



Application of geospatial tools in the assessment of Flood hazard impact on social vulnerability of Malda district, West Bengal, India

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ABSTRACT

Social vulnerability assessment is a dynamic process, which varies from place to place. In the present study, the social vulnerability index (SVI) of Malda district has been prepared because of several impacts of flood inundation. The flood inundation layer has been generated using multi-temporal remote sensing data. The flood inundation layer is prepared from real-time Synthetic Aperture Radar (SAR) data. For social vulnerability assessment, the most efficient indicators are household composition, age & sex composition, and underprivileged population (SC & ST). Economic and educational data has been collected from the Census of India Handbook 2011. All these data are combined with the district's village database on the GIS platform. The weightage overlay analysis method is applied to generate the social vulnerability index of the study area, where the multi-influencing factor (MIF) technique has been used for determining the influencing factors. The social vulnerability index has categories into Very High (4%), High (37%), Moderate (32%) and Low (27%). The social vulnerability index is being further intersected with the flood inundation layer to build a database for the most vulnerable area of this district. It has been observed that 70 villages are in Very High zones, 662 villages are in High, 578 villages are in Moderate and 479 villages are in Low zones. This study will help the disaster manager and stakeholders about the vulnerable situation of the study area and also depict the importance of geospatial techniques in disaster management.

1. Introduction

Flood hazard is the most devastating and frequently occurring natural disaster noticed over the entire globe (Floods, 2020; Kundzewicz and Schellnhuber, 2004; Maisels, 2003). Except for the Egyptian civilization, a flood is always associated with large-scale destruction (Hassan, 1997; Macklin and Lewin, 2015; Maisels, 2003). Flood occurs when the existing stream/river/lakes overflow and spread through the usually dry and comparatively flat land surface (Ritchie and Roser, 2014). Floods can be categorized into flash flood (heavy rainfall), riverine floods (snow or ice melt and rain), and coastal floods (storm surge). Riverine flood is the most common type of flood on the planet earth (Jain et al., 2018). According to a World Bank report (World Bank, 2021), out of the total population affected by various kinds of disasters, between 1998 and 2017, flood alone was responsible for affecting 80–90% (2 billion) of total deaths. World Resource Institute (WRI) has predicted that the number of people impacted by flood disasters will be doubled by 2030 (Ward et al.,

2020). In Asia, flood disaster shares 44% of all inundationous phenomenon; affecting 70% of the total population. It accounts for 58% of all disaster-mediated deaths in Asian countries (IFRC, 2016; UNDRR, 2020; UNODDR, 2004). Asian countries include India, China, Bangladesh, Pakistan, Vietnam, Malaysia, Indonesia, etc. Among these countries (Ashraf et al., 2017), India ranked 1st in terms of devastation occurring flood (see Figs. 16–18).

India has an extensive network of perennial river systems with more than 260 million hectares of the catchment area. These rivers have more than 2000 billion cubic meters of annual discharge (Central Water Commission, 2020). This blessing also acts as a curse for habitations residing around the river's banks or in the catchment areas. Around forty million hectares of India's geographical area is classified as flood-prone area, which is 12.17% of India's total geographical area (Mohapatra and Singh, 2003; Saini & S.P., 2012). World Bank and the Global Facility for Disaster Reduction and Recovery have estimated that 8% of India's land area is under the continuous flood disaster threat. Indo-Ganga-Brahmaputra plain

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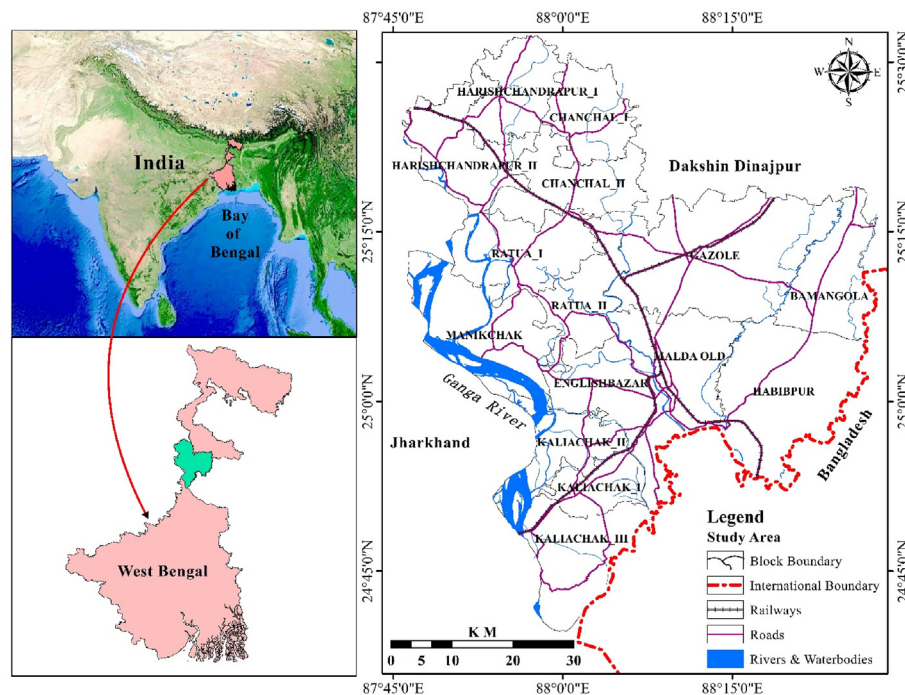


Fig. 1. The Study area (Malda District) Map.

carries 60% of India's total river flow, and hence this area is highly flood-affected (Ashok Ghosh and Bose, 2020). In India, the most flood-vulnerable area is the Ganga-Brahmaputra-Meghna plain. According to a North-eastern Space Application Centre (2006) survey, more than 6000 km² is affected by the river Brahmaputra alone in Assam (NESAC, 2013). Overall, the flood has been invading more than 6 million hectares of land per year in India (highest in 1978 when 17.8 million hectares of land was affected in a single year).

The West Bengal state of India is home to many rivers. It is situated in the lower course of almost all the rivers. Due to the river's sluggishness arising out of siltation in the river beds, rivers frequently breach the banks in the monsoon season. This breach is responsible for the flooding in the nearby areas. In West Bengal, 37660 Km² (42%) area is under the continuous threat of flood (WBDM & CDD, 2021). The highest flood-affected districts are Medinipur, Malda, Murshidabad, North Dinajpur, and Jalpaiguri. Out of the 341 blocks in the state, 111 are affected by floods every year (Desai, 2013). Malda is a frequently flooded district in the state. In the recent 2017 flood, almost 14 districts of West Bengal were affected, including 200 villages from West Medinipur and 15 villages from Malda district (Mondal and Mandal, 2018). After assessing the data (river bank breach and submergence) from the last 45 years, it can be observed that an average of 30 villages is inundated almost every year (most vulnerable in low-lying areas). Eight blocks (Harishchandrapur - II, Ratua - I, English Bazar, Gazole, Malda (Old), Kaliachak - I, Kaliachak - II, Kaliachak - III) out of sixteen blocks from the Malda district are severely affected by the riverine flooding from river Ganga. Considering the large-scale destruction and vulnerability (both social and economic), it is necessary to properly assess the impact of flood inundation and work on the vulnerability prediction for the early mitigation of the effects arising out of inundations (Abhishek Ghosh and Kar, 2018).

Vulnerability includes Physical Vulnerability (Douglas, 1999), Economic Vulnerability (Briguglio et al., 2009), Political Vulnerability (Sarewitz et al., 2003), Social Vulnerability, cultural Vulnerability etc. (Adger, 2006; Ligon and Schechter, 2003; Yoon, 2012). Social vulnerability assessment (Cutter, 1996; Jaman et al., 2021; Kind et al., 2020; Koks et al., 2015; Tascón-González et al., 2020) is a future prediction tool for warning people before a disaster. Through the vulnerability assessment, we can identify the most volatile location of a specific area (S'ahel,

2016). It is linked directly with the geographical location. It is a pre-mitigation process to save society (or a group of people) by analysing the area-specific several sensitive structural and non-structural information. Social Vulnerability assessment is a newly inclusive entity of the disaster risk reduction process, which deals with the ground level community-based unstable situation (Addis, 2023; Ali et al., 2020; Mubialiwo et al., 2022). Due to limited data availability, this area of research has been neglected by researchers and policymakers. This unenthusiastic ignorance of the social vulnerability angle on the disaster risk reduction process has created a complicated situation for the post-disaster cost estimation procedure. Vulnerability assessment is related to the pre-disaster mitigation process important for reducing casualties when disaster hits human habitations (Atmanand, 2003). The introduction of geospatial tools on social vulnerability assessment (Chowdhury et al., 2021) is a significant side, which easily handles the various social-related field survey-based data.

GIS is the most valuable and helpful tool for mapping, visualization, and analysing flood inundation and demographic data. The main focus of this study is to generate a village-level social vulnerability map by integrating the flood inundation layer and social perspectives parameter.

1.1. Description of the study area

Malda district is known as the gateway of North Bengal. It covers a 3733.00 km² area, divided into 15 blocks, 11 municipalities, 146-g panchayat, and 1789 villages (Malda, SDO, office, 2020) (Malda.gov.in). The geographical extent of this district is 24° 40' 20" - 25° 32' 08" North Latitude and 87° 45' 50" - 88° 28' 10" East Longitude (Fig. 1). The Malda district comes under the lower Ganga basin, where the Ganga River flows from west to east (Malda, SDO, office). Other rivers in the district are Fulahar, Mahananda, Tangan, and Purnovoba (Abhishek Ghosh and Kar, 2018). The elevation varies between 10m and 62 m and rainfall 1600 mm- 1400 mm—most of the area covers 20m contour line of this study area. According to the Census of India 2011 (District handbook, 2011) the total population of the district is 11,060,148.00 persons, and the district's population density is 1157 persons per square kilometre. This district was severely affected by the flood. The major flooded years of Malda dist. are 2019, 2017, 2016, 2009, 2004, 2003, 2000, 1997, 1994,

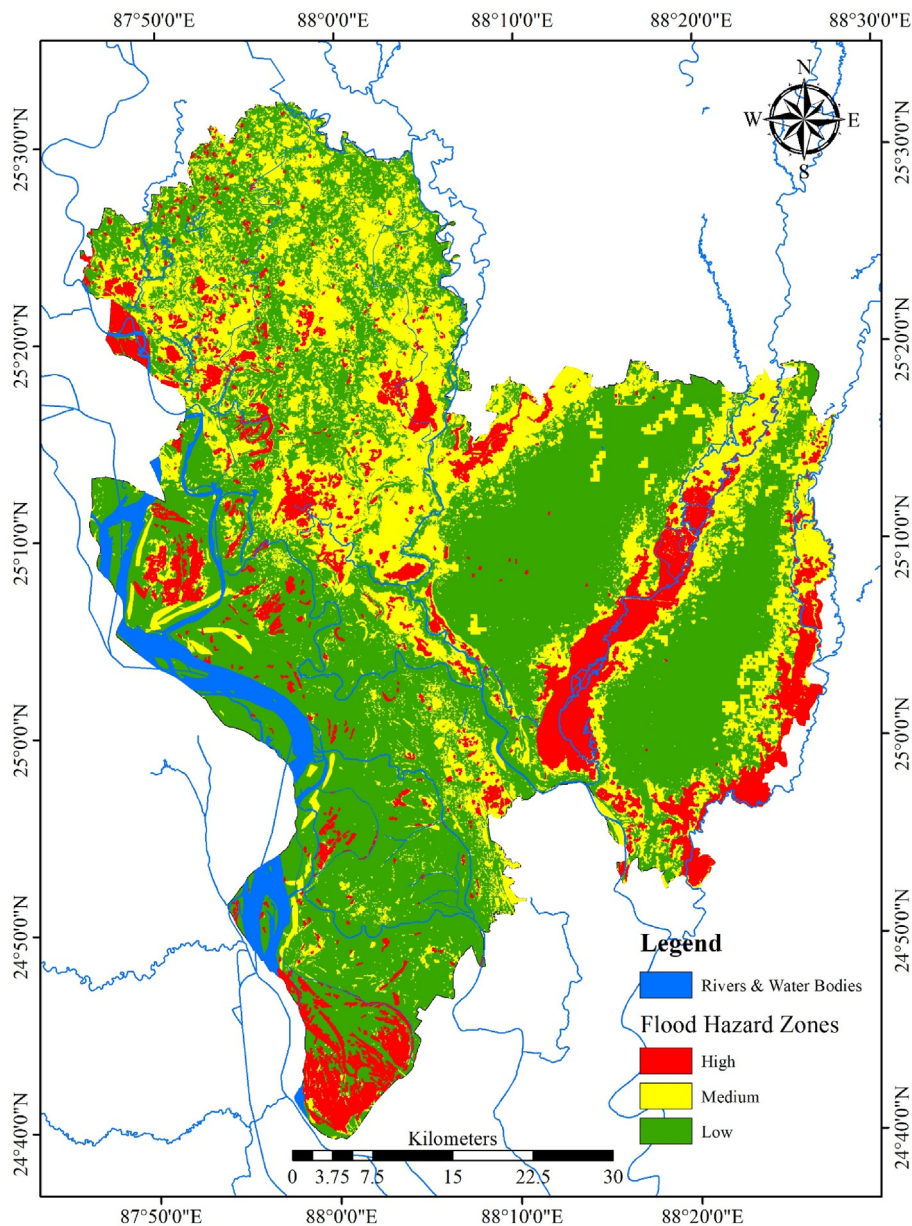


Fig. 2. Flood inundation map.

Table 1
MIF (multi-influence factors).

Parameters	Major (A = 1)	Minor (B = 0.5)	(A + B)	MIF
Households	1 + 1	0.5 + 0.5+0.5 + 0.5+0.5	4.5	13.43
Population Density	1 + 1+1	0.5 + 0.5+0.5 + 0.5	5	14.93
Female Pop.	1 + 1	0.5 + 0.5	3	8.96
Under 06y	1 + 1	0.5 + 0.5+0.5	3.5	10.44
Above 60y	1	0.5	1.5	4.48
SC Pop.	1 + 1+1	0.5	3.5	10.44
ST Pop.	1 + 1+1	0.5	3.5	10.44
Illiteracy Rate	1 + 1	0.5	2.5	7.46
Working Pop	1	0.5 + 0.5+0.5 + 0.5+0.5	3.5	10.44
Handicap Pop.	1 + 1+1		3	8.96
Σ(A + B)			33.5	100

1992, 1991, 1984, 1981, 1977, 1973, 1972, etc. According to the West Bengal Disaster Management Department, this district's most flood-influencing blocks are Harischandrapur - II, Ratua - I, English Bazar, Gazole, Malda (Old), Kaliachak - I, II, & III, even others blocks also suffered by flooding issues during the monsoonal heavy rainfall occurs. In October of 2019, it was reported that over 50,000 families were severely impacted by the flood, which affected approximately 2.5 million people in the Malda area. For this rationale and the determination of this district's socially vulnerable area, this district has been chosen as the research area for the development of a mapping of social vulnerability at the village level.

The main purpose (objective) of this research is to use geospatial analysis to determine the degree of social vulnerability in the Malda District at the village level.

2. Materials and methods

In the current study, both primary and secondary data have been used. The primary multi-dated microwave Synthetic Aperture Radar

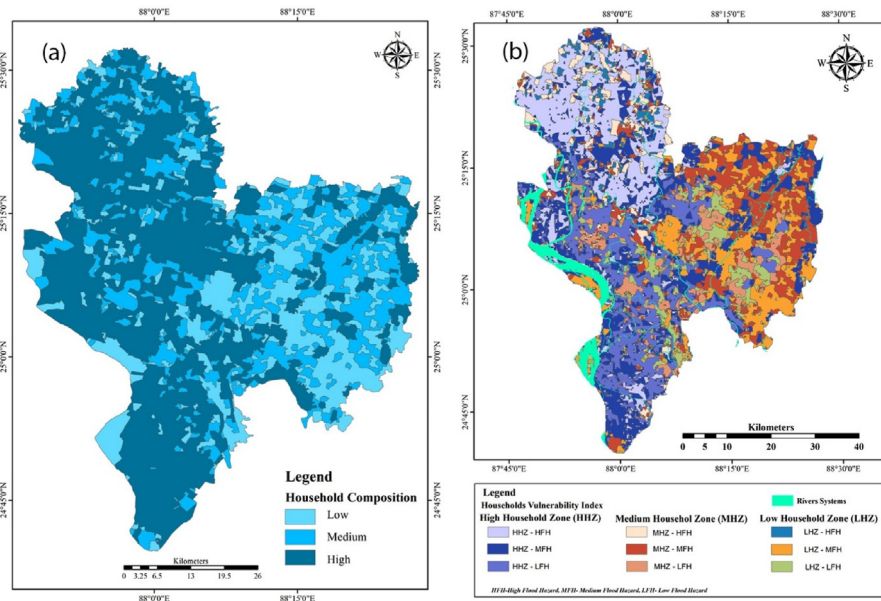


Fig. 3. a: Household composition (density) map & Fig. 3 b: Household composition vulnerability index map.

(SAR) data of sentinels-1A (ESA satellite, C-Band, spatial resolution 5x20m, polarization VV and VH) and AlosPulsor DEM have been collected (Copernicus, 2014) from the Alaska website (De Zan and Guarnieri, 2006). The rainfall data have been collected from the Center for Hydrometeorology and Remote Sensing (CHRS) data portal. The secondary data was collected from the census of India (2011). The Secondary data of Malda district include the Household composition, population density, and female population, population of (children) below six years and above 60 years (aged), scheduled castes and scheduled tribes population, illiteracy rate, working population, and Handicap Pop. Population. The detailed field survey has been carried out using handheld GPS (Flowchart 1).

2.1. Generation of flood inundation map

The flood inundation layer has been prepared using the multi-dated and multi sensor's SAR (Synthetic Aperture Radar) and MSS (multi-spectral scanner) data that are RADARSAT, Sentinels-1A, and Landsat. Active SAR sensors produce microwave waves and monitor reflected signals. SAR works in all-weather situations, including severe rains and cloud cover, unlike optical sensors, which use visible or infrared light and are affected by clouds. This all-weather capacity makes SAR data credible for flood analysis when optical imagery is restricted or occluded. SAR data acquisition day and night is essential for flood monitoring and emergency response. SAR microwave signals may penetrate clouds, foliage, and light soil to record flood extent and changes that optical imaging cannot. This is crucial for estimating flood damage in heavily vegetated regions. In this study, Sentinel-1 SAR data has been used to generate the inundation layer. Firstly, the sigma_0 image has developed from this SAR data by applying the geometrical and radiometric calibration on SNAP (Gomathi et al., 2019; Mandal et al., 2023). The terrain was corrected using DEM (AlosPulsor) for this sigma_0 image, and it was converted from a linear to a non-linear dB (decibel) image (Gomathi et al., 2019). Then, the converted dB image was classified (ISO unsupervised classification) with the help of the threshold value of flooded area pixels (Borah et al., 2018). These pixels were used for the generation of the flood inundation layer of this district. On another side from MSS data, the flood Inundation layer was generated with the help of ArcGIS software, based on the spectral reflectance value. These all generated

flood inundation layers (1976 to 2021) were integrated and super-imposed to develop the Flood Hazard layer of this district (Flowchart 1) (Dung et al., 2021; Hsu et al., 2011; Periyasamy et al., 2018). The flood hazard layer is categorized into High Flood Hazard (HFH), Moderate Flood Hazard (MFH), and Low Flood Hazard (LFH) zones (Fig. 2).

2.2. Multi-influencing factor (MIF) for social vulnerability

The multi-influencing factor is used to determine the influencing factors of each parameter based on the proficiency opinion of experts (Aroca-Jiménez et al., 2020; Dyer et al., 1992; Mandal et al., 2021; Pham et al., 2021; Soheli et al., 2022a). The multi-criteria decision-making tool is a qualitative technique to predict the vital social vulnerability influencing factors depending upon the various parameter's interrelationships (Mavhura et al., 2017). The relationship is varied based on the time and place. The above secondary parameters were classified into two groups as Major (Direct influence) and Minor (Inverse influence) and it is represented as "A" and "B" for Major and Minor respectively. To determine the MIF factor, 1 and 0.5 (half of the major value) values are assigned for Major and Minor respectively (Table 1). Further, the following formula (1) has been applied to get the actual influencing value of MIF. The major and minor influencing parameters for each social perspective parameter were considered depending upon the straight or inverse linked with different selected parameters regarding the present study area's social situation. The major influencing value (1) was assigned for every individual factor by observing the direct involvedness parameters, and a minor influencing value (0.5, half of the major) was assigned for the same factors, according to the indirect (inversely) influences (Flowchart 2). Both values were added, and using the equation (1) MIF of each factor was determined.

$$MIF = \frac{(A + B)}{\sum (A + B)} * 100 \dots\dots\dots (1)$$

Where 'A' = Major effect and 'B' = Minor effect.

The flood inundation map was integrated with the secondary data to assign weightage. This weightage was used for the generation of the social vulnerability index (SVI) by integrating with MIF using ArcGIS software (Dandapat and Panda, 2017; Fernandez et al., 2016; Pham et al., 2021).

Table 2
Demographic Parameters and their classes.

Parameters	Classes	No. of village	High Flood Inundation (HFZ)	Medium Flood Inundation (MFH)	Low Flood Inundation (LFH)	Total Flood Inundation area	Percentage (%)	Weights
Households composition	Low (LHZ)	703	74.70	428.95	192.37	695.99	18.64	2
	Medium (MHZ)	517	167.68	450.69	214.91	833.39	25.32	3
	High (HHZ)	569	615.23	757.75	534.14	1907.48	55.09	5
Population density	Low (LPZ)	267	29.62	169.95	63.20	263.05	7.04	2
	Moderate (MPZ)	644	100.26	433.02	194.78	728.77	19.52	3
	High (HPZ)	825	667.87	893.74	535.07	2103.69	56.35	5
	Very High (VHPZ)	53	59.84	140.67	140.06	341.33	16.94	5
Female Population	Low (LFPZ)	177	18.61	127.02	40.70	186.37	4.99	2
	Medium (MFPZ)	830	136.52	559.12	247.06	942.93	29.25	4
	High (HFPZ)	782	702.48	951.24	653.27	2307.56	65.81	5
Population 06 years age	Low (L6PZ)	594	49.33	379.86	160.31	589.46	15.79	3
	Medium (M6PZ)	599	166.32	487.99	246.08	900.49	25.12	4
	High (H6PZ)	596	642.94	769.54	533.55	1946.91	58.15	5
Population above 60 years age	Low (L60PZ)	209	22.52	46.17	142.11	211.13	5.65	2
	Moderate (M60PZ)	750	112.95	520.11	237.68	870.57	23.32	3
	High (H60PZ)	801	694.74	874.49	562.71	2132.11	57.11	5
	Very High (VH60PZ)	29	27.39	100.67	94.73	223.03	13.17	5
Illiteracy Rate	Low (LILP)	272	28.05	183.70	64.05	276.15	7.39	2
	Moderate (MILP)	658	95.87	443.81	201.72	743.58	19.91	3
	High (HILP)	805	648.48	852.71	541.18	2043.02	54.72	4
	Very High (VHILP)	54	85.20	157.15	131.62	374.10	17.02	5
SC Population	Low (LSCPZ)	944	393.13	605.06	298.68	1297.04	34.74	2
	Medium (MSCPZ)	761	400.72	796.34	484.21	1681.29	45.03	4
	High (HSCPZ)	58	63.76	235.98	158.73	458.52	20.28	4
ST Population	Low (LSTPZ)	1334	721.97	1018.39	590.93	2331.27	62.45	3
	Medium (MSTPZ)	406	70.40	483.49	251.92	805.86	22.58	5
	High (HSTPZ)	49	65.24	135.51	98.85	299.73	14.77	4
Working Population	Low (LWPZ)	222	29.16	144.41	555.66	229.30	6.94	2
	Moderate (MWPZ)	795	152.79	526.71	239.81	919.33	24.62	3
	High (HWPZ)	747	650.24	869.79	557.64	2077.81	55.66	4
	Very High (VHWPZ)	28	27.90	97.43	89.12	214.38	12.74	5
Handicapped Population	Low Handicap (HPz)	271	26.25	181.26	66.25	273.76	7.33	2
	Medium Handicap (HPz)	898	190.25	649.37	321.44	1161.09	31.64	4
	High Handicap (HPz)	621	641.10	807.69	554.22	2003.03	60.65	5

3. Results and discussion

Malda district of West Bengal is one of the most flood-prone areas in India because the area is situated beside the Lower Ganga river basin and the area receives heavy rainfall during monsoon season in a short spell of time. Investigating the social vulnerability index on the periphery of the study area is very important because the area is very isolated and socio-economically backwards. After conducting preliminary research and a pilot survey of the most inundated area of Malda district, socially vulnerable criteria were selected for this study. In this study, the social vulnerability index has been derived by integrating the flood inundation layer and social vulnerability indicators.

3.1. Household composition

The total number of households is 841231. For the social vulnerability assessment, the household composition of the Malda district has been categorized (Fig. 3a) into high (<150), medium (150-400), and low (>400) zones based on the geometrical mean (Table 2)(Shiva Prasad Sharma et al., 2018). From this household composition map, the

household vulnerability index has been prepared (Fig. 3b) after intersecting with the flood inundation layer. Using this value the high, medium and low household zonation areas were calculated as 565.09%, 28.82% and 18.64% (Table 2) of the Malda district and weightage is assigned concerning the value as 2, 3 and 5. The MIF for the "household composition" parameter (13.43 %) has been determined, according to the major (Population Density, Working Pop) and minor (Illiteracy Rate, under 06y, above 60y, SC Pop., & ST Pop.) relation with other social prospective indicators. Both the values of weightage of household and MIF were used to generate the social vulnerability index.

3.2. Population density

The population density of the study area is 1157/km² and the total population is 11,060,148 (Census Commissioner, 2011; Census of India, 2021). It is an essential factor for the social vulnerability index because most of the area is coming under a high-density zone which is more vulnerable than the low-density zone (Haki et al., 2004). The village-level population density map of Malda district (Fig. 4a) has been prepared based on the concentration of population. The population

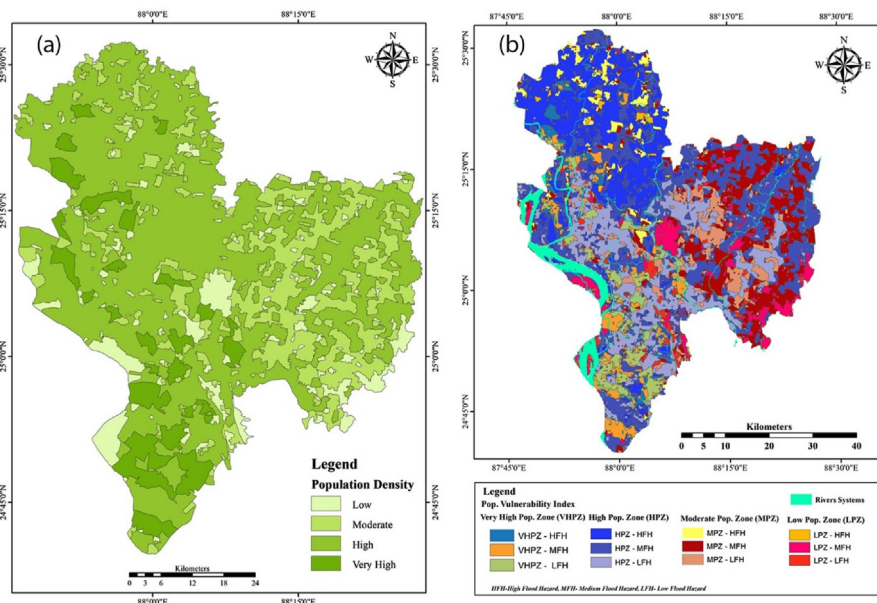


Fig. 4. a: Population density map & Fig. 4(b): Population density vulnerability index map.

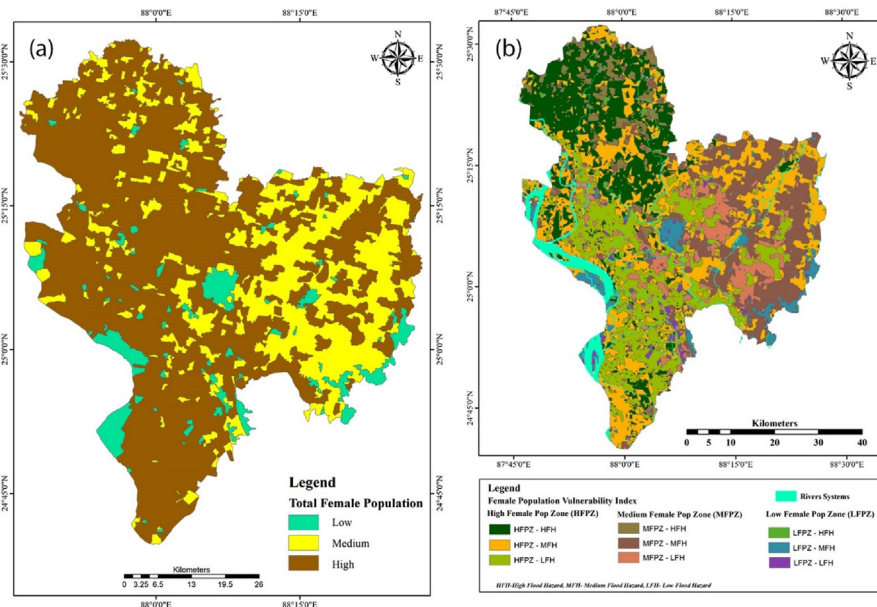


Fig. 5. a: Female population density map & Fig. 5 b: Female population vulnerability index map.

density map has been categorized into Very High ($>800/\text{km}^2$), High ($600\text{--}800/\text{km}^2$), Moderate ($400\text{--}600/\text{km}^2$), and Low-density ($<400/\text{km}^2$) zones (Fig. 5 a.). Each sub-class of the Population density map has been intersected with the flood inundation layer to generate the district Population vulnerability index (Fig. 4b). From this, the Population Vulnerability Index map has been obtained as the Very High zone is 16.94%, High zone is 56.35%, Moderate Zone is 19.52%, and Low Zone is 7.04%. Based on this value, the weights of sub-categories have been determined (Armaş and Gavriş, 2013) for Malda district (Table 2), these are 5, 5, 3 and 2. The multi-influencing factor (MIF) has been calculated (14.96 %) by examining the interconnection linked with different social perspective indicators. The major influencing indicators of Population Density are Households, Female Pop., Illiteracy Rate, and Minor influencing indicators are under 06y, above 60y, SC Pop., ST Pop (Table 1). Both weights of population density and MIF value of population density

have been used to delineate the social vulnerability index of this District.

3.3. Female population

Gender is the most common and significant parameter of social vulnerability (Yee et al., 2019) aspect. In society, female populations are more deprived and marginalized in comparison to the male population (Armaş and Gavriş, 2013). In this present study, the total female population (total 5,195,070) (Census of India, 2011) of Malda district has been categorized into high (>800), medium ($400\text{--}600$), and low (<400) zones (Table 2), according to the concentration of female population (Fig. 5a). It has been found that the high, medium and low female population zones are 65.81%, 29.25%, and 4.99% (Dandapat and Panda, 2017) were influenced by flood inundation (Table 2). Considering the area under flood inundation zones, the weightages of the female

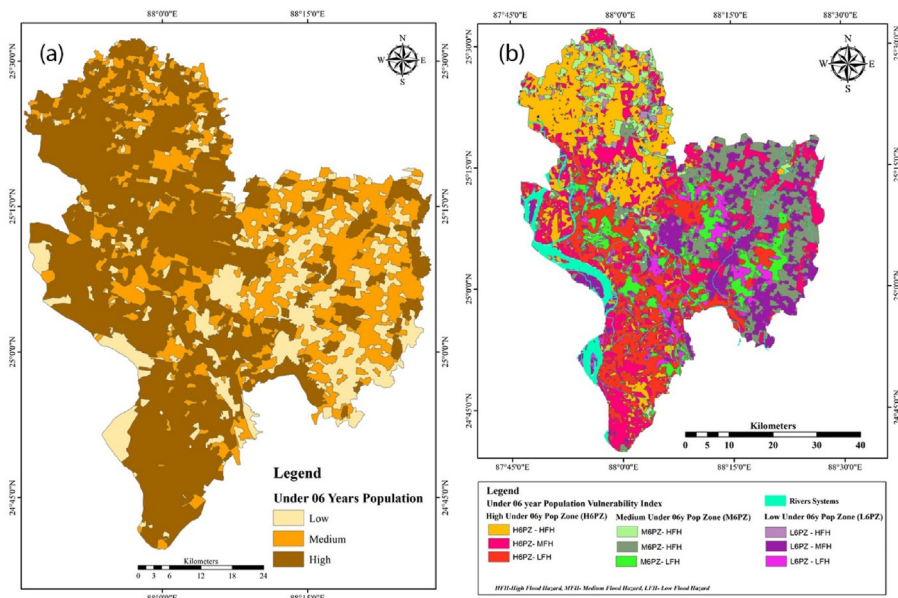


Fig. 6. a: Under 06 Years population density map & Fig. 6 b: Under 06 Years population vulnerability index map.

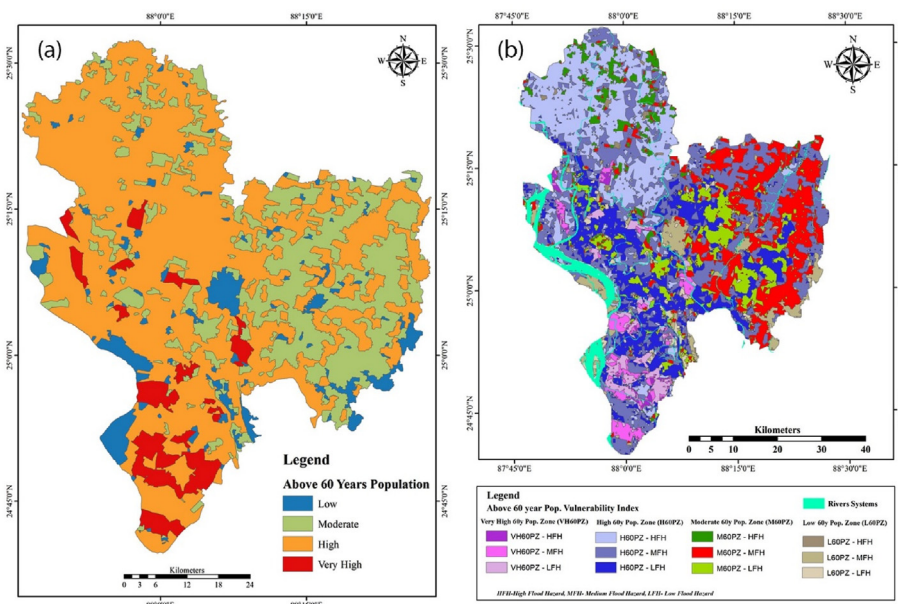


Fig. 7. a: Above 60 Years population density map & Fig. 7 b: Above 60 Years population vulnerability index map.

population's sub-groups are assigned (Table .2) as 5, 4 and 2 (Tascón-González et al., 2020). It is observed that the concentration of the female population (Fig. 5b) is high in the western part of this district. The MIF value of the female population is 8.96 %, which has been generated based on the direct (Major) and inverse (Minor) relations with other social indicators (Table .1). The female population is majorly influenced by Population Density, Illiteracy Rate, and under 06yrs population, Working Population group. After that, the whole weights and MIF value were used to calculate the final social vulnerability index of the Malda district.

3.4. Age group composition

In the process of social vulnerability assessment, the age group takes a crucial role (Flanagan et al., 2020). It is directly related to the social

vulnerability index. In this study, the two age groups have been considered as a parameter of SVI, one is < 06 years population (1,327,146 children), and another group is > 60 years population (294978 persons). Both groups are more socially volatile than the middle-aged population (Shiva Prasad Sharma et al., 2018). The population of these two groups occupy 22.7% of the total population of this district. During the disaster, these are the most suffering population group in society because they are the dependent population group of the district. The <06 years (Children) population is categorized into High <06 years (>253), Medium <06 years (100-253), and Low <06 years (<100) (Fig. 6a). The population group who are above 60 years are also categorized into four as Very high (>1000), high (750- 1000), moderate (200-750), and low (<200) (Fig. 7 a & Table 2). Both aged group populations (<06 years & >60 years) have been separately integrated with flood inundation layer and obtain the

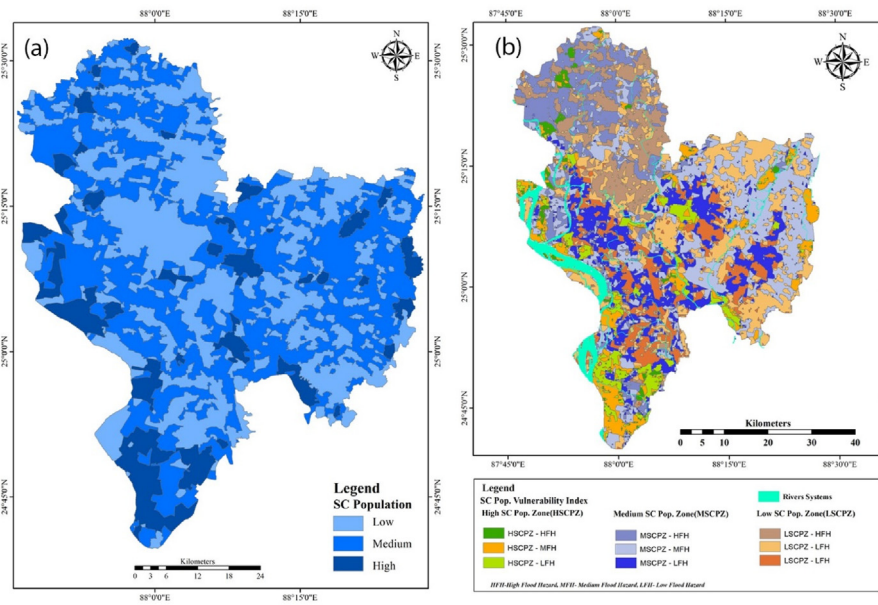


Fig. 8. a: SC population density map & Fig. 8 b: SC population vulnerability index map.

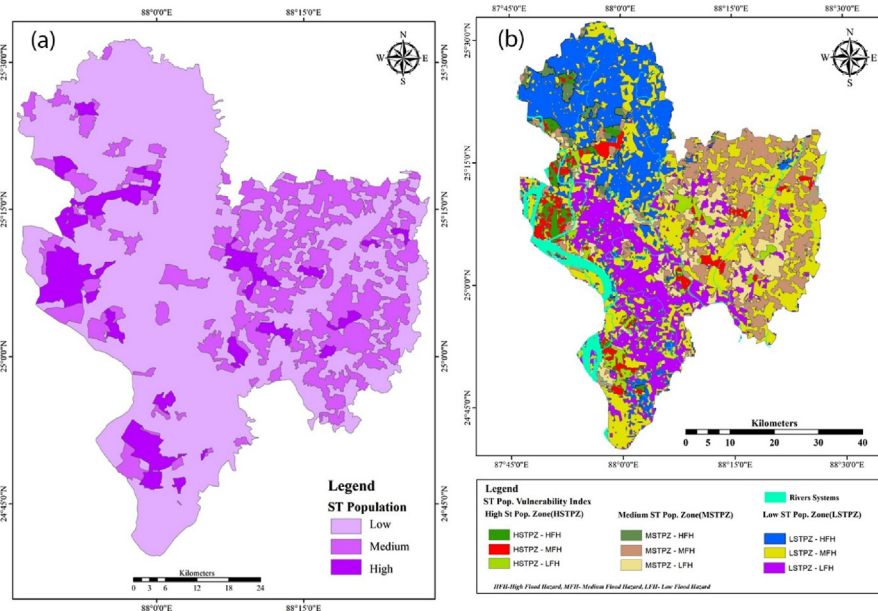


Fig. 9. a: St population density map & Fig. 9 b: St population vulnerability index map.

<06 years population vulnerability index (Fig. 6b) and >60 years population vulnerability index (Fig. 7b). It has been observed that the <06 years population groups 58.15% in high, 25.12% in moderate, and 15.79 % in low population zone, and in the same way >60 years population groups 13.17 % in very high, 57.11 % in high, 23.32 % in moderate, and 5.65 % in low population zone area falls under the Flood inundation layer. Based on this value, each aged groups (<06 & >60) subclasses weightage has been assigned. The weights of <06 years age groups were 5, 4, 3, and >60 years age groups were 5, 5, 3, and 2 (Table 2). After that, the MIF value have been determined (Table 1) for both age groups (10.44 % & 4.48 %) by observing the inter relation with different social prospective parameters. Further these weights and MIF value of both age groups have been used to develop the social vulnerability Index of Malda district.

3.5. SC and ST population (socially underprivileged groups)

The SC (scheduled caste) & ST (scheduled tribe) populations generally come under the BPL (Below Poverty level), and are mostly underprivileged from most of the social facilities (Flanagan et al., 2020). The total SC population of the study area is 828892, and ST is 317788. The SC & ST population is the most important influencing factor for SVI (Armas and Gavriş, 2013). In the study area, together 28.9% of the population is inhabited under this group. So it is easy to say that these population groups can take the most critical role during social vulnerability (Yoon, 2012) assessment. According to the concentration of both SC & ST group's populations has been categorized (Fig. 8 a & Fig. 9a) into High, Medium, and Low (Table 2). Each group (SC & ST) further individually intersected with the flood inundation layer on the GIS platform and

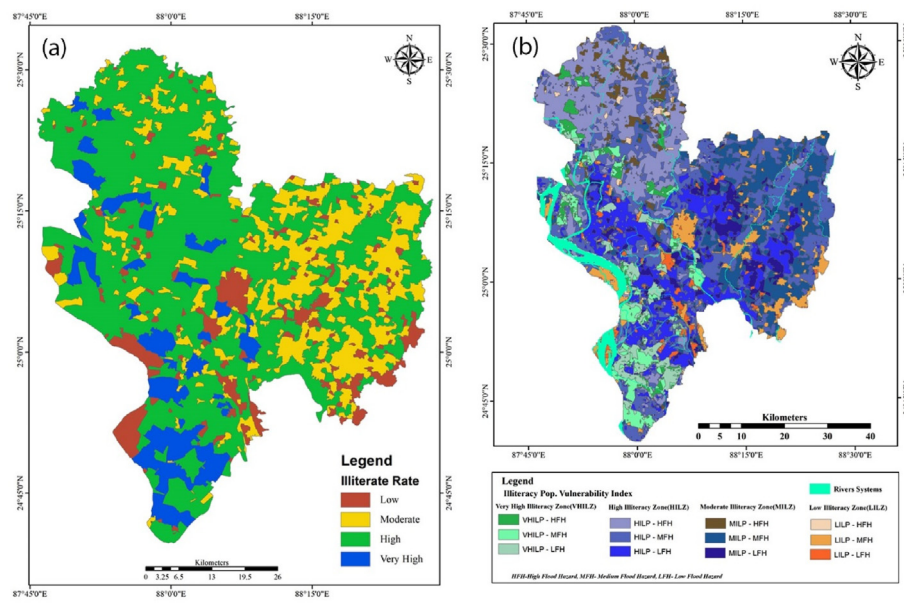


Fig. 10. a: Illiterate population density map & Fig. 10 b: Illiterate population vulnerability index map.

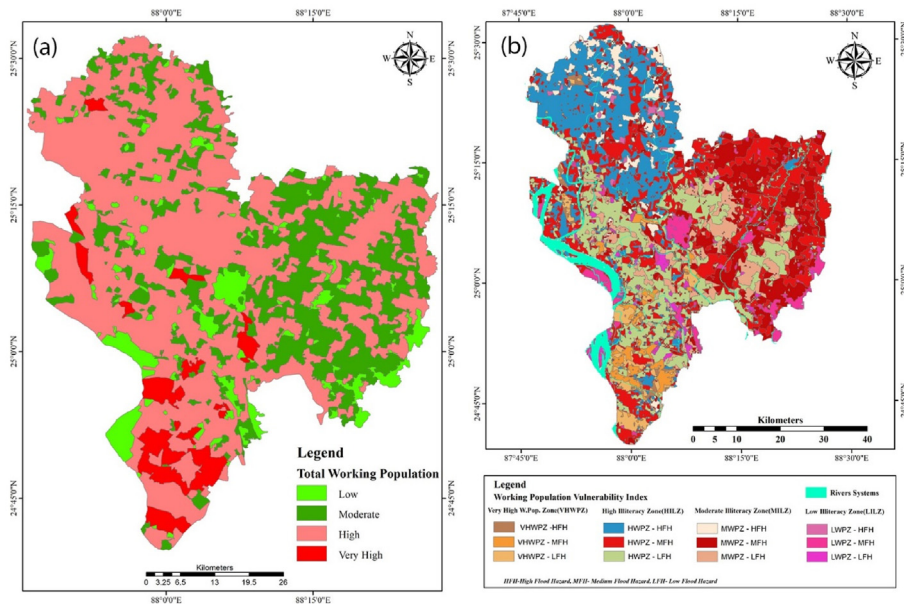


Fig. 11. a: Working population density map & Fig. 11 b: Working population vulnerability index map.

generated the SC population vulnerability index (Fig. 8b) and ST population vulnerability index (Fig. 9b). From this value, the area under the flood inundation zone is obtained for both parameters. The SC Populations are 20.28 % high 45.03 % moderate 34.74 % low sc population zone and ST Populations are 14.77 % high, 22.28 % moderate, and 62.45 % low. It has been observed that, in the SC vulnerability index, medium population group falls under the maximum flood-affected area (45.03%), and the same way ST vulnerability index category low population group falls under the maximum flood-affected (62.45%) area (Table .2). Based on this value, the weightage for both SC & ST groups population has been assigned (Table .2). The weightage of SC population groups subclasses are 4, 4, and 2; likewise, SC population groups sub categorizes weights are 4, 5, and 3.

3.6. Illiterate population

Education is the most important factor for social vulnerability delineation. Education is directly associated with social empowerment and vulnerability (Flanagan et al., 2020). In this study for demarcating SVI, the illiteracy rate has been taken as a parameter because illiterate people are more vulnerable than literate (Shiva Prasad Sharma et al., 2018). The total illiterate population of the Malda district is 1890938. The male and female illiterate populations are 11.28% and 20.23% respectively (Census of India, 2011). The village-level illiterate people are categorized into four groups (Fig. 10a); these are very high (>5000), high (500-5000), moderate (100-500), and low (<100). From this value, the illiterate population under flood inundation zone has been calculated.

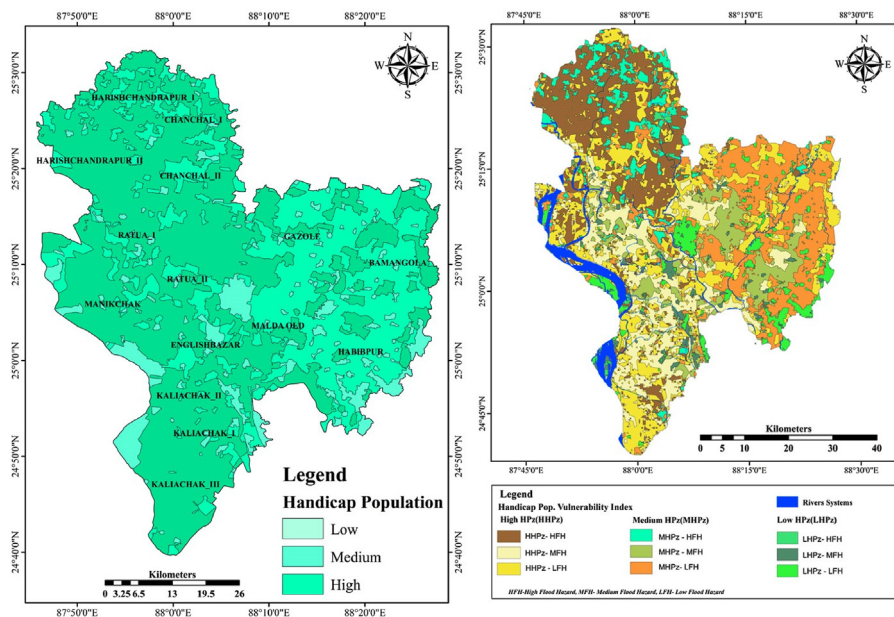


Fig. 12. a: Handicap population density map & Fig. 12 b: Handicap population vulnerability index map.

The percentage-wise vulnerabilities are 17.02% very high, 54.72% high, 19.91% moderate and 7.39% low illiterate population. Depending on this value the weightages has been assigned for all sub categories of illiteracy (Table 2). The MIF value of this parameter (7.46 %) has calculated based on the major and minor (inverse) relation among the different social sensitive parameters of SVI (Table 1). The major inflective parameters of illiteracy population groups are SC & ST population and minor effective parameter is Handicap Pop. population. Further, weights and MIF (Multi influencing Factor) value has used to delineate the SVI of this District (Fig. 10b).

3.7. Working population

Based on the economy and income, the whole population has been divided into two categories. One is working and the other is non-working Pop. (Aroca-Jiménez et al., 2020; Yohe et al., 2002). Both are equally important in the social vulnerability assessment because, during flood inundation, working populations are better equipped with the resources needed for survival than the non-working Pop. population. The total working and non-working. population of the district is 1529212 and 2432637, respectively. Based on the economic classes, the working population has been classified (Shiva Prasad Sharma et al., 2018) into subclasses by considering the density of working ability. The working population has classified into (Fig. 11a), Very High (>5500), High (500-5500), Moderate (50-500), and Low (<50) (Table 2). The vulnerability index (Fig. 11b) of working population groups has been determined by intersecting with the flood inundation layer of Malda district. It has been observed from this map that, working population groups comprise 12.74 % of Very high, 55.66 % of High, 24.52 % of Moderate, and 6.94 % of Low falls under the flood inundation zones. According to this value, the weightages of every subclass of both parameters have been assigned (Table .2) (Armaş and Gavriş, 2013). The weights of the Working Population groups are 5, 4, and 3 respectively. It has been observed that the working population (MIF- 10.44 %) is majorly influenced by Population density and minorly influenced by Households, SC Pop., ST Pop., <06years, >60 years. (Table 1).

3.8. Handicap population

People with cognitive impairments such as mental retardation (MR), mental illness (MI), or multiple disabilities (MD), as well as those with

sensory impairments such as impaired vision, hearing, speech, or movement, are counted as handicapped populations. There are 84158 persons who identify as disabled in the Malda district (Govt. of W.B., 2021). This metric is crucial for assessing the social precariousness of the Malda district. The handicapped population in each village was divided into groups using geometric means. Disabled population density is broken down into three categories here: high (>10), medium (10-5) and low (5). As a result of this intersection with the inundation layer, the vulnerability index for the handicapped population has been calculated; this is important because people in this category are especially vulnerable to flooding. Those people are classified as members of the "dependent" population (Sohel et al., 2022b). The defined map shows that there is a sizeable disabled population. 60.65 % of the population has a severe disability (high), 31.64 % have a moderate handicap (medium), and 7.33 % have a slight handicap (low). Taking into account the reliance and density of the district's disabled population, we were able to determine the relative importance of each of these groups. The ratios are 5:4:2. By analyzing their correlation with other socially vulnerable variables, we were able to determine their relative importance. It has a MIF value of 8.96.

3.9. Social vulnerability index (SVI)

The social vulnerability index denotes the potential negative effects on society caused by external stresses on human health and the economy. Such stresses involve naturally or artificially (human-made) induced disasters. Social vulnerability depends on the social structure, economic stability, educational level, Public Safety, and health consciousness, etc. In this study, the social vulnerability index has been determined by selecting the sensible social perspective parameters of population density, female population, the population of (children) below six years (<06) age vulnerability Index, aged person population (>60 years), scheduled castes (SC) population, scheduled tribes (ST) population, illiteracy rate in the district, working population, Handicap Pop. population (Flanagan et al., 2020; Nguyen et al., 2017). These all parameters have been classified into sub-classes based on the geometrical mean. The weightage overlay analysis technique has been performed to generate the Social vulnerability index depending upon the Weights and multi-influencing value (MIF) values of each social vulnerability indicator. The weights of each parameter are determined based on their individual vulnerability index, which is used to calculate the social

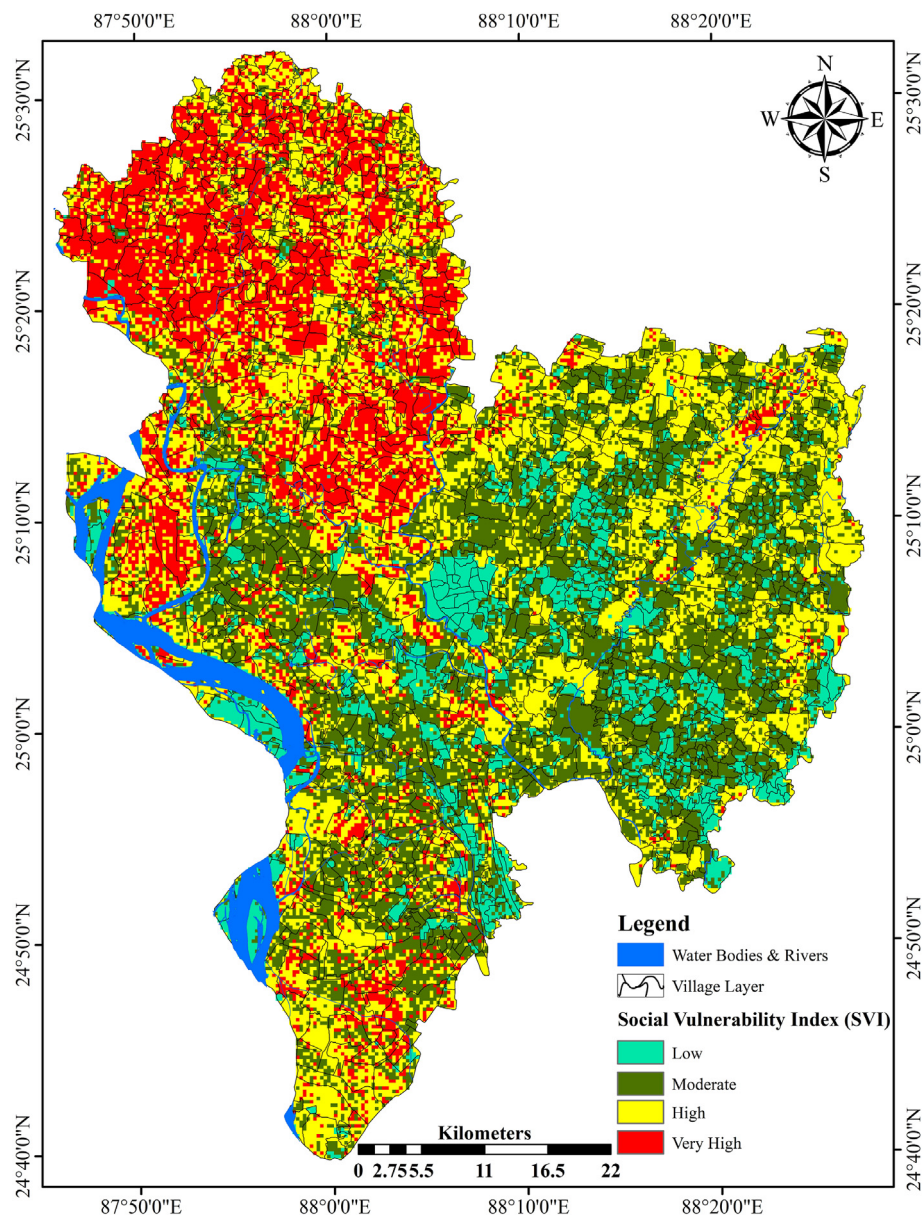


Fig. 13. Social vulnerability index map.

Table 3
Social vulnerability Index (SVI).

SVI	Flood Hazard Zones	No. of Village	% of Damages	Area km ²
Very High (VHSVI)	HFH & MFH	70	4%	149.32
High (HSVI)	HFH	662	37%	1381.21
Moderate (MSVI)	MFH & LFH	578	32%	1194.56
Low (LSVI)	MFH	479	27%	1007.91
TOTAL		1789	100	3733

vulnerability index of Malda District by overlay analysis method (Fig. 13). The field investigation based on risk information from the study area also considered during MIF calculation. The social Vulnerability Index (SVI) of Malda district is classified into Very High SVI (VHSVI), high SVI (HSVI), moderate SVI (MSVI), and Low SVI (LSVI) (Table 3). According to the area, the Very High SVI zone, High SVI zone, Moderate SVI zone and Low SVI zone are calculated as 149.32 km² (4%), 1381.21

km² (37%), 1194.56 km² (32%), 1007.91 km² (27%) respectively (Table 3). The SVI has again intersected with the flood inundation layer to delineate and understand the more vulnerable zonation of the study area due to the impact of flood inundation. It is estimated from the ongoing analysis that 70 villages of this district are very high (VHSVI), 662 villages fall in high (HSVI), 578 villages are in Moderate (MSVI), and 479 villages ((LSVI) are less socially vulnerable. In this study, it has also been identified the Concentrated vulnerability Indexes for SVI categories. The very high social vulnerability index is mostly influenced by the high and medium vulnerable indexes of all social perspective indicators; likewise, the HSVI high, Medium and types, MSVI is Medium and Low types and the LSVI group is influences by the Low vulnerability indexes of all parameters (Table 4).

$$SVI = [(HH_W * HH_{MIF}) + (PD_W * PD_{MIF}) + (TFP_W * TFP_{MIF}) + (PU06y_W * PU06y_{MIF}) + (PA60y_W * PA60y_{MIF}) + (TillP_W * TillP_{MIF}) + (SC_W * SC_{MIF}) + (ST_W * ST_{MIF}) + (TWP_W * TWP_{MIF}) + (HP_W * HP_{MIF})] \dots \dots \dots (2)$$

[Where, SVI= Social Vulnerability Index, HH= Household, PD= Population Density, TEP = Total Female Population, PU06y = Population

Table 4
Blockwise Distribution of Socially vulnerable People and distribution of SVI Area.

Blocks Name	% of Affected Population	Area wise Distribution			
		Very High SVI	High SVI	Moderate SVI	Low SVI
Harishchandrapur I	6.25	0	131.58	35.06	0.61
Harishchandrapur II	7.75	0	202.92	15.54	1.16
Chanchal I	3.06	0	123.74	37.51	1.66
Chanchal II	8.53	0	166.49	34.15	2.71
GAZOLE	9.94	4.60	188.53	26.79	6.32
Ratua I	10.39	13.54	132.54	25.73	3.61
Ratua II	4.08	16.99	242.40	27.22	25.06
Englishbazar	15.58	15.90	211.73	10.75	18.46
Old Malda	13.72	8.41	101.11	6.06	36.42
Manikchak	7.56	16.99	242.40	27.22	25.06
Bamangola	4.21	2.77	167.02	56.39	25.44
Habibpur	6.42	6.94	104.25	78.77	35.41
Kaliachak-I	13.94	2.21	347.51	157.47	5.93
Kaliachak-II	10.87	0	124.09	82.20	0.70
Kaliachak-III	9.49	0	181.98	161.81	54.82

under 06 years, **PA60y** = Population above 60 years, **TillP** = Total Illiterate Population, **SC** = Scheduled caste, **ST** = Scheduled tribe, **TWP** = Total Working Population, **HP** = Total Handicap Pop. Population, **W=** Weights, **MIF** = Multi influencing Factor]

3.10. Blockwise distribution of socially vulnerable people

Blockwise social vulnerable population distribution has been calculated based on census and block-level survey-based data. It has been observed, that among 15 blocks of the Malda district, six blocks (English Bazar- 15.58%, Kaliachak-I-13.94%, Old Malda- 13.72%, Kaliachak-II- 10.87%, Gazole 9.95%, and Kaliachak-III- 9.49%) population are highly agonized because of dissimilarity social issues during a flood (Fig. 14). The area-wise distribution of SVI of this district is highest noticed in Kaliachak-1 (513.14 km²) and lowest in Chanchal-I (162.92 km²). Among all blocks of the Malda district, the distribution of SVI is uneven. The Very High SVI types socially vulnerable areas (including High SVI, Moderate SVI, and Low SVI) only observed in Gazole (4.6 km²), Ratua-I (13.54 km²) & II (16.99 km²), English Bazar (15.9 km²), Old Malda (8.41 km²) Manikchak (16.99 km²), Bamangola (2.77 km²), Habibpur

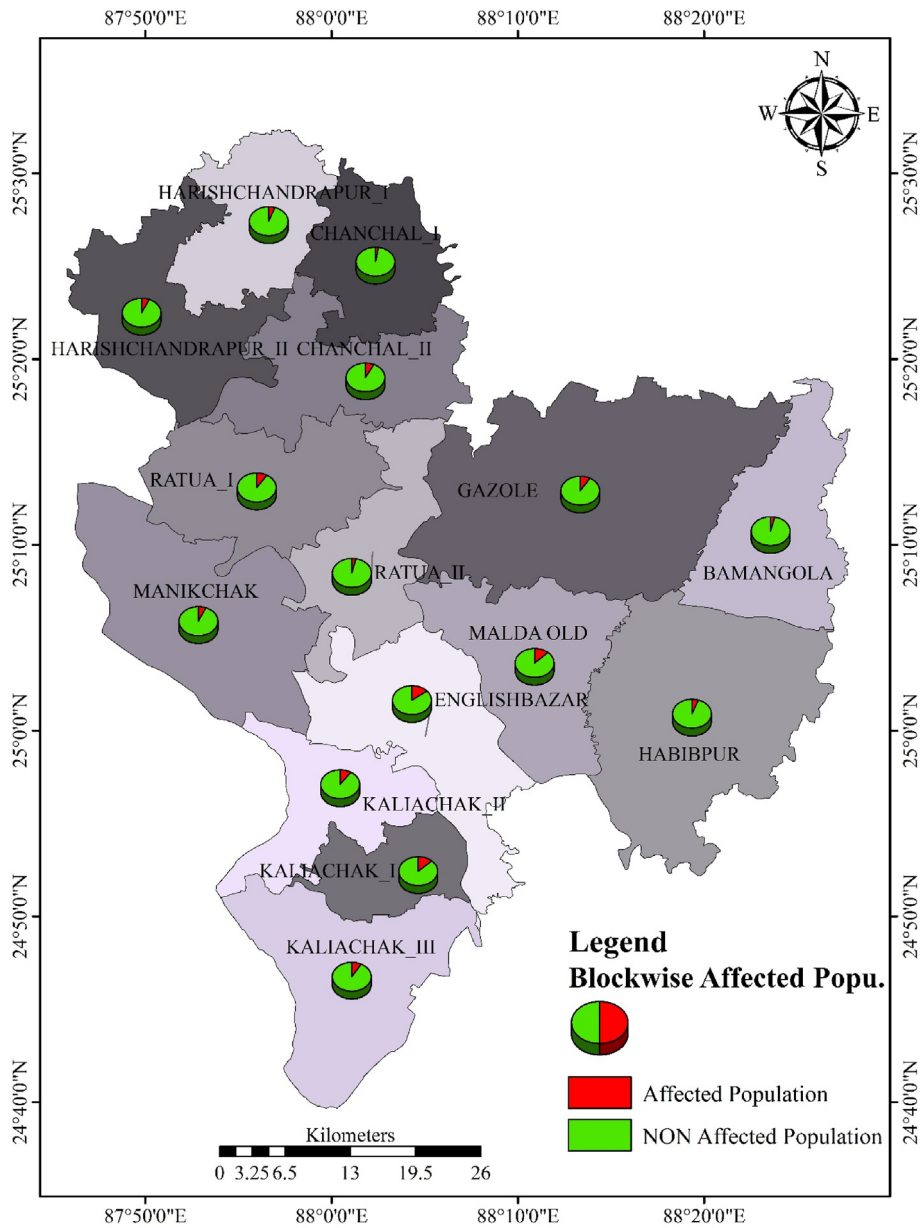
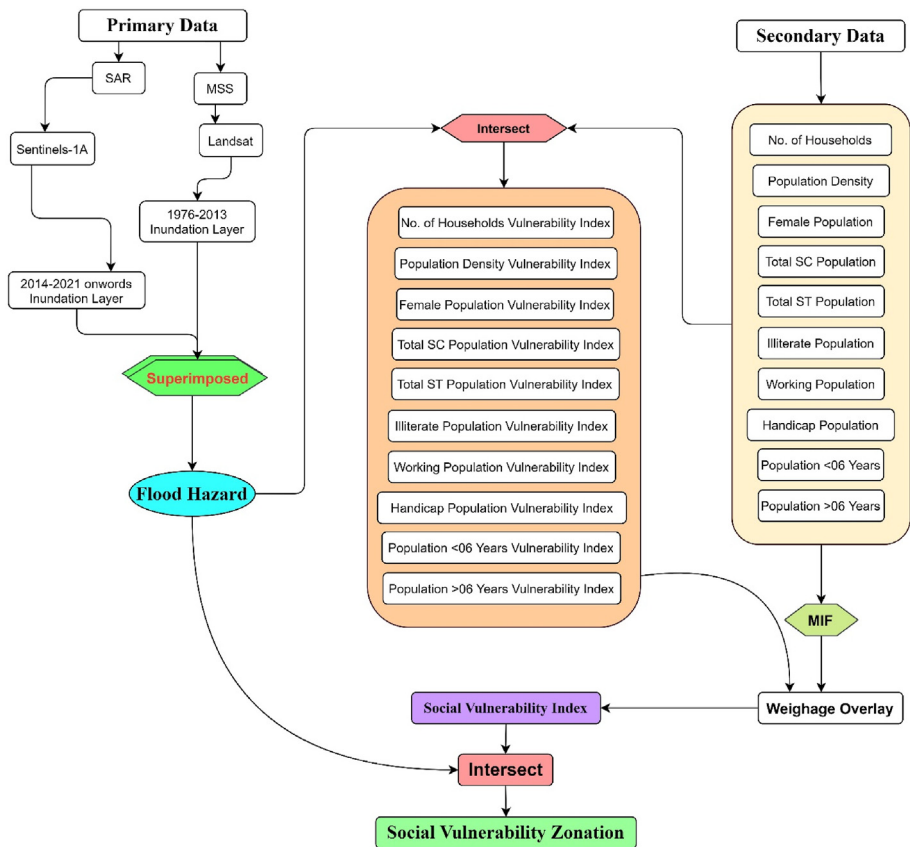
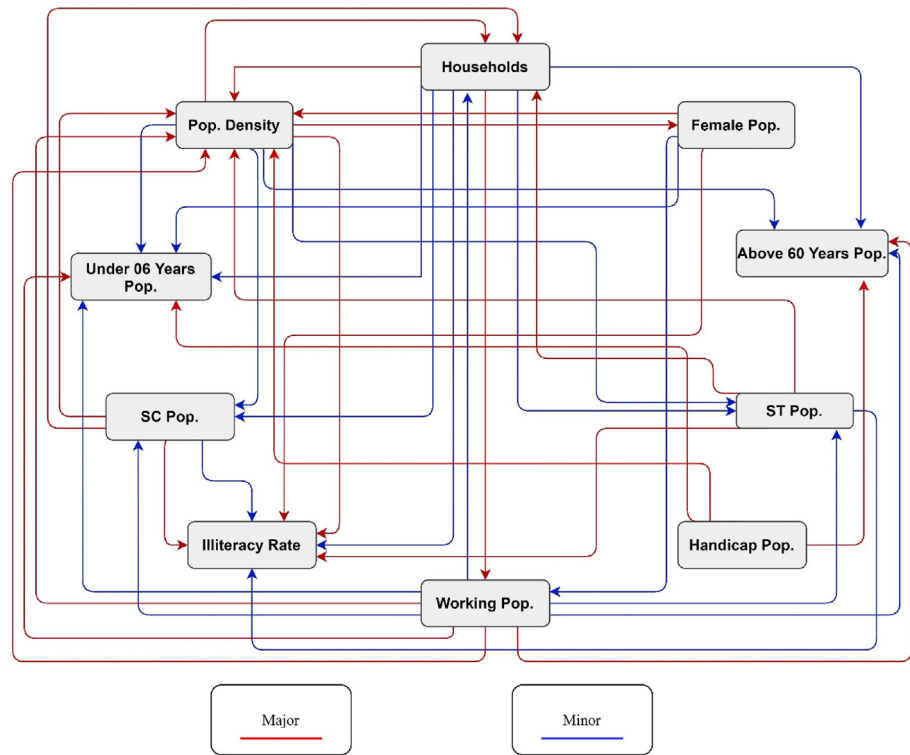


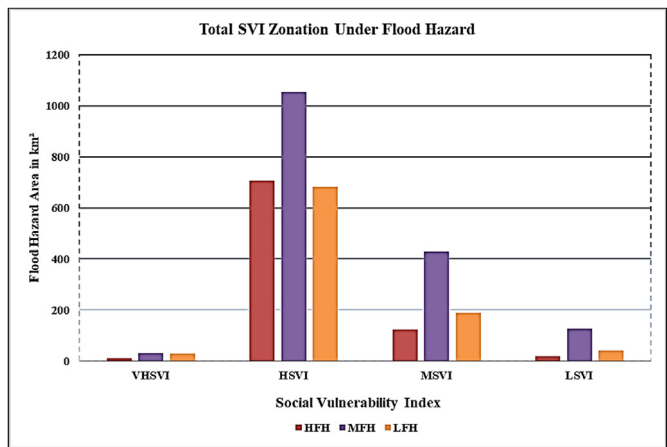
Fig. 14. Blockwise socially affected Population.



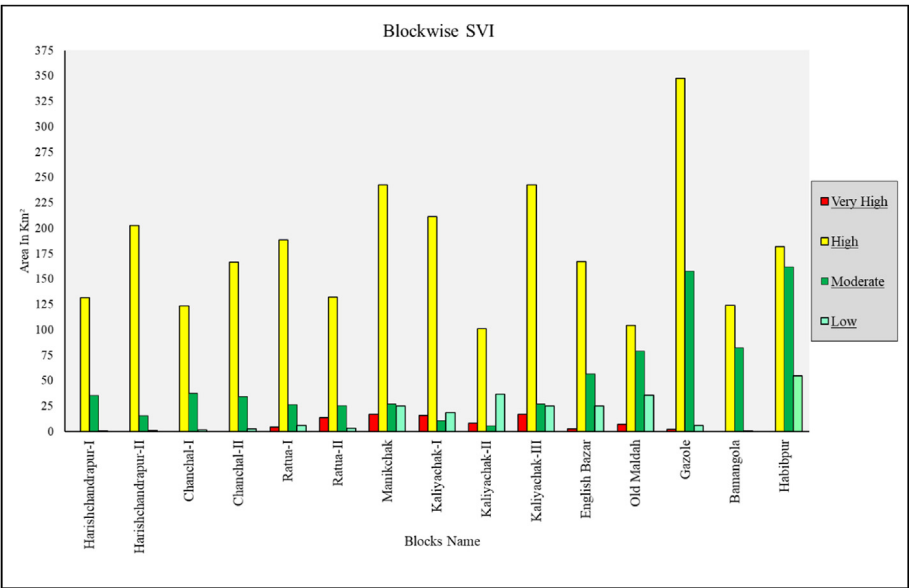
Flowchart 1. Methodology flowchart.



Flowchart 2. Multi Influencing Relation between difference parameters.



Bar Graph.1. Social Vulnerable area under the Flood Inundation.



Bar Graph.2. Blockwise distribution of SVI, malda.

(6.94 km²), and Kaliachak-I (2.21 km²) blocks (Table 4.) These nine blocks are more problematic blocks than other blocks of the district (Bar Graph.2) (see Fig. 15).

4. Conclusion

This study has been designed to develop an approach based on Multi-influencing factor (MIF) decision-making and GIS to assess the flood risk by integrating the flood inundation layers with social vulnerability indicators at the village level of Malda district. It is a silent volatile condition, which can accelerate harm to the community if any destructive events (disaster) start. The social vulnerability of Malda district has been determined using the most effective functional parameters. It is a comparative assessment that correlates the impact of social and demographic infrastructure on the study area. The MIF has been filled by local-level priorities based on risk informatics data, which was decided during the field visit with local-level experts' interaction. The flood inundation layer is prepared using SAR datasets, where the flood inundation layer is created by applying threshold value methods. Elevation and slope have been acquired from AlosPulsor DEM, and the rainfall map

is from TRMM. The village-level social vulnerability index and flood inundation layer have been intersected on the GIS platform, and the most critical or vulnerable zones (due to flood effect) have been demarcated (Table 3). It has been observed and identified that 70 village (4%) falls under the Very High SVI zone, 662 villages (37%) come under the High SVI zone, 578 villages fall under the Moderate SVI zones (32%), and 27% area falls under the low SVI zone, which covers 479 villages of this district's (Table 3). It is also observed that the Very High and high SVI zones come under the High and medium type flood inundation, followed by Moderate and low SVI zones fall under the mostly medium flood inundation area, but Moderate SVI zones some parts identified in the Low inundation area. The village-level social vulnerability map will help very precisely during and after the flood recovery strategy of this district. This study will also provide the necessary information to the disaster managers and district authority for identification of the ground-level vulnerable community and establishing flood shelters along the neediest part of this district.

Statements & declarations

The authors declare that this research work is original and not submitted anywhere for publication, and there is no conflict of interest with individuals or organizations.

Furthermore, the authors state that no entity or person offered financial backing for this study.

CRediT authorship contribution statement

Kajal Kumar Mandal: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Kesavan Dharanirajan:** Writing – review & editing, Methodology. **Muraree Lal Meena:** Writing – review & editing, Validation, Conceptualization. **Toushif Jaman:** Validation, Formal analysis, Data curation, Conceptualization. **Sohel Rana:** Visualization, Formal analysis.

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