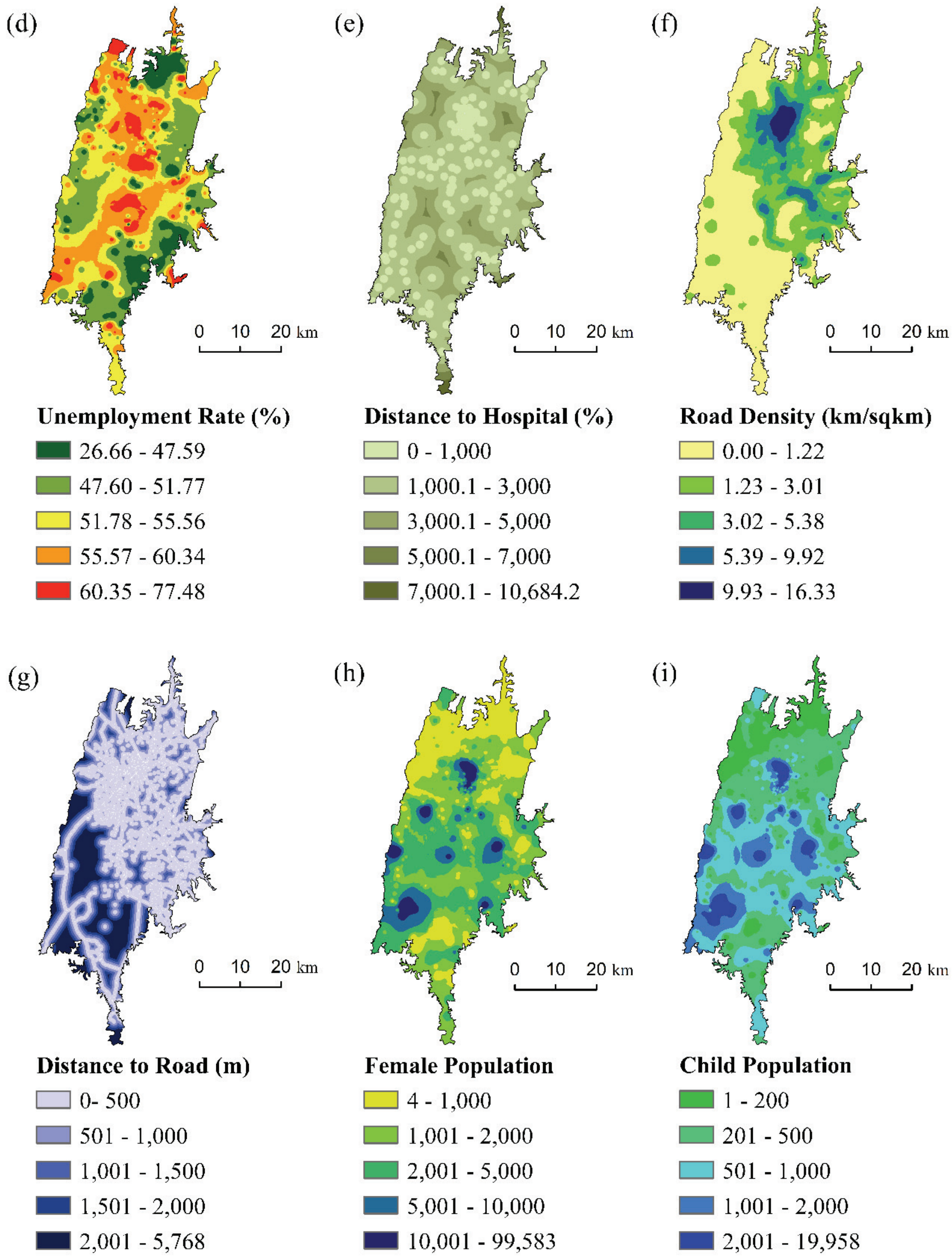


Fig 3. Flood vulnerability thematic layers

Flood Vulnerability Layers

For the selected seven vulnerability parameters, each thematic layers are classified into five categories, and the details of the classification schemes are shown in Table 5. The population of a region also includes vulnerable populations such as children, women, and older people (Gupta and Dixit, 2022). Therefore, areas with higher populations are more vulnerable to flood disasters. The population distribution in the study area ranges from 8 to 194548, Fig 3(a). A higher rating is assigned to the Very High flood level because this category has the maximum population range (Mitra et.al., 2022). Likewise, population density is another parameter that is directly related to the vulnerability of a region. The population density value ranges from 1 person per sq km to 13,192 persons per sq km, Fig 3(b). In this parameter, the maximum rating is also given to the very high sub-category, as it accounts for the maximum value range (Ganji et.al., 2022).

Sl. No.	Parameters	AHP Weight	Class	Range	Flood Level	Area in sq km	Area in %	Rating
1	Total Population (TP)	0.297	1	<2,000	Very Low	470.201	23.978	0.056
			2	2,000 - 5,000	Low	872.461	44.492	0.096
			3	5,000 - 8,000	Medium	310.127	15.815	0.157
			4	8,000 - 10,000	High	90.922	4.637	0.257
			5	>10,000	Very High	217.226	11.078	0.434
2	Population Density (PD)	0.297	1	1 - 500	Very Low	409.667	20.891	0.056
			2	500 - 1000	Low	832.463	42.452	0.096
			3	1000 - 1500	Medium	386.104	19.690	0.157
			4	1500 - 2000	High	125.864	6.419	0.257
			5	2000 - 13,192	Very High	206.839	10.548	0.434
3	Illiteracy Rate (IR)	0.047	1	8.77 - 25.88	Very Low	103.729	5.290	0.035
			2	25.89 - 31.58	Low	232.007	11.831	0.068
			3	31.59 - 36.86	Medium	483.661	24.665	0.134
			4	36.87 - 43.62	High	504.977	25.752	0.260
			5	43.63 - 62.62	Very High	636.563	32.462	0.503
4	Unemployment Rate (UR)	0.031	1	26.66 - 47.59	Very Low	215.447	10.987	0.062
			2	47.60 - 51.77	Low	528.933	26.974	0.099
			3	51.78 - 55.56	Medium	559.251	28.520	0.161
			4	55.57 - 60.34	High	508.527	25.933	0.262
			5	60.35 - 77.48	Very High	148.778	7.587	0.416
5	Distance to Hospital (DH)	0.078	1	0 - 1,000	Very Low	390.160	19.898	0.050
			2	1,000 - 3,000	Low	1088.170	55.498	0.088
			3	3,000 - 5,000	Medium	423.031	21.575	0.151
			4	5,000 - 7,000	High	48.177	2.457	0.259
			5	7,000 - 10,684.2	Very High	11.219	0.572	0.451
6	Road Density (RD)	0.087	5	0 - 1.22	Very High	1006.680	51.337	0.451

			4	1.23 - 3.01	High	510.418	26.029	0.259
			3	3.02 - 5.38	Medium	302.341	15.418	0.151
			2	5.39 - 9.92	Low	103.883	5.298	0.088
			1	9.93 - 16.33	Very Low	37.616	1.918	0.050
7	Distance to Road (DR)	0.164	1	0- 500	Very Low	1251.82	63.8378	0.056
			2	500 - 1,000	Low	305.13	15.5604	0.096
			3	1,000 - 1,500	Medium	152.976	7.80117	0.157
			4	1,500 - 2,000	High	97.0938	4.9514	0.257
			5	2,000 - 5,768	Very High	153.918	7.8492	0.434

Table 5. Selected flood vulnerability parameters

The higher the illiteracy rate of a region, the higher the vulnerability to floods. Other study also uses literacy rate in place of illiteracy rate (Senan et.al., 2023). The values of illiteracy rate range from 8.77 per cent to 62.62 per cent, and it is divided into five groups using natural breaks method, Fig 3(c). Similarly, the unemployment rate is also divided based on natural breaks method. The unemployment rates are observed in the central, northwestern and southwestern parts of the study area, Fig 3(d).

Fig 3(e) shows the distance to hospital map, classified into five sub-classes. It ranges from 0 - 1,000m (very low) to 7,000m - 10,684.2m (very high). Areas far away from medical facilities are more vulnerable, and vice versa. More than 70 per cent of the study area falls under very low to low vulnerability zones.

Road density is another important vulnerability parameter shown in Fig 3(f). It is also classified by natural breaks into five sub-classes. The higher the value of road density, the lower is the vulnerability. The value of road density ranges from 0 to 1.22 km/sq.km (very high) to 9.93 to 16.33km/sq.km (very low), and a higher rating is given to the lower density.

Lastly, the parameter distance to road is manually grouped into five sub-classes based on the literature, very low (0- 500m) to very high (2,000m - 5,768m), Fig 3(g). This parameter has a higher AHP weight of 16.4 per cent. Each subclass, except the very high class, has a class range of 500m, and a higher rating is proportionally assigned to this very high sub-category. Wijesinghe et.al. (2023) also assigned similar weight to this parameter. In contrast to this study, their study gives lower rating to the areas farther away form the road.

AHP model output

The computed CR value for flood vulnerability is shown in Table 6, and the CR values for sub-classes of each thematic layer achieve a satisfactory level of consistency (> 0.10).

Table 6. Consistency check result for AHP.

λmax	n	CI	CR
7.071	7	0.012	.009

The highest weight is assigned to population (29.7%) and population density (29.7%), followed by distance to road (16.4%), road density (8.7%), distance to hospital (7.8%), illiteracy rate (4.7%) and unemployment rate (3.1%). Based on pixel value, the Imphal valley, the final FVZ map is classified into five flood vulnerability classes (very high, high, medium, low and very low) using natural breaks method (Fig 4). In terms of percentage, the area-wise coverage for each of the five FVZ map sub-classes is represented graphically using four different classification methods, viz. natural breaks, geometrical interval, quantile and equal interval, Fig 5. The maximum area coverage in the very high vulnerability category is observed in the quantile interval classification, and the minimum extent is observed in the equal interval classification. In the very low vulnerability class, the maximum arial coverage is observed in the equal interval classification, followed by natural breaks.

Flood Vulnerability Zonation (FVZ)

The final aim of this study is to develop a flood vulnerability zonation (FVZ) map. Therefore, the FVZ map (Fig. 4) is classified into five zones: very low, low, moderate, high and very high. In Imphal valley, the maximum area (1206.405 sq km), which accounts for 66.355% is under very low to low vulnerability category. Moderately vulnerable zones have an aerial extent of 323.839 sq km (17.812%). Whereas, the high and the very high vulnerability zones occupy smaller areas, 218.686 sq km (12.028%) and 69.178 sq km (3.805%) respectively. The high and very high vulnerability zones are found in almost all five valley districts. These areas fall in the greater Imphal region, Mayang Imphal (Imphal West District), Nambol, Bishempur and Moirang (Bishnupur District), Lilong, Thoubal and Sangaiyumphal (Thoubal District), and Hiyanglam and Kakching (Kakching District). These areas are associated with high population (>10,000) and population density (>1500). Out of the seven selected vulnerability parameters, total population, population density, and distance to road account for 75.8 per cent. The Imphal valley is historically prone to flooding. The devastating floods in 2024 and 2025 affected these high to very high-vulnerable areas the most.

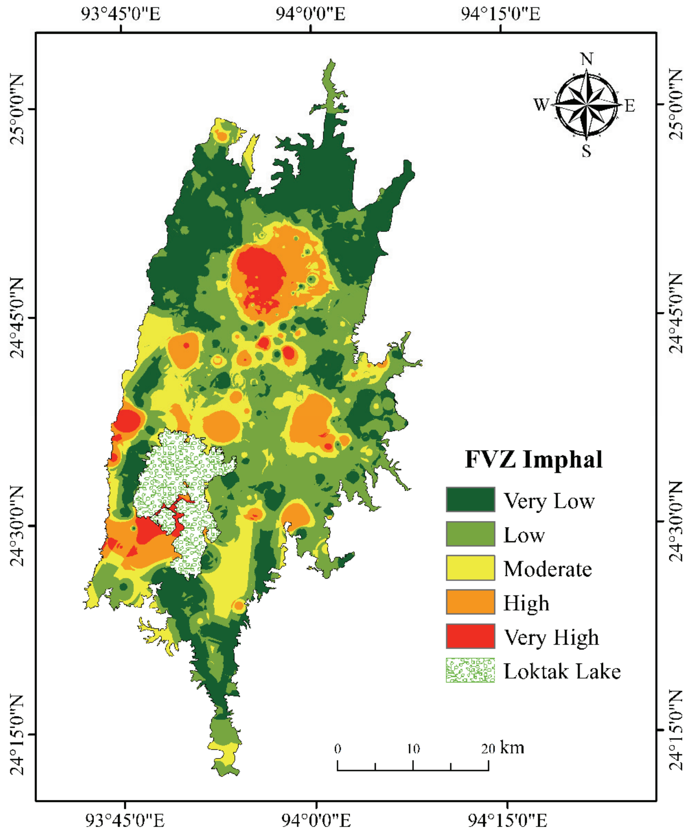


Fig 4. FVZ map of Imphal

Sensitivity analysis

Table 7 shows the sensitivity analysis of the FVZ map. The parameters total population (30%), population density (30%) and distance to road (16%) are given the highest weight, but on the basis of statistical output, these three parameters have a mean effective weight of 29.79 per cent, 31.06 per cent and 11.00 per cent, respectively. The highest difference between the mean effective and empirical weights is observed in the parameter distance to road (2.14%). Road density (8.7%) and distance to hospital (7.8%) are given moderate weight, while illiteracy rate (4.7%) and unemployment rate (3.1%) assign minimum weights. The maps of the effective weights of the seven vulnerability parameters are given in Fig 6.

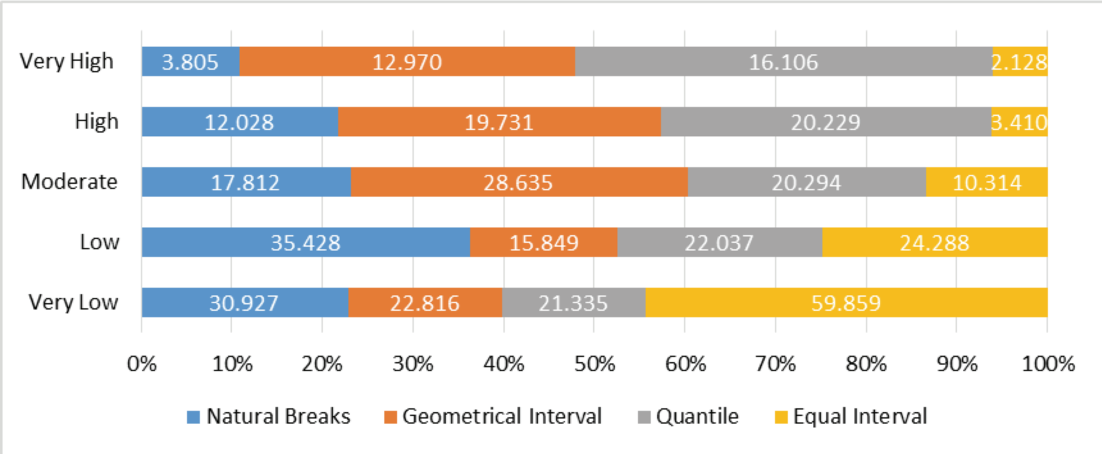


Fig 5. Vulnerability zones areas in per cent using different classification schemes

Table 7. Descriptive statistics of single-parameter sensitivity analysis of flood vulnerability

Thematic Layers	**Empirical Weight (%)**	**Effective Weight in %**			
		Min	**Max**	**Mean**	**SD**
TP	30	7.30	69.97	29.79	11.62
PD	30	9.22	74.71	31.06	11.74
IR	5	0.50	31.00	6.45	4.96
UR	3	0.84	19.31	4.62	2.74
DH	8	1.20	30.93	7.06	4.39
RD	9	1.20	30.58	6.76	4.13
DR	16	2.80	58.31	14.26	11.00

Conclusion

The Imphal Valley is prone to flooding due to its geographical setting, which is a flat terrain surrounded by hill ranges. A comprehensive flood vulnerability zonation map would help people identify areas more likely to be affected by floods. Proper flood management strategies and adaptation measures significantly reduce the losses from flood disasters. Previous studies have successfully implemented a GIS-based MCDM-AHP model using hydrological, geological, demographical, and land-use/land-cover indicators parameters (Hadi et.al. 2017; Chakrabortty et.al. 2022; Mitra et.al., 2022; Gupta and Dixit, 2022; Senan et.al. 2023). This research has applied an integrated GIS and RS-based AHP method to delineate flood vulnerability zones, Fig 4. This method has become more popular, particularly in data-scarce countries (Ramkar and Yadav, 2021; Ray, 2025). This study utilised the socio-demographic, hydrological and infrastructural factors. This research has identified total population, population density and distance to road as the highly affected variables, followed by distance to river, road density, distance to hospital and unemployment rate. In flood vulnerability zonation study, total population and population density parameters are given equal and maximum weight, followed by land-use/land-cover (Mitra et.al, 2022). The number of parameters used and the weightage assigned vary from one study to another (Rashetnia and Jahanbani 2021; Pathan et.al. 2022; Khan et.al. 2023).

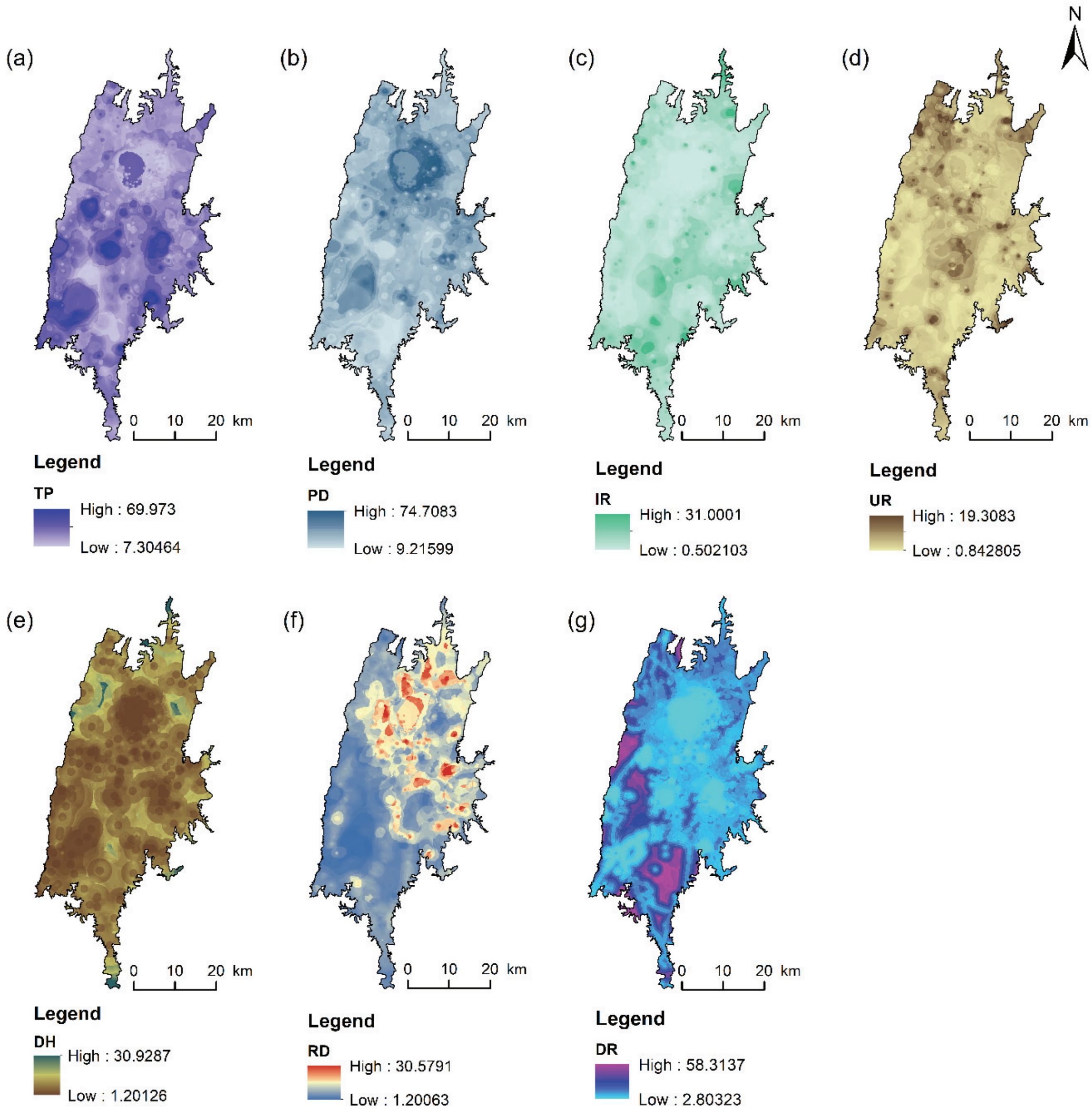


Fig 6. Single-parameter sensitivity analysis of thematic layers

The novelty of this study lies in its comprehensive analysis of flood vulnerability across the entire Imphal Valley, incorporating all major factors commonly used in similar research worldwide. Unlike previous works, no such study has been conducted in this specific region, making this an important contribution by generating a detailed Flood Vulnerability Zonation (FVZ) map for the Imphal Valley. The study is particularly relevant in light of the rising frequency of flood-related disasters. Gaining insights into flood behaviour and its underlying dynamics is essential for improving flood management strategies, especially at the household level.

This research draws from a broad base of global literature while serving as a timely documentation of flood vulnerability within the Imphal valley. Recent flood events underscore the urgency of this work. At the end of May 2024, Imphal East, Imphal West, and Bishnupur districts experienced severe flooding due to river overflows and embankment breaches caused by heavy and continuous rainfall linked to Cyclone Remal. Again, in early July of the same year, more flooding occurred due to intense monsoon rains, which led to river overflows and fresh breaches at multiple sites in Imphal.

In 2025, devastating floods struck again in late May and early June. Beginning on 31 May, this event caused widespread destruction, particularly affecting agriculture, with over 115.59 hectares of cropland damaged. Relief and evacuation efforts were actively carried out, with more than 4,000 people relocated to nearly 80 relief camps. Tragically, a 57-year-old man lost his life in Imphal West. According to media reports, over 165,000 individuals were affected by flash floods triggered by river swelling and breaches along the Imphal, Kongba, and Iril rivers.

This study develops a Flood Vulnerability Zonation (FVZ) map for the Imphal Valley by integrating Multi-Criteria Decision Analysis (MCDA) and the Analytic Hierarchy Process (AHP) within a Geographic Information System (GIS) environment. The vulnerability assessment is based on multiple indicators obtained from secondary data sources, with AHP used to assign weights to each factor. These weighted thematic layers are combined using GIS tools to produce the final FVZ map. The map was validated using the single parameter sensitivity analysis approach to ensure reliability.

The results indicate that approximately 66.36 per cent of the area falls under very low to low flood vulnerability. The medium vulnerability zone covers just over 17 per cent of the region, while 15.83 per cent is categorised as high to very high vulnerability. There is a need for special attention, strategic planning and targeted allocation of resources, particularly in these high-vulnerability to very high-vulnerability zones.

The limitations of this research study lie in the use of older datasets, image resolutions, data interpolation, etc. For instance, the use of the 2011 census data is quite old. Nevertheless, it is the latest population dataset, authentic and freely accessible for the state of Manipur. The spatial resolution of 30m x 30m is a large areal unit. Higher resolution images could produce more reliable outputs. To enhance the accuracy, the study recommends that future researchers focus on using the latest available demographic data and applying advanced models such as machine learning (ML) and artificial intelligence (AI), as well as hybrid models.

Ultimately, these findings provide valuable insights that could help local authorities, planners and decision makers adopt sustainable flood risk management strategies. Also, researchers can replicate this methodology in other regions.

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