Community-Scale Assessment of Flood-Related Public Health Vulnerability Using Multi-Criteria AHP in Northwestern Bangladesh

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Abstract. Bangladesh faces heightened flood vulnerability due to climate change, particularly in riverine areas where health impacts are severe. The study aims to estimate the public health vulnerability in Dimla Upazila (Nilphamari district) using the Analytical Hierarchy Process (AHP), incorporating expert-weighted indicators: socio-demographics, WASH infrastructure, healthcare access, flood intensity, relief availability, and adaptation capacity. 315 households from six unions were randomly
15   selected and structured survey were performed in 2019. Results reveal the contribution of all indicators to public health vulnerability whereas flooding intensity has been the most influencing factor, followed by relief accessibility, healthcare service accessibility, WASH infrastructure availability, and the adoption of adaptation capacity. The findings indicate that the northern region (Purba Chhatnai) exhibits the highest vulnerability due to its low socioeconomic status and limited access to relief services. In contrast, Tepa Kharibari—a centrally located union adjacent to the river—experiences frequent flooding but
20   demonstrates moderate vulnerability owing to robust DRR measures, underscoring that physical exposure alone does not determine health risks. This study pioneers an integrated approach that connects household-level vulnerabilities, infrastructure robustness, and post-disaster responses to reveal previously unrecognized patterns in public health vulnerability in flood-prone regions worldwide. The findings demonstrate that combining proactive risk reduction with reactive emergency measures significantly enhances community health resilience, offering a transformative approach to disaster management. Furthermore,
25   the research outcomes can assist policymakers in identifying gaps within the existing public health infrastructure of flood-prone areas, enabling the adoption of targeted DRR interventions to foster healthier and more resilient communities.

Keywords: public health, analytical hierarchical process (AHP), expert opinion, flood vulnerability, north-western Bangladesh

1 Introduction

Climate change has significantly amplified both the frequency and severity of flooding events, leading to escalating public health crises through the proliferation of waterborne and vector-borne diseases (Achanta et al., 2001), (Alam et al., 2018),(Ramin & McMichael, 2009). The health impacts of flooding extend far beyond immediate mortality, encompassing complex secondary effects including mass displacement, food insecurity, respiratory illnesses, and the destruction of critical health infrastructure (Kovats et al., 2003),(WMO, 2015). These challenges are further compounded by socio-economic factors that disproportionately affect vulnerable populations, creating intricate patterns of health vulnerability across different communities (Ahern et al., 2005),(Du et al., 2010),(Phung et al., 2016). Bangladesh, which has a unique geographic position as a low-lying deltaic plain, combined with its extreme population density, makes it particularly vulnerable to recurrent flood disasters and its impacts (Afjal Hossain et al., 2011),(Rahman & Salehin, 2013). Approximately 35% of the whole country got flooded in 2020 (NAWG Bangladesh, 2020) and the Sylhet flood of 2022 is termed as the worst flood in this region in 122 years (Rumpa et al., 2023).

The relationship between flood exposure and health outcomes has been demonstrated in various global contexts (Flores et al., 2024),(KaTurner et al., 2019),(Suhr & Steinert, 2022). For instance, as demonstrated in (Saulnier et al., 2018), a direct link between seasonal flooding and health risks, but the key influencing indicators remain understudied, limiting the clarity needed for future interventions. A critical review (Lowe et al., 2013) of numerous PubMed studies was conducted and found that while factors like age, gender, socioeconomic status, and flood severity influence flood-related health outcomes, research remains limited on non-demographic risk factors. A research in Mombasa, Kenya revealed how household characteristics, WASH infrastructure, and environmental factors collectively influence health vulnerability during floods (Okaka & Odhiambo,2019a). Similar dynamics are evident in Bangladesh, where studies have documented the catastrophic consequences of compromised WASH facilities during floods, including the widespread contamination of water sources and subsequent disease outbreaks (Shahid, 2010),(Shimi et al., 2010). Historical evidence from the 1998 floods showed that economically disadvantaged populations suffered disproportionately from diarrheal diseases due to limited access to clean water (Kunii et al., 2002).

While existing research has made valuable contributions to understanding flood-related health vulnerabilities, significant knowledge gaps remain. Previous studies have either focused on specific diseases (Hashizume et al., 2008),(Nahar et al., 2014),(Schwartz et al., 2006) or assessed e change impact on public health (Kundzewicz & Takeuchi, 1999),(Lee et al., 2021), (Shahid, 2010) or employed aggregated district-level analyses (Lee et al., 2021), potentially obscuring important variations at the household level. The 2021 study, while identifying regional vulnerability patterns in north-western Bangladesh, acknowledged the limitations of district-level data in capturing micro-scale disparities. This highlights the critical need for research that examines vulnerability through a household-level lens, accounting for the complex interplay of structural, economic, and environmental factors that determine health outcomes during floods.

This study addresses these research gaps through three primary objectives: (1) developing a comprehensive household-level vulnerability assessment framework that integrates hazard exposure, demographic characteristics, WASH infrastructure, healthcare access, and adaptive capacity; (2) identifying spatial patterns of health vulnerability within flood-prone communities; and (3) evaluating the effectiveness of existing disaster risk reduction strategies. Our research makes several novel contributions to the field, including the development of a micro-scale assessment methodology that reveals intra-community vulnerability variations, and the demonstration of how combined proactive and reactive measures can significantly enhance health resilience. Focusing on the devastating 2020 floods that affected 35% of the country (NAWG Bangladesh, 2020), this study provides policymakers with actionable insights for targeted interventions, while offering a transferable framework for flood-vulnerable regions worldwide.

The findings of this research will enable government agencies, NGOs, and health professionals to identify critical gaps in current disaster response systems and develop more effective, localized strategies for reducing public health vulnerabilities during flood events. By bridging the divide between macro-level vulnerability assessments and household-level realities, this study aims to contribute to more equitable and effective disaster risk reduction policies in Bangladesh and similar flood-prone regions.

2 Material and Methods

This study employs a mixed-methods approach combining household surveys, expert judgments, and geospatial analysis to assess public health vulnerability in Bangladesh's Teesta River floodplain. Data were collected from 315 households across six unions in Dimla Upazila through structured questionnaires, capturing socio-demographic, WASH, healthcare access, flood conditions, and disaster adaptation indicators. The AHP was used to weigh vulnerability factors based on expert opinions, followed by normalization and aggregation to compute a composite vulnerability index. Statistical analyses (correlation, regression) identified key determinants of vulnerability, while GIS mapping visualized spatial patterns using Inverse Distance Weighting (IDW). The methodology integrates quantitative and qualitative insights to evaluate flood-induced health risks and inform resilience-building strategies.

2.1 Study Area

A significant number of rivers flow through the northern region of Bangladesh. The Teesta floodplain is one of the largest basins in the north-western part of the country (Mondal et al., 2021a). This region is highly vulnerable to floods occurring almost yearly due to its geographical location. The Nilphamari district is located upstream of the Teesta Basin, with significant rivers named Teesta, Dharla, and Brahmaputra flowing on the right side of the basin (Mondal et al., 2020). The right banks of the rivers are highly vulnerable and regularly affected by flood events, river bank erosion, and drought (BBS, 2020). Floods

in 1998, 2004, 2008, 2017, and 2020 are some of the significant and severe flood events that have devastated this area (Ahmed
95   & Hussain, 2009).

This study has focused on a small area of the Teesta floodplain, i.e., the Dimla Upazila (sub-district) (Fig01) which is located
in the north-eastern part of the Nilphamari District (Mondal et al., 2021b), with the Teesta River flowing through it (BBS,
2020). This Upazila is bordered by West Bengal, India on the north, Jaldhaka Upazila (under Nilphamari district) on the south,
Hatibandha Upazila (under Lalmanirhat district) on the east, and Domar Upazila (under Nilphamari district) on the west (BBS,
100   2013). The Gozaldoba Teesta Barrage in West Bengal, India, established for irrigation purposes, is on the Northern side of the
Dimla Upazila (Al-Hussain et al., 2021). The key informants during the field visit informed that when the rainfall increases in
the adjacent part of India (of the study area), the probability of flooding rises there and therefore they open the sluice gates of
the Gajoldoba Barriage to reduce their risk which results that the water flowing down to the northern part of Bangladesh
through the Brahmaputra River and cause flooding along the riverbank areas. This condition worsens if the rainfall in
105   Bangladesh continues as it increases the peak of the water level height. The Dimla Upazila is one of the worst affected regions
considering the number of affected people in frequent disasters (Rahman et al., 2018). It has an area of 326.80 sq. km. and the
male-female ratio of the area is 1.009:1 among the 283, 438 population (BBS, 2014). This Upazila consists of 10 union
parishads. Agriculture is the major livelihood option of the people of this area (BBS, 2014).
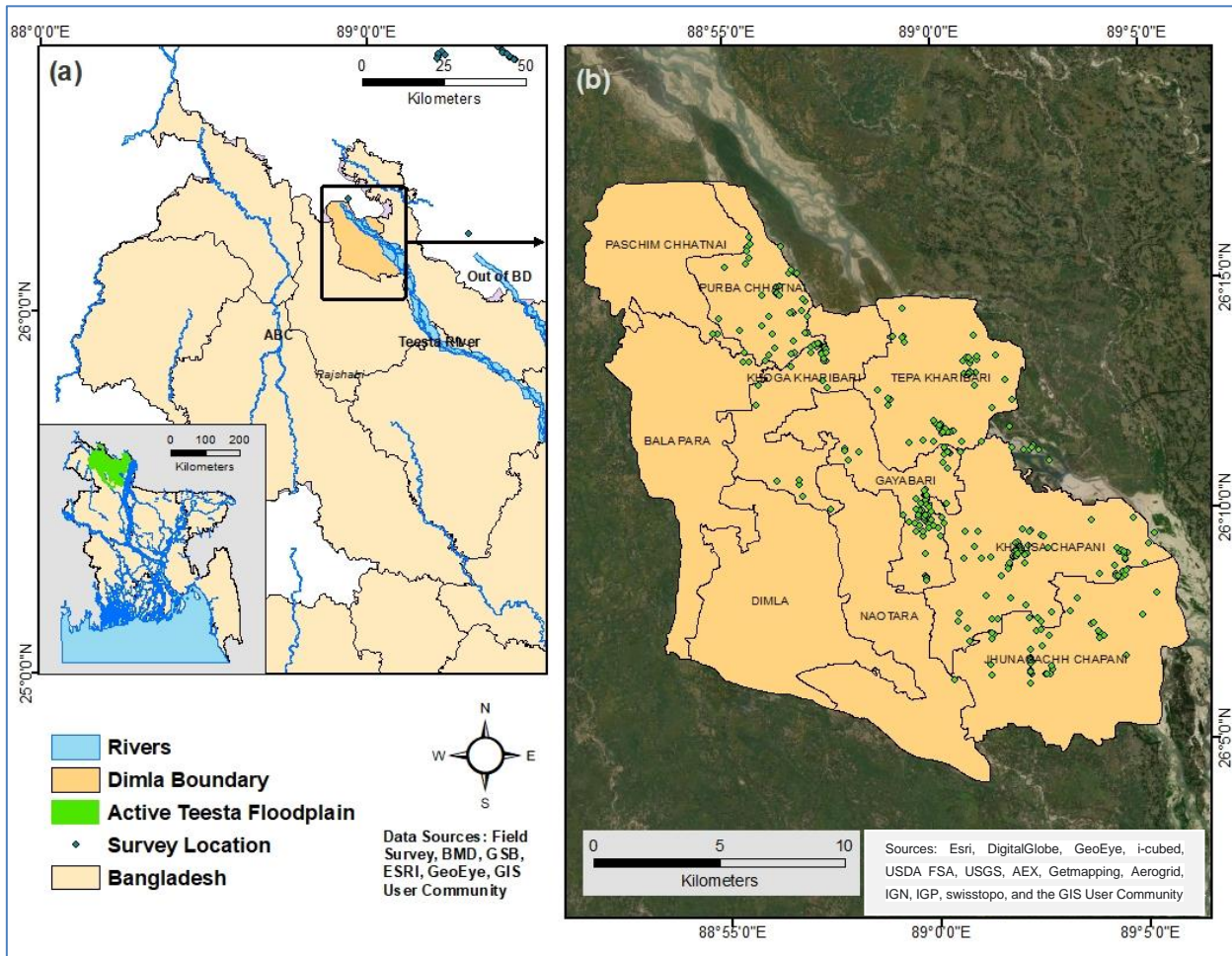
Fig01: Study Area location (a) the Dimla Upazila location in the Northwestern part of Bangladesh along the Teesta floodplain; and (b) the surveyed households in different unions of the Dimla Upazila (illustrated by the author; field survey 2019)

2.2 Sample size selection

A total of 315 samples were collected from six unions named Jhunagachh Chapani, Khalisha Chapani, Khoga Kharibari, Paschim Chhatnai, Purba Chhatnai, Gayabari and Tepakhribari of the Dimla Upazila (BBS, 2014). The Upazilas were selected purposely based on: low, moderate and high flood- affected regions according to the key informants (Upazila Nirbahi Officer (UNO—the executive head of the Sub District administration) and local NGOs (BRAC, ASA, and RDRS). In this study, to estimate the sample size, firstly the population has been projected for 2019 (the study year). The following formula (Goodman, 1968) has been used to project the population.

$$x(t) = x_0 \times (1 + r)^{\,t}$$

Here, $x(t)$ denotes the projected population. The data for x_0 is the population according to (BBS, 2020); r is the population growth rate (1% as (Chowdhury & Hossain, 2019)) and t is the time period (8 years). Since we have selected one surveyor

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from each household to understand the picture of the whole, we have estimated the household number (for x_0) rather than the total population. The projected household number for 2019 is 67444.

After calculating the household number, the following equation (Smith, 2000) has been used to calculate the sample number.

125   *Necessary sample size= ((z-score)² x standard deviation x (1-Standard deviation)) / (margin of error)²*

For this research, we have taken a 90% confidence interval with a margin error of +/- 10%. Then the ideal sample size is 270. Since we cover six unions of the Dimla Upazila, we expanded the sample size and conducted a total number of 315 sample surveys. The survey numbers from each union have been tried to represent the population size of the unions correspondingly

130   (Table 1).

Table 1: Survey numbers according to union (representation of the presentation)

Union	Population (According to the 2011 BBS Census)	Population Percentage	Sample Number	Sample Percentage
Gayabari	5227	11.62	45	14.29
Jhunagach Chapani	11199	24.89	63	20
Khalisha Chapani	10446	23.22	75	23.81
Khoga kharaibari	5810	12.91	32	10.16
Purba Chatnai	4472	9.94	35	11.11
Tepa kharibari	7836	17.42	65	20.63
Total	**44990**	**100**	**315**	**100**

(Source: Illustrated by the author; field survey 2019)

2.3 Data collection

135   A field visit was conducted in October 2019 to collect household-level data through a structured questionnaire survey. Information related to socio-economic demography, WASH infrastructure availability healthcare service accessibility, flood hazard intensity, relief accessibility and adaptation strategies (Fig02) has been collected from 315 households followed by simple random sampling in six Upazilas. The questions were asked in the native language (Bangla) and each questionnaire took around 30 minutes. Each data variables were collected through binary responses (yes=1, no=0) and Likert scales (table-

140   2). Additional open-ended questions were also pursued to gain deeper insights into their perspectives and the broader circumstances of vulnerability. Participants were selected from each household, with preference given to the household head; alternatively, any adult family member aged 18 or older was included. The UNO, local NGOs (BRAC, ASA, RDRS) and Upazila Health & Family Planning Officer of the area were the key informants who provided the overview of the area in the initial phase of the survey.
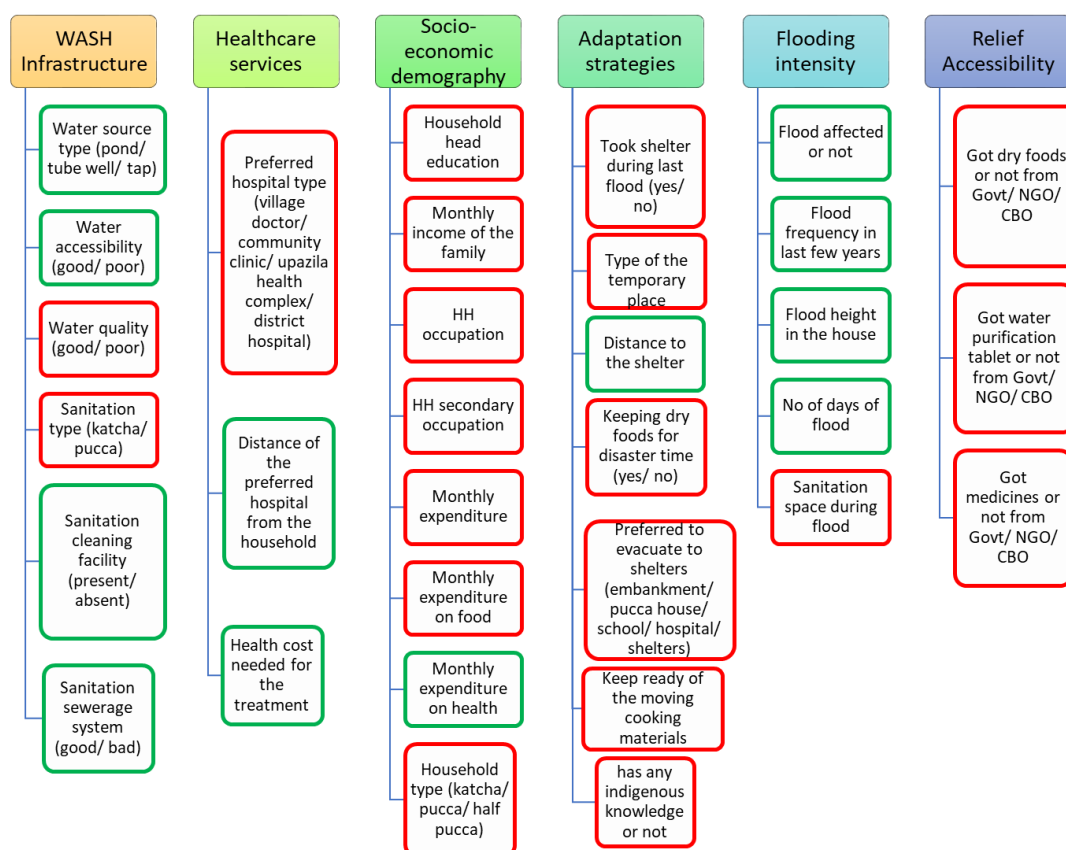
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Fig02: The indicators under the major categories taken for the vulnerability assessment (the green one shows the benefit criteria and the red one shows the cost criteria) (illustrated by the author; field survey 2019)

There are six categories and 32 indicators in total to assess the vulnerability. Primarily, the categories were selected after reviewing the literature (Ahern & Kovats, 2006), (Acharya & Silori, 2024), (Few & Matthies, 2006), (Islam, 2017), (Laura

150 Tascón-González et al., 2020), (Matsuyama et al., 2020), (Okaka & Odhiambo, 2019a), (Okaka & Odhiambo, 2019b), (Paterson et al., 2018), (Phung et al., 2016), (Shah et al., 2020), (Shimi et al., 2010). After that, the experts help to finalize the indicators under the six categories. One indicator can influence the vulnerability in two ways: some accelerate the vulnerability and some lessen the vulnerability such as: better WASH facilities will lessen the public health vulnerability and vice versa (Fig02).

155   Table 2: The description of the variables of this study

Variables	Descriptors	Measurement	Values
Demographic characteristics			
Age	Age of the respondent?	18-30	20.30%
		31-40	28.50%

		41-50	23.50%
		51-60	14.40%
		60+	13.30%
Gender	Gender of the respondent?	Male	64%
		Female	36%
Marital Status	Marital status of the respondent?	Married	95.30%
		Unmarried	2.20%
		Widow	2.20%
		Separated	0.30%
Education	Education class of the respondent?	No Answer	1.70%
		Illiterate	17.30%
		Can sign, read, and write only	24.30%
		Class 2-9	32.40%
		Secondary School Certificate (SSC)	14.50%
		Higher Secondary School Certificate (HSC)	4.80%
		Graduation	5%
Household Head's (HH) highest education level	Highest education class of the household head?	Illiterate	14%
		can only sign	20.70%
		have primary education	27.90%
		'Didn't complete secondary school (SSC)	18.50%
		completed secondary school (SSC)	9.70%
		completed higher secondary school (HSC)	5.20%
		Graduation	4%
HH primary occupation		Agriculture	43.80%

	Primary Occupation of the household head?	Day labor	22.6%
		Business (both formal and informal)	19%
		Homemaker	11.6%
		Unemployed	3%
HH secondary occupation	Secondary Occupation of the household head?	No secondary job	65.40%
		Day laborer/ Farming/ Fishing/ Poultry	9.80%
		Businessman	18.70%
		Informal economy	4.80%
		Formal economy	1.30%
Monthly income (BDT)	Monthly income of the family?	1500-5000	10.50%
		5001-10000	45.20%
		10001-20000	31.50%
		20001-35000	9.40%
		35000+	3.40%
Monthly expenditure (BDT)	Monthly expenditure of the family?	2000-5000	13.40%
		5001-10000	55%
		10001-25000	29.80%
		25001-50000	1.50%
		50000+	0.30%
Monthly expenditure on food (BDT)	Monthly expenditure of the family on food?	300-1500	2.60%
		1501-3000	21.80%
		3001-5000	36.60%
		5001-10000	33.10%
		10000-15000	5.30%
		15000+	0.60%
Monthly expenditure on health (BDT)	Monthly expenditure of the family on health issues?	100-500	23.70%
		501-1500	46.70%
		1501-3000	22.80%
		3001-6000	5.90%
		6000+	0.90%
Household type	What is your household type	Thatched	70.80%

		Pucca	5.10%
		Semi-pucca	24.10%
Disease Outbreak			
Diarrhea	Did your family members suffer from diarrhea during/ after the last flood?	Yes	37.79%
		No	62.21%
Fever	Did your family members suffer from fever during/ after the last flood?	Yes	8.12%
		No	91.88%
Malaria	Did your family members suffer from malaria during/ after the last flood?	Yes	5%
		No	95%
Typhoid	Did your family members suffer from typhoid during/ after the last flood?	Yes	2%
		No	98%
Skin disease	Did your family members suffer from skin disease during/ after the last flood?	Yes	11.66%
		No	88.34%
WASH infrastructure availability			
Water accessibility	From where do you get water for maximum time of the year?	Tube well	94.90%
		Tap	2.50%
		Pond	2.60%
Water safety	What is the quality of the water that you use?	Safe water	76.20%
		Unsafe water	23.80%
Water availability/ accessibility	Do you get enough water for your daily purpose?	Good	87.60%
		Poor	12.40%
Sanitation type	What is your sanitation type?	Thatched	92.70%
		Pucca	7.30%
Sanitation cleaning facilities	How is your cleaning facility available?	Present	37.50%
		Absent	62.50%
Sanitation sewerage system	How is your sanitation sewerage system?	Good	43.50%
		Poor	56.50%
Flooding severity			
Flood affected (in the last flood) or not	Have you been affected by a flood in the last 5 years?	Yes	55.60%
		No	44.40%
Flood frequency in the last few years	Can you tell me how many times a flood hit your house in the last 5 years?	0	9.50%
		3-Jan	81%
		6-Apr	7.60%
		8-Jul	1.90%
Flood height in the house	Can you tell me about the flood height in your house?	0-2	55.20%
		5-Mar	19.30%

		8-Jun	3.40%
Number of days of the flood	How many days (max) you live in flood water in the last 5 years?	0-5	73%
		10-Jun	15.60%
		20-Nov	5.70%
		21-45	3.50%
		45+	2.20%
Sanitation option during floods	What was your sanitation option during flood?	-	-
Healthcare service accessibility			
Preferred hospital type	In which hospital do you prefer to go for treatment?	Town hospital	18.40%
		Upazila Health complex	14.90%
		Community clinic	24.40%
		Village doctor	41.90%
Distance from household (KM)	How far the preferred hospital is from your home?	0-5	71.30%
		15-Jun	13.50%
		16-25	6.30%
		26-50	2.50%
		50+	6.40%
Treatment cost (BDT)	How must cost is required for the treatment on an average each time?	0-300	59.60%
		301-1000	18.80%
		1001-5000	17.90%
		5001-10000	2.80%
		10000+	0.90%
Adaptation measures			
Took shelter during the last flood	Did you take any shelter during the last flood?	Yes	67.90%
		No	32.10%
Type of the temporary place	Where did you take place temporarily during a flood?	No	32.10%
		Embankment	40%
		'Neighbor's house	11.10%
		'Relative's house	9.50%
		Town	3.80%
		Others (school/ shelter)	3.50%
Distance to the shelter (KM)	How far is the place from your home?	0-2	93.70%
		7-Feb	5.70%

		10-Aug	0.30%
		10+	0.30%
Preferred to evacuate to shelters (embankment/ pucca house/ school/ hospital/ shelters)	Did you prefer to go to any shelter (school/ flood shelter/ pucca house/ embankment/ hospital etc.)?	Yes	62.20%
		No	37.80%
Keep dry foods for flood time	Did you store dry foods for flood time?	Yes	36.25%
		No	63.75%
Keep ready the moving cooking materials	Did you keep cooking materials with you during the evacuation?	Yes	26.30%
		No	73.70%
has any indigenous knowledge or not	Do you have any sort of indigenous knowledge to flood?	Yes	82.50%
		No	17.50%
Relief Accessibility			
Got dry foods or not from Govt/ NGO/ CBO	Did you get dry foods from GO/ NGO/ CBO/ or others?	Never	69.80%
		Sometimes	19%
		Always	11.10%
Got medicine or not from Govt/ NGO/ CBO	Did you get medicines from GO/ NGO/ CBO/ or others?	Never	89.20%
		Sometimes	8.90%
		Always	1.90%
Got water purification tablet or not from Govt/ NGO/ CBO	Did you get a water purification tablet from GO/ NGO/ CBO/ or others?	Never	87.60%
		Sometimes	9.20%
		Always	3.20%

(Source: Illustrated by the author; field survey 2019)

2.4 Normalization of all indicators

In the pre-processing stage, raw indicator values for each household were normalized to a common scale to facilitate aggregation in the vulnerability assessment following multi-criteria analysis, as the factors are both quantitative and qualitative with different units, they need to be harmonized for better comparison. Therefore, the linear max-min dimensionless method for cost and benefit criteria has been used in this study as it has the advantage of removing the convertible units (Jahan & Edwards, 2015).

Benefit criteria: $\quad n_{ij} = \dfrac{r_{ij} - r_j^{min}}{r_j^{max} - r_j^{min}}$

Cost criteria: $n_{ij} = \dfrac{r_j^{max} - r_{ij}}{r_j^{max} - r_j^{min}}$

The factors have been divided into two criteria based on their characteristics (Fig.02). Those that are positively impacted by the vulnerability are considered as the benefit criteria i.e. poor water quality increases the vulnerability of the household to different health hazards. Similarly, the factors that are inversely related to public health vulnerability are considered as cost criteria i.e. the presence of proper sanitation facilities decreases the vulnerability related to public health.

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2.5 Analytical Hierarchy Process (AHP) method

The AHP method is one of the most significant and widely used weighting methods in the multi-criteria decision-making process by decision-makers and researchers (Kara, 2019), (Shim, 1989). It follows a pairwise comparison of all the considered categories to measure relatively, considering the value within 1-9 (Saaty scale) in the analysis (Saaty, 2014) where higher

175 values indicate stronger preference for Parameter A over B (Table 3). The eigenvector method was applied to convert pairwise comparisons (Table 3) into normalized criterion weights: for each expert, a square matrix A was created, where elements a_{ij} represented the Saaty-scale preference of parameter *i* over *j*. For each expert, a square matrix AA was created, where elements a_{ij} represent Saaty-scale preferences of parameter i over j.

Table 3: Expert-based pairwise comparison matrix of AHP parameters with Saaty-scale preferences

No.	Parameter X	Parameter Y	Preferable Parameter (X/Y)	Degree of Preferences (Scale 1-9)
1.	WASH facilities	Hospital facilities	-	[Value, e.g., 3]
2.		Household characteristics	-	-
3.		Adaptation strategies	-	-
4.		During disaster situation	-	-
5.		Access to relief	-	-
6.	Hospital facilities	Household characteristics	-	-
7.		Adaptation strategies	-	-
8.		During disaster situation	-	-
9.		Access to relief	-	-
10.	Household characteristics	Adaptation strategies	-	-
11.		During disaster situation	-	-
12.		Access to relief	-	-
13.	Adaptation strategies	During disaster situation	-	-
14.		Access to relief	-	-
15.	During disaster situation	Access to relief	-	-

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A total number of fifteen (15) experts from different domains took part in this assessment. These experts are academicians and practitioners from disaster management, environmental science, health science, and the public health domain. These experts are chosen based on their educational background (relevant domain), work experience in a suitable background (minimum 3

years), and their interests in the topic. They gave expert judgments by ranking the pairs from 1 (equal importance) to 9 (extreme
importance) following the Saaty scale (Table 4) as it is the most used and follows pairwise comparison comparing each
criterion with another, individually (Afshari et al., 2010).

Table 4: Brief explanation of the Saaty scale (Saaty, 2014)

Intensity of importance	Definition
1	Equal importance
3	Weak importance of one over the other
5	Essential or strong importance
7	Demonstrated importance
9	Absolute importance
2, 4, 6, 8	Intermediate values between the two adjacent judgments

The consistency ratio (CR) of all the judgments is kept within 10% to indicate a reasonable level of consistency within the
pairwise comparison (Afshari et al., 2010),(M. A. Chowdhury et al., 2021). If any individual expert's perception doesn't follow
the consistency ratio, then the whole process was rechecked, and then again consider the consistency ratio within 10%. The
consistency ratio is defined as:

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

Here, the consistency index (CI) provides a measure of departure from consistency. The consistency index is calculated as:

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

Where,

λ = the average value of the consistency vector,

n = the number of criteria

2.6 Estimation of public health-related vulnerability

The vulnerability is estimated by multiplying the weighted average (derived from the weighted sum model that has been used
by summing up the total weighted value of each category and then dividing it by the total number of indicators under the
category) with the normalized value of each indicator (Laura Tascón-González et al., 2020). Finally, all the values of the
categories are summed up and divided by the total number of the categories (six categories) to find the vulnerability value for
each household. Later, the average vulnerability was calculated for each union. The vulnerability was measured through the
following questions:

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$$V_S = \sum_{i=1}^{n} \frac{(S_{1wn} + S_{2wn} + \ldots\ldots\ldots + S_{kwn}) * S_{nv}}{k}$$

$$V_T = V_S + V_T + \ldots + V_Z$$

210   Where,

S, T, ………., Z = Different categories

$S_{1,2,\ldots\ldots,n}$ = Indicators under S category

S_w = Weighted average of each indicator

S_{nv} = Normalized value of S category

215   k = Total number of households

V_T = Total Vulnerability

2.7 Statistical Analysis

In this study, several statistical analysis such as correlation, regression, and frequency analysis was adopted. Frequency
220   analysis has been performed to understand the overall scenario of the factors within the respondent groups. The regression
analysis is performed in two types: one is between the individual union vulnerability value with their category value and
another is between the public health vulnerability value and the categories (linear regression analysis).

$$y = \beta_0 + \beta_1 X + \text{€}$$

The linear regression is analysed with the above equation where y is termed as the dependent variable (the target variable on
225   which the study is considering to imply) and X is termed as the independent or explanatory variable (the input datasets which
are self-sustaining). β_0 and β_1 are the parameters of the model (these are the intercepts and reflect the relationship between
the dependent and independent variables). The parameter β_0 is termed as an intercept and β_1 is termed as the slope parameter.
The unobservable error component € accounts for the failure of data (error) to lie on a straight line and represents the
difference between the true and observed realization of y. In the analysis of public health vulnerability and the categories, the
230   dependent variable is the vulnerability value and the independent variable is the six category values. In the other analyses (the
regression has been run separately), the individual categories are the dependent variables and the individual union vulnerability
value is the independent variable. In the linear regression analysis between the categories and the union-wise public health
vulnerability value, the average value of the categories for the individual unions has been taken. Moreover, the correlation has
been performed among the six categories.

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2.8 GIS Analysis

The study area map and the vulnerability maps have been prepared in ArcGIS 10.8 environment. The union vulnerability is
shown as the average value of the unions. In the case of the household vulnerability map, IDW tool has been used to make the
vulnerability value to raster data. The classes have been determined manually.

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3 Results

3.1 Demographic characteristics

Among the studied households (Table 2), most of the household heads (64%) were male, and the remaining (36%) were female. The highest (28.5%) number of respondents were in the age group of 31–40 years, followed by 23.5% of 41–50 years and

245   14.4% of 51–60 years. The rest were below 31 age or above 60 ages. Among the respondents, 95.3% were married, 2.2% were found unmarried, 2.2% were widows and 0.3% were separated. In terms of principal livelihood, the highest (43.8%) were involved in agriculture (farming, fishing, and poultry), followed by 22.6% of day labourers, 19% were involved in business activities (both informal and formal altogether), 11.6% were housewife and only remaining 3% were unemployed. As regards the level of literacy, almost 28.2% of them attended/ completed secondary school education and 27.9% had primary education.

250   Also, 14% of the household heads were illiterate, around 20.7% could sign, read, and write only, 5.20% passed the higher school certificate and only 4% were graduated. The monthly average household income was found Tk. 13,803. The highest 45.2% of the households' income was BDT 5001-10000, followed by 31.5% of BDT 10001 to 20000, 10.5% BDT 1500-5000, 9.4% of 20001-35000, and the lowest only 3.4% had BDT 35000+.

3.2 Disease outbreak after a flood in the study area and the surrounding factors that affect it

255   Different types of water-borne diseases are very common in flood-prone areas after any flood event. Among them, diarrhoea, typhoid, skin diseases, dysentery, cholera, and meningitis are very common (Shahid, 2010). Along with these, cold symptoms along with fever are regular during the flood. The impacts are not even limited to these; death from drowning, flash flooding, injuries and wounds, electric shocks, burns and explosions, hypothermia, and psychological effects are also some of the impacts of floods (Laura Tascón-González et al., 2020). In the study area (Fig03), the respondents reported that diarrhoea (>35%) is

260   the most common phenomenon during and after flood occurrence. Skin diseases (>10%) and fever (~ 9%) were also found to be common in the area. Around 5% and 1% of respondents reported that they suffered from malaria and typhoid during the last flood, respectively. They visit doctors or other health complexes depending on the severity of the health situation.
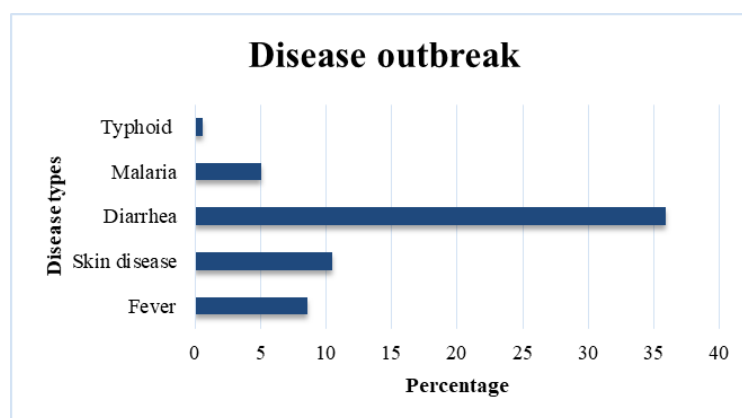

Fig03: Percentage of diseases affected in the study area

265   (Source: Illustrated by the author; field survey 2019)

Table 5 summarizes the prevalence (%) of five diseases—diarrhea, malaria, fever, typhoid, and skin disease—across different age groups and genders. Diarrhea was the most common ailment, particularly among individuals aged 20–35 (88.32%) and males exhibited a higher prevalence of diarrhea (87% vs. 76.5%). Malaria showed higher prevalence in the 20–35 age group
270 (16.21%) and was more frequent in males (13.68%) than females (2.94%). Fever was substantially greater in females (32.35%) compared to males (14.54%). Typhoid had low overall prevalence, with the highest rate in the 46–60 age group (2.83%) and was rare in males (0.8%) but slightly more prevalent in females (2.9%), while skin disease was most common in the 26–45 age group (33.33%) but equally prevalent across genders (20.5%). These findings suggest variations in disease susceptibility based on age and sex.

275   Table 5: Disease distribution among different demographic people (given in percentage)

	Diarrhea	Malaria	Fever	Typhoid	Skin Disease
Age					
20-35	88.32	16.21	22	1.7	21
26-45	75.28	8.34	13.8	0	33.33
46-60	82.71	0	15.79	2.83	15.79
61-75	76.19	10.15	19.05	0	14.29
Gender					
Male	87	13.68	14.54	0.8	20.5
Female	76.5	2.94	32.35	2.9	20.5

(Source: Illustrated by the author; field survey 2019)

3.3 Union-wise public health vulnerability calculation

The union-level assessment of public health vulnerability yielded unexpected findings, as illustrated in Fig04. While existing
280 flood vulnerability studies (Ferdous & Mallick, 2019) identify the Brahmaputra River's north-western bank in Dimla Upazila as particularly flood-prone, our analysis reveals a distinct pattern in health outcomes. Key informant interviews confirmed that Tepa Kharibari Union experiences the most severe flooding due to its geographical positioning along the river, with some residents living on the opposite bank. However, contrary to expectations, our results demonstrate that Purba Chhatnai - the northernmost studied union - exhibits the highest public health vulnerability. The second most vulnerable area was Jhunagach
285 Chapani in the extreme south, while Gayabari, located centrally at a distance from the riverbank, showed the lowest vulnerability among the studied unions. This spatial distribution suggests that flood exposure alone does not fully determine health vulnerability, highlighting the importance of other contributing factors.
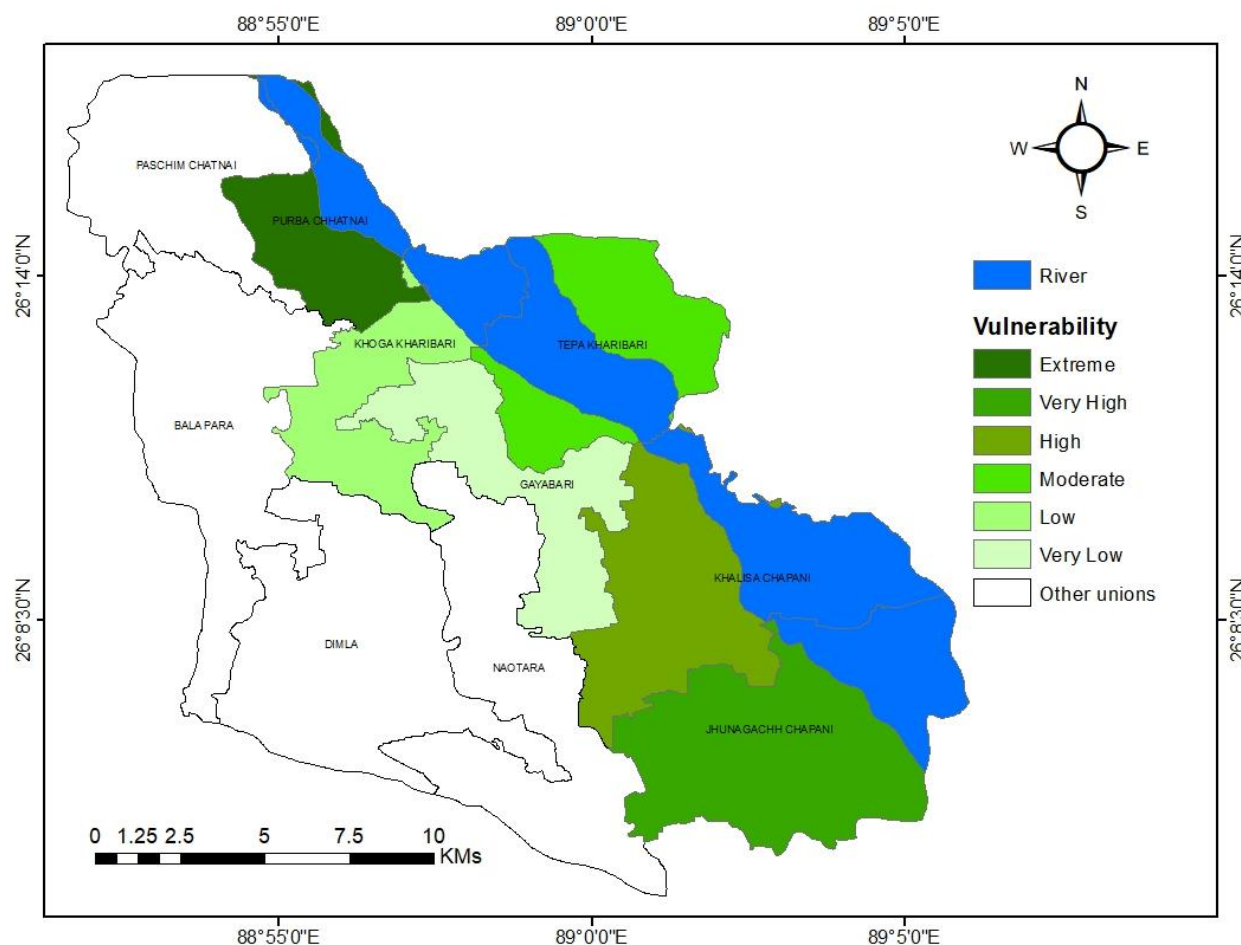
17

Fig04: Public Health Vulnerability map according to the studied unions

(Source: Illustrated by the author: field survey 2019)

The analysis reveals that Purba Chatnai's position as the most vulnerable union stems from multiple interrelated factors (Table 3). The area's pronounced socio-economic challenges - with approximately 20% of residents living in extreme poverty (Ferdous & Mallick, 2019) - directly contribute to inadequate household conditions and substandard WASH facilities. Existing literature and our findings both confirm that while various adaptation measures have been implemented across Dimla Upazila, Purba Chatnai's adaptation capacity remains particularly weak (Ferdous & Mallick, 2019). Compounding these issues, the union receives disproportionately less attention in relief distribution despite its flood exposure, collectively exacerbating its public health vulnerability.

Jhunagach Chapani's status as the second-most vulnerable union reflects its dual burden of severe flood impacts coupled with minimal adaptation capacity and restricted relief access. In contrast, Tepa Kharibari demonstrates how institutional support can mitigate vulnerability - despite being the most flood-affected union (Table 6), its moderate public health vulnerability

18

ranking stems from robust NGO interventions that enhance both adaptation strategies and relief accessibility. Gayabari presents an interesting case where relative economic advantage and social capital translate to both superior adaptation approaches and easier relief procurement, despite its lower baseline flood risk. Key informant interviews corroborate these spatial patterns,

305 confirming Tepa Kharibari's high flood exposure alongside Gayabari's comparatively protected position.

Table 6: Comparative vulnerability metrics across study unions

Union Name	WASH infrastructure	Socio-economic demography	Healthcare services	Relief accessibility	Adaptation strategies	Flooding intensity
Gayabari	6.14	11.91	10.09	17.31	6.06	2.94
Jhunagach Chapani	6.28	11.78	10.71	18.69	6.54	4.84
Khalisha Chapani	6.33	14.01	10.95	17.17	6.40	4.34
Khoga kharaibari	6.78	14.40	10.41	17.12	6.29	4.52
Purba Chatnai	6.34	15.29	10.12	18.00	6.78	4.44
Tepa kharibari	6.42	13.15	10.75	17.21	5.35	5.23

(Source: Illustrated by the author; field survey 2019)

310 Table 6 provides empirical support for the observed vulnerability patterns, revealing significant variations across unions. Purba Chatnai emerges as the most vulnerable area, exhibiting the highest household deprivation score (15.29) and relatively poor relief accessibility (18.00), despite reporting higher adaptation strategy scores (6.78) - a paradox suggesting potential gaps between planned and implemented measures. Tepa Kharibari presents an interesting case of resilience, maintaining only moderate vulnerability despite recording the most severe flooding conditions (5.23), which appears mitigated by better hospital

315 facilities (10.75) and relief access (17.21). Notably, its surprisingly low adaptation strategy score (5.35) implies that institutional support may compensate for individual preparedness. Jhunagach Chapani's position as second-most vulnerable aligns with its combination of extreme flooding (4.84) and limited relief access (18.69), while Gayabari's advantage becomes clear through its minimal flood exposure (2.94) and superior relief accessibility (17.31). The data particularly highlights how relief systems (ranging 17.12-18.69) and hospital access (10.09-10.95) show less variation than household characteristics

320 (11.78-15.29) or flood severity (2.94-5.23), suggesting these structural factors may serve as critical equalizers in vulnerability

mitigation. These findings reinforce that while flood intensity establishes baseline risk, the interplay of socio-economic conditions and institutional support systems ultimately determines health outcomes.

However, the vulnerability map (Fig05) clearly demonstrates that riverside areas exhibit significantly higher vulnerability levels, particularly along the Brahmaputra's right bank where communities face very high to extreme public health risks. In
325 contrast, the inland union surrounding Gayabari maintains consistently low vulnerability scores. Field interviews with right bank residents confirm this disparity, revealing critical service gaps that force dependence on left bank facilities during emergencies. Respondents reported lacking essential infrastructure on the right bank, necessitating hazardous cross-river movements during floods that compound their health vulnerabilities. This spatial analysis underscores how geographic isolation from core union services exacerbates vulnerability, even within the same administrative boundaries, highlighting the
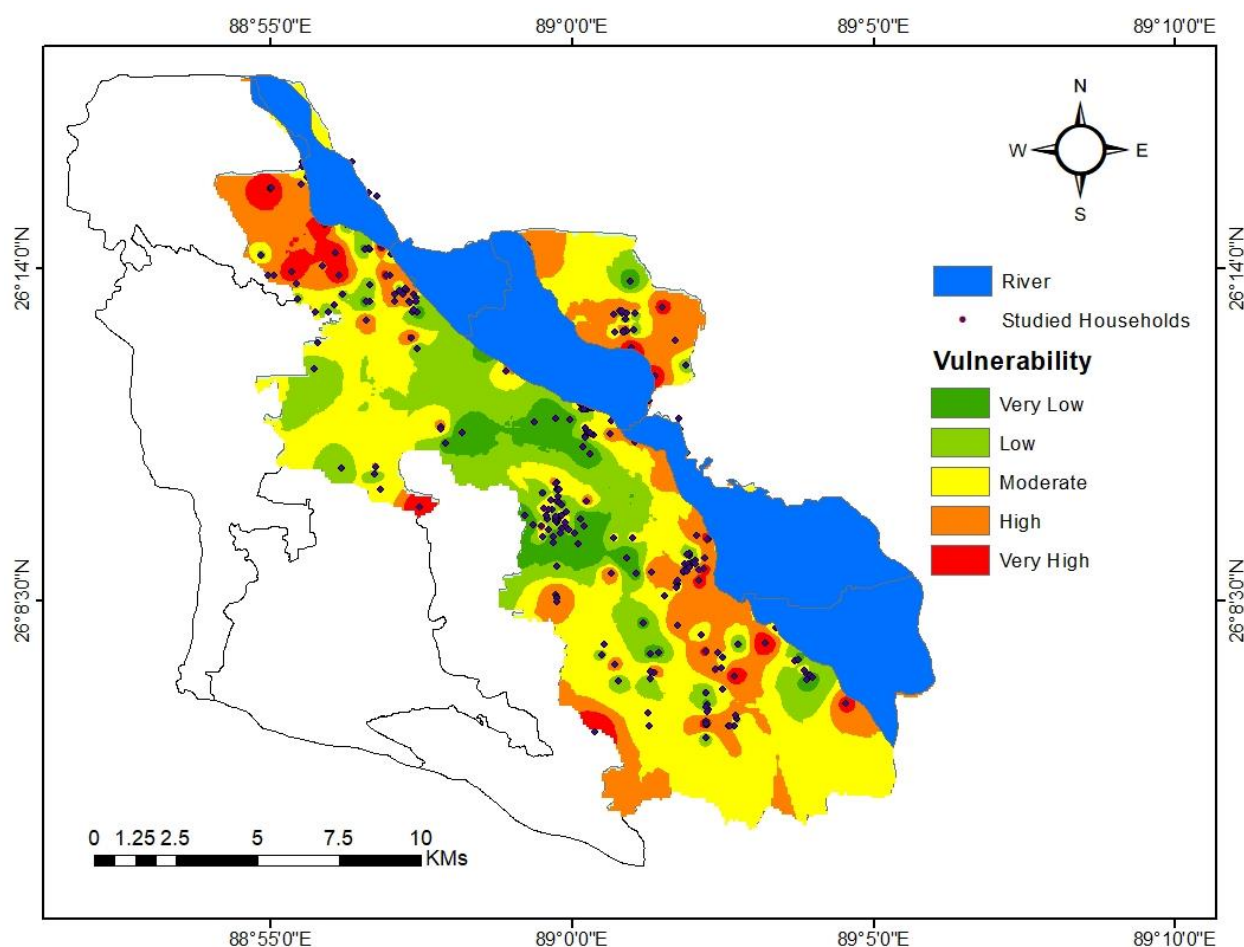330 need for targeted interventions in these high-risk riverside settlements.

Fig05: Public Health Vulnerability map of the studied unions (according to household vulnerability)

(Source: Illustrated by the author: field survey 2019)

20

3.4 Relationship between the categories and public health vulnerability

In this study, the six categories can be divided into three disaster management phases: the pre-disaster or normal period, during disaster period, and the post-disaster recovery period (Fig06).
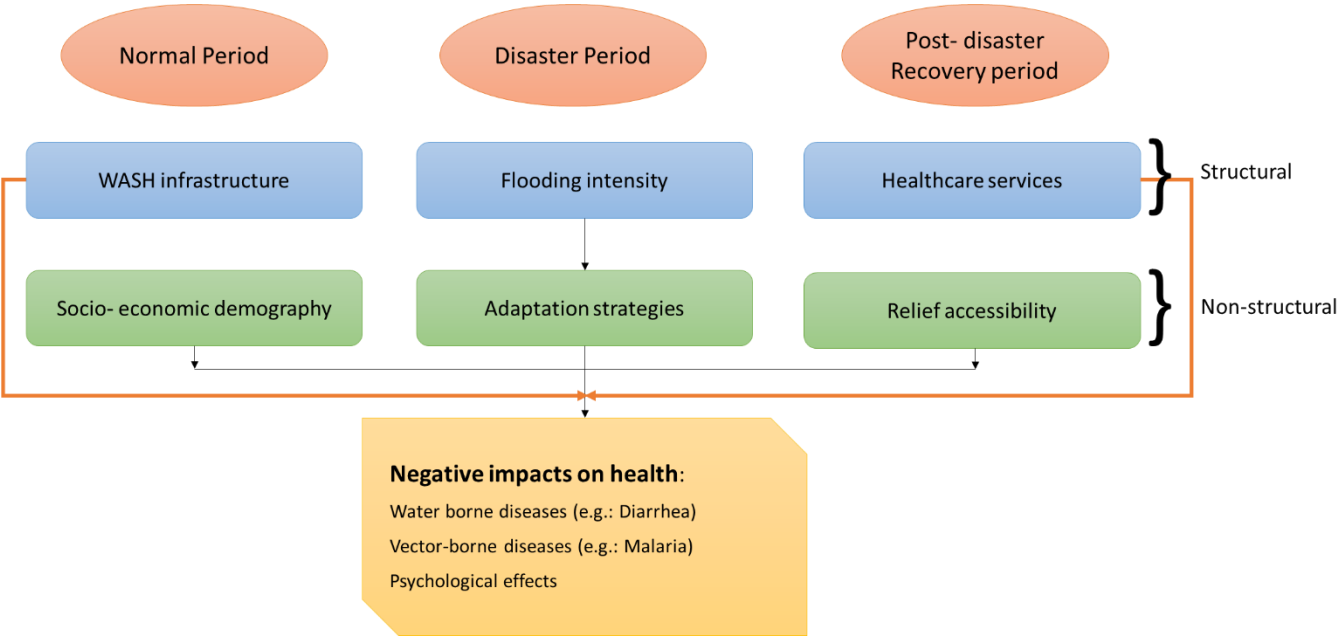
Fig06: Flow chart showing the categories affecting the health status

(Source: Illustrated by the author; field survey 2019)

Household socio-economic characteristics—including the education, occupation, income, and health expenditure of the household head—play a critical role in shaping health outcomes during both normal and pre-disaster periods. Additionally, access to proper Water, Sanitation, and Hygiene (WASH) infrastructure is essential for maintaining good health. During disasters, the severity of flood conditions and the adoption of adaptation strategies (e.g., food storage) significantly influence household resilience and health. Post-disaster recovery, meanwhile, depends on healthcare accessibility and relief availability, collectively determining overall health quality.

These factors can be categorized into structural (WASH facilities, disaster-induced housing conditions, sanitation status, and healthcare infrastructure) and non-structural elements (household socio-economic status, adaptation strategies, and relief access). Structural and non-structural components interact dynamically: improved household conditions facilitate better WASH infrastructure, enhancing disaster resilience, whereas economic constraints exacerbate vulnerability by limiting adaptive capacity and healthcare access.

The correlation analysis (table 7) reveals significant relationships among key resilience factors. A weak but positive correlation exists between relief accessibility and adaptation strategies (r = 0.098, p = 0.027), suggesting that better relief access may slightly improve adaptive capacity. More notably, adaptation strategies show a moderate negative correlation with flooding state (r = -0.254, p < 0.001), demonstrating their effectiveness in mitigating flood impacts. Household characteristics also negatively correlate with flooding state (r = -0.115, p = 0.042), indicating that socioeconomically advantaged households experience less severe flood effects. Most prominently, WASH facilities strongly associate with household characteristics (r = 0.031, p = 0.002), highlighting how better socioeconomic status enables improved WASH infrastructure, a crucial determinant of health resilience. These findings collectively emphasize the interconnectedness of structural and non-structural factors in shaping disaster resilience and health outcomes.

Table 7: Correlation between the categories

Categories	Pearson Correlation	Significance
Relief Accessibility Adaptation strategies	0.098*	0.027
Adaptation strategies Flooding State	-.254**	0.000
Household Characteristics Flooding State	-0.115*	0.042
WASH facilities HH characteristics	0.031**	0.002

*Correlation is significant at the 0.05 level (2-tailed)

**Correlation is significant at the 0.01 level (2-tailed)

(Source: Illustrated by the author; field survey 2019)

The relationship between public health vulnerability and the six categories has been examined through linear regression analysis (Table 8). The model shows that it includes 99.6% of data (R^2) and it demonstrates that all measured factors significantly contribute to public health vulnerability (p < 0.01 for all variables). Flooding intensity shows the strongest association (β = 0.037), indicating that worsening flood conditions increase health vulnerability most substantially. Relief accessibility (β = 0.034), healthcare services (β = 0.033), and WASH infrastructure (β = 0.032) exhibit nearly equal impacts, followed closely by socioeconomic factors (β = 0.031) and adaptation strategies (β = 0.029). The consistent positive coefficients reveal a dose-response relationship where each unit deprivation in any factor proportionally increases health vulnerability. These findings quantitatively confirm that both structural (WASH, healthcare) and non-structural (socioeconomics, adaptation) elements collectively determine community resilience, with flood intensity being the most

critical risk amplifier. The results underscore the need for integrated interventions addressing all these dimensions to effectively reduce public health vulnerability. However, all of these factors hold only a 1% error, which makes it clear that all these factors have a great influence on public health vulnerability.

380   Table 8: Relationship between the categories and public health vulnerability

Categories	Measurement (B)	Measurement statement	Significance (p)
WASH infrastructure	.032	One unit deprivation of WASH facilities will increase 0.032 units of public health vulnerability	0.00
Socio- economic demography	.031	One unit decrease in the quality of HH characteristics will increase 0.031 units of public health vulnerability	0.00
Relief accessibility	.034	One unit deprivation of access to relief will increase 0.034 unit of public health vulnerability	0.00
Adaptation strategies	.029	One unit absence of adaptation strategies will increase 0.029 units of public health vulnerability	0.00
Flooding intensity	.037	One unit worsening of disastrous (flood) condition will increase 0.037 units of public health vulnerability	0.00
Healthcare services	.033	One unit deprivation in hospital facilities will increase 0.033 units of public health vulnerability	0.00

(Source: Illustrated by the author; field survey 2019)

4 Discussion

This study reveals a critical insight: while flood intensity significantly impacts household health, other factors—such as relief accessibility, disaster preparedness, and institutional support—play an equally vital role in mitigating vulnerability. A striking

385   example from this study is Tepa Kharibari Union, which experiences the highest flood frequency and severity (Fig.03) yet

exhibits lower public health vulnerability due to robust government and NGO interventions, including timely relief distribution and community resilience programs. This underscores that both proactive (pre-disaster) and reactive (during/post-disaster) measures are indispensable for safeguarding health. Proactive initiatives (e.g., training, soft loans, awareness campaigns) enhance adaptive capacity, while reactive measures (e.g., emergency relief, medical aid) ensure immediate recovery—

390   demonstrating that an integrated approach maximizes resilience.

To systematically reduce flood-induced health risks, all six identified factors (WASH infrastructure, socioeconomic conditions, relief systems, adaptation strategies, flood severity, and healthcare access) must be embedded in national and local development plans. Bangladesh's Climate Change Strategy and Action Plan (CCSAP) already acknowledges climate-related health threats (Shahid, 2010), but further action is needed:

395

1. Enhanced WASH and Healthcare Systems – Ensure safe water, sanitation, and hygiene facilities alongside equitable access to medical services, particularly in flood-prone zones

2. Risk-Inclusive Urban Planning – Implement elevated housing (plinth levels), flood-resistant shelters, and hazard-zoned land use to minimize exposure

400   3. Multi-Stakeholder Collaboration – Strengthen partnerships between government agencies, NGOs, and communities to deliver:

    a. Pre-disaster: Training, early warning systems, and livelihood support (e.g., soft loans)

    b. During-disaster: Emergency WASH kits, mobile clinics, and evacuation protocols

    c. Post-disaster: Targeted relief distribution and mental health support

405   4. Community-Centric Approaches – Adopt bottom-up planning to align interventions with local needs, emphasizing food security, adaptive farming, and hygiene education

5 Conclusions

Bangladesh's pursuit of 'Vision 2041' hinges on fostering a healthy and resilient society through equitable access to healthcare

410   and robust WASH infrastructure. However, as a disaster-prone nation, Bangladesh faces significant public health risks exacerbated by floods and other hazards, necessitating a comprehensive assessment of vulnerability drivers. Achieving Vision 2041's goal of a healthy, resilient Bangladesh demands dual emphasis on prevention and response. By prioritizing inclusive policies, infrastructure hardening, and cross-sector coordination, the nation can transform vulnerability into resilience— ensuring that even the most flood-affected communities, like Tepa Kharibari, thrive despite climatic adversities. The lessons

415   here extend beyond Bangladesh, offering a blueprint for integrated disaster-health governance in vulnerable regions worldwide.

Author Contribution

Nafisa Nuari Islam: conceptualization, methodology, data curation, analysis, investigation, writing -original draft.

420 Tonoy Mahmud: methodology, data curation, investigation, writing- review, and editing.

Shamima Ferdousi Sifa: methodology, data curation, writing- review, and editing.

Md. Asif Rafsan: methodology, data curation, writing- review.

A. S. M. Maksud Kamal: supervision, resources, conceptualization.

Md. Shakhawat Hossain: supervision, resources, conceptualization.

425 Md. Zillur Rahman: supervision, resources, conceptualization, writing- editing.

Competing interests

The author(s) declare no competing interests.

430 **Data availability**

The research data can be shared upon reasonable request, subject to ethical approvals.

Ethics approval

The author ensures that the work described has been carried out following The Code of Ethics of the World Medical
435 Association (Declaration of Helsinki) for experiments involving humans. (Ref: ERC/FBST/JUST/2023-138: Faculty of
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References

445 Achanta, A., Adhikary, S., Cruz, R. V., Trick, L. J., Purohit, A. N., Soegiarto, A., Soesanto, S., & Tingsabadh, C.
(2001). The regional impacts of climate change - an assessment of vulnerability. IPCC Special Report. In R.
T. Watson, M. C. Zinyowera, R. H. Moss, & Dokken (Eds.), *"Tropical Asia."*

Acharya, A., & Silori, R. (2024). A probable framework for flood-induced risk evaluation for water supply,
sanitation and hygiene. *Water Sustainability and Hydrological Extremes: Quantity, Quality, and Security*,
450 237–253. https://doi.org/10.1016/B978-0-443-21499-8.00012-X

Afjal Hossain, M., Imran Reza, M., Rahman, S., & Kayes, I. (2011). Climate Change and its Impacts on the
Livelihoods of the Vulnerable People in the Southwestern Coastal Zone in Bangladesh. In *Climate Change
Management* (pp. 237–259). https://doi.org/10.1007/978-3-642-22266-5_15

Afshari, A., Mojahed, M., & Yusuff, R. (2010). Simple additive weighting approach to personnel selection
455 problem. *International Journal of Innovation, Management and Technology*, *1*(5), 511–515.
https://doi.org/10.7763/IJIMT.2010.V1.89

Ahern, M., Kovats, R. S., Wilkinson, P., Few, R., & Matthies, F. (2005). Global health impacts of floods: Epidemiologic evidence. *Epidemiologic Reviews*, *27*, 36–46. https://doi.org/10.1093/epirev/mxi004

Ahern, M., & Kovats, S. (2006). The health impacts of floods. In *Flood Hazards and Health: Responding to Present and Future Risks* (pp. 28–53). Taylor & Francis. https://doi.org/10.4324/9781849771351

Ahmed, A. U., & Hussain, S. G. (2009). *Climate Chnage and Livelihood: An Analysis of Agro-Ecological Zones of Bangladesh*.

Al-Hussain, S. J., Paul, S. K., & Hossain, M. N. (2021). Comparative Assessment of Vulnerability to Drought and Flood in the Lower Teesta River Basin: A SWOT Analysis. *Asian Journal of Geographical Research*, *4*(1), 20–33. https://doi.org/10.9734/ajgr/2021/v4i130124

Alam, G. M. M., Alam, K., Mushtaq, S., Khatun, M. N., & Leal Filho, W. (2018). Strategies and barriers to adaptation of hazard-prone rural households in Bangladesh. *Climate Change Management*, 11–24. https://doi.org/10.1007/978-3-319-64599-5_2

BBS. (2013). *District Statistics 2011 Nilphamari* (Issue December).

BBS. (2014). Population & Housing Census-2011. *Bangladesh Bureau of Statistics*, *2*, 163–164.

BBS. (2020). *Statistical Yearbook Bangladesh 2020* (Issue May).

Chowdhury, M. A., Sabrina, H., Zzaman, R. U., & Islam, S. L. U. (2021). Green building aspects in Bangladesh: A study based on experts opinion regarding climate change. *Environment, Development and Sustainability*, *0123456789*. https://doi.org/10.1007/s10668-021-01823-0

Chowdhury, M. N. M., & Hossain, M. M. (2019). Population Growth and Economic Development in Bangladesh: Revisited Malthus. In *American Economic & Social Review* (Vol. 5, Issue 2). https://doi.org/10.46281/aesr.v5i2.326

Du, W., Fitzgerald, G. J., Clark, M., & Hou, X. Y. (2010). Health impacts of floods. *Prehospital and Disaster Medicine*, *25*(3), 265–272. https://doi.org/10.1017/S1049023X00008141

Ferdous, J., & Mallick, D. (2019). Norms, practices, and gendered vulnerabilities in the lower Teesta basin, Bangladesh. *Environmental Development*, *31*(June 2018), 88–96. https://doi.org/10.1016/j.envdev.2018.10.003

Few, R., & Matthies, F. (2006). Flood hazards and health: responding to present and future risks. *Choice Reviews Online*, *44*(03), 44-1555-44–1555. https://doi.org/10.5860/choice.44-1555

Flores, A. B., Sullivan, J. A., Yu, Y., & Friedrich, H. K. (2024). Health Disparities in the Aftermath of Flood Events: A Review of Physical and Mental Health Outcomes with Methodological Considerations in the USA. *Current Environmental Health Reports*, *11*(2), 238–254. https://doi.org/10.1007/s40572-024-00446-7

Goodman, L. A. (1968). An elementary approach to the population projection-matrix, to the population reproductive value, and to related topics in the mathematical theory of population growth. In *Demography* (Vol. 5, Issue 1, pp. 382–409). https://doi.org/10.1007/BF03208583

Hashizume, M., Wagatsuma, Y., Faruque, A. S. G., Hayashi, T., Hunter, P. R., Armstrong, B., & Sack, D. A. (2008). Factors determining vulnerability to diarrhoea during and after severe floods in Bangladesh. *Journal of Water and Health*, *6*(3), 323–332. https://doi.org/10.2166/wh.2008.062

Islam, S. (2017). An assessment of Women Vulnerability for Flooding Hazard and Socio Economic Condition : A Case Study on Char Gonai of Tepamadhapur Union , Kaunia , Rangpur , Bangladesh. *Imp. J. Interdiscip. Res.*, *3*(4), 211–231.

Jahan, A., & Edwards, K. L. (2015). A state-of-the-art survey on the influence of normalization techniques in ranking: Improving the materials selection process in engineering design. *Materials and Design*, *65*(May 2016), 335–342. https://doi.org/10.1016/j.matdes.2014.09.022

Kara, Y. (2019). Measuring the Sustainability of Cities in Turkey with the Analytic Hierarchy Process. *Open Journal of Social Sciences*, *07*(04), 322–334. https://doi.org/10.4236/jss.2019.74025

KaTurner, A., Lyle, S., & Tong, S. (2019). Floods and human health: A systematic review. *Environment*

International, *1*(47), 37–47. https://doi.org/10.1016/j.envint.2012.06.003

Kovats, S., Ebi, K. L., & Menne, B. (2003). *Methods of assessing human health vulnerability and public health*
505   *adaptation to climate change*. *1*.

Kundzewicz, Z. W., & Takeuchi, K. (1999). Flood protection and management: Quo vadimus? *Hydrological
        Sciences Journal*, *44*(3), 417–432. https://doi.org/10.1080/02626669909492237

Kunii, O., Nakamura, S., Abdur, R., & Wakai, S. (2002). The impact on health and risk factors of the diarrhoea
        epidemics   in   the   1998   Bangladesh   floods.   *Public   Health*,   *116*(2),   68–74.
510   https://doi.org/10.1038/sj.ph.1900828

Laura Tascón-González, Montserrat Ferrer-Julià, Maurici Ruiz, & Eduardo García-Meléndez. (2020). Social
        Vulnerability Assessment for Flood. *Water*, *12*, 558.

Lee, D., Ahmadul, H., Patz, J., & Block, P. (2021). Predicting social and health vulnerability to floods in
        Bangladesh. *Natural Hazards and Earth System Sciences*, *21*(6), 1807–1823. https://doi.org/10.5194/nhess-
515   21-1807-2021

Lowe, D., Ebi, K. L., & Forsberg, B. (2013). Factors increasing vulnerability to health effects before, during and
        after floods. *International Journal of Environmental Research and Public Health*, *10*(12), 7015–7067.
        https://doi.org/10.3390/ijerph10127015

Matsuyama, A., Khan, F. A., & Khalequzzaman, M. (2020). *Bangladesh Public Health Issues and Implications to*
520   *Flood Risk Reduction*. 115–128. https://doi.org/10.1007/978-981-15-0924-7_8

Mondal, M. S. H., Murayama, T., & Nishikizawa, S. (2020). Assessing the flood risk of riverine households: A
        case study from the right bank of the Teesta River, Bangladesh. *International Journal of Disaster Risk
        Reduction*, *51*(January), 101758. https://doi.org/10.1016/j.ijdrr.2020.101758

Mondal, M. S. H., Murayama, T., & Nishikizawa, S. (2021a). Determinants of household-level coping strategies
525   and recoveries from riverine flood disasters: Empirical evidence from the right bank of teesta river,
        Bangladesh. *Climate*, *9*(1), 1–18. https://doi.org/10.3390/cli9010004

Mondal, M. S. H., Murayama, T., & Nishikizawa, S. (2021b). Examining the determinants of flood risk mitigation
        measures at the household level in Floods are the most common hazard in Bangladesh adversely affecting the
        lives and livelihoods of millions of riverine people . Flood-affected households adopt a variety. *International
530   Journal of Disaster Risk Reduction*, *64*. https://doi.org/https://doi.org/10.1016/j.ijdrr.2021.102492.

Nahar, N., Blomstedt, Y., Wu, B., Kandarina, I., Trisnantoro, L., & Kinsman, J. (2014). Increasing the provision
        of mental health care for vulnerable, disaster-affected people in Bangladesh. *BMC Public Health*, *14*(1).
        https://doi.org/10.1186/1471-2458-14-708

NAWG Bangladesh. (2020). *Monsoon Floods 2020: Coordinated Preliminary Impact and Needs Assessment* (Issue
535   July).   https://reliefweb.int/report/bangladesh/bangladesh-monsoon-floods-2020-coordinated-preliminary-
        impact-and-needs-assessment

Okaka, F. O., & Odhiambo, B. D. O. (2019a). Health vulnerability to flood-induced risks of households in flood-
        prone informal settlements in the Coastal City of Mombasa, Kenya. *Natural Hazards*, *99*(2), 1007–1029.
        https://doi.org/10.1007/s11069-019-03792-0

540 Okaka, F. O., & Odhiambo, B. D. O. (2019b). Households' perception of flood risk and health impact of exposure
        to flooding in flood-prone informal settlements in the coastal city of Mombasa. *International Journal of
        Climate Change Strategies and Management*, *11*(4), 592–606. https://doi.org/10.1108/IJCCSM-03-2018-
        0026

P. Shim, J. (1989). Bibliographical research on the Analytic Hierarchy Process (AHP). *Socio-Economic Planning
545   Sciences*, *23*(3), 161–167. https://doi.org/10.1016/0038-0121(89)90013-X

Paterson, D. L., Wright, H., & Harris, P. N. A. (2018). Health risks of flood disasters. *Clinical Infectious Diseases*,
        67(9), 1450–1454. https://doi.org/10.1093/cid/ciy227

Phung, D., Rutherford, S., Dwirahmadi, F., Chu, C., Do, C. M., Nguyen, T., & Duong, N. C. (2016). The spatial

550   distribution of vulnerability to the health impacts of flooding in the Mekong Delta, Vietnam. *International Journal of Biometeorology*, *60*(6), 857–865. https://doi.org/10.1007/s00484-015-1078-7

Rahman, M., Hiya, H., Auyon, S., & Islam, M. (2018). Exploring the status of disaster risk reduction focusing coping strategies in Rangpur division of Bangladesh. *Progressive Agriculture*, *29*(3), 195–204. https://doi.org/10.3329/pa.v29i3.40004

Rahman, R., & Salehin, M. (2013). *Flood Risks and Reduction Approaches in Bangladesh* (pp. 65–90).
555   https://doi.org/10.1007/978-4-431-54252-0_4

Ramin, B. M., & McMichael, A. J. (2009). Climate change and health in sub-Saharan Africa: a case-based perspective. *EcoHealth*, *6*(1), 52–57.

Rumpa, N. T., Real, H. R. K., & Razi, M. A. (2023). Disaster risk reduction in Bangladesh: A comparison of three major floods for assessing progress towards resilience. *International Journal of Disaster Risk Reduction*, *97*.
560   https://doi.org/10.1016/j.ijdrr.2023.104047

Saaty, T. L. (2014). Analytic Heirarchy Process. *Wiley StatsRef: Statistics Reference Online*, 1–11. https://doi.org/10.1002/9781118445112.stat05310

Saulnier, D. D., Hanson, C., Ir, P., Alvesson, H. M., & von Schreeb, J. (2018). The effect of seasonal floods on health: Analysis of six years of national health data and flood maps. *International Journal of Environmental*
565   *Research and Public Health*, *15*(4). https://doi.org/10.3390/ijerph15040665

Schwartz, B. S., Harris, J. B., Khan, A. I., LaRocque, R. C., Sack, D. A., Malek, M. A., Faruque, A. S. G., Qadri, F., Calderwood, S. B., Luby, S. P., & Ryan, E. T. (2006). Diarrheal epidemics in Dhaka, Bangladesh, during three consecutive floods: 1988, 1998, and 2004. *American Journal of Tropical Medicine and Hygiene*, *74*(6), 1067–1073. https://doi.org/10.4269/ajtmh.2006.74.1067

570 Shah, A. A., Ye, J., Shaw, R., Ullah, R., & Ali, M. (2020). Factors affecting flood-induced household vulnerability and health risks in Pakistan: The case of Khyber Pakhtunkhwa (KP) Province. *International Journal of Disaster Risk Reduction*, *42*. https://doi.org/10.1016/j.ijdrr.2019.101341

Shahid, S. (2010). Probable impacts of climate change on public health in Bangladesh. *Asia-Pacific Journal of Public Health / Asia-Pacific Academic Consortium for Public Health*, *22*(3), 310–319.
575   https://doi.org/10.1177/1010539509335499

Shimi, A. C., Parvin, G. A., Biswas, C., & Shaw, R. (2010). Impact and adaptation to flood: A focus on water supply, sanitation and health problems of rural community in Bangladesh. *Disaster Prevention and Management: An International Journal*, *19*(3), 298–313. https://doi.org/10.1108/09653561011052484

Smith, S. M. (2000). Determining Sample Size. In *Qualitative Health Research* (Vol. 10, Issue 1, pp. 3–5).
580   https://doi.org/10.1177/104973200129118183

Suhr, F., & Steinert, J. I. (2022). Epidemiology of floods in sub-Saharan Africa: a systematic review of health outcomes. *BMC Public Health*, *22*(1), 1–15. https://doi.org/10.1186/s12889-022-12584-4

WMO. (2015). Health and Sanitation Aspects of Flood Management. In *World Meteorological Organization* (Issue 23).
585   http://www.apfm.info/publications/tools/Tools_23_Health_and_Sanitation_Aspects_of_Flood_Management .pdf