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Flood risk and household losses: Empirical findings from a rural community in Khyber Pakhtunkhwa, Pakistan

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ABSTRACT

This study evaluates the effects of household-level flood risk on post-flood losses in Pakistan. Pakistan experienced devastating flooding, leading to numerous fatalities, extensive destruction of homes, and millions of displaced or otherwise affected individuals. Using survey data from households in Chitral District, we apply indicators from the literature on exposure, sensitivity, and adaptive capacity to generate actual vulnerability scores for households. We then determine household-level risk as a function of vulnerability and hazard. Finally, we employ Kruskal–Wallis one-way variance analysis to measure the association between household risk and flood impact in terms of both agricultural and non-agricultural losses. The findings indicate that loss due to floods is not a random function of nature's impact; instead, households with higher levels of risk also face higher agricultural and non-agricultural losses. These results emphasize the importance of addressing underlying risk factors to reduce household vulnerability rather than simply responding to post-crisis emergencies.

1. Introduction

Water-related disasters represent an increasingly dire global problem, posing severe economic and social threats to households, particularly in rural and low-income contexts [1,2]. During the 20-year period ending in 2015, floods and other water-related events accounted for nearly 90% of all natural disasters, affecting nearly 3.2 billion people and causing an estimated US$300 billion in economic losses [3]. The impact of flooding is only expected to worsen in the coming years, affecting up to 40% of the global population by 2050 [4].

Pakistan, the focus of this study, has faced severe flooding nearly every decade since the 1950s. Flooding has caused the deaths of hundreds of people, damaged thousands of homes, and the displacement or livelihood disruption of millions of individuals [5,6]. The country faced a series of floods in 1950, 1973, 1976, 1988, 1992, 1997, 2010, 2011, 2012, 2015, and 2022, whereas the 2010 flood was the most damaging in its history [7]. The 2010's flood spanned six months, affecting 45 out of 135 districts in the country and causing approximately 9.7 billion USD worth of damages [8]. It affected 20 million people, destroyed 1.1 million houses, and damaged 436 healthcare facilities [9]. According to UNICEF [10] reported, the floods in 2022 affected 33 million people, took more than 1700 lives, and damaged more than 2.2 million homes. Most of the water systems in the affected areas were damaged by the storms. This

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forced more than 5.4 million people, including 2.5 million children, to leave their homes. Moreover, the extreme weather continues to affect Pakistan in many ways. In April 2023, damage and deaths were caused by heavy rain in Khyber Pakhtunkhwa (KP) province. Six people died and 15 received injuries, and houses fell down [11]. In addition to destroying infrastructure and causing human and capital loss, those and other floods in Pakistan have had profound negative effects on social stability [12]. Importantly, rural communities made up of minority ethnic groups tend to be the most severely affected [5].

The adaptive capacity of ethnic communities in Pakistan to floods related disasters is limited due to households' low-risk assessments. Low-risk assessments are mainly due to a lack of early warning systems and poor awareness about risks and adaptation measures [13,14]. Such situations result in poor response to flood risks due to low preparedness and poor adaptive capacity for multi-hazard vulnerabilities. Poor adaptive capacity further escalates their vulnerabilities and damage potential to a greater extent in rural settings as compared to urban areas [15,16]. To improve preparedness of rural communities to flood hazards, more focus has been paid by many national and international agencies on building communities' risk assessments and adaptation capacities [17]. The association between risk assessment and adaptation capacity to floods is of paramount significance for developing appropriate responses to reducing households' flood vulnerability [18,19]. Therefore, understanding rural households' vulnerability to flood, risk assessments, and their adaptive capacity over time is important for building effective mitigation plans for reducing flood damages [20–22].

The three components that make up flood risk are the hazard (the potential severity and/or frequency of floods), the exposed population, and the system's vulnerability [23]; accurately estimating these factors is essential for developing effective countermeasures to mitigate risks, given the significant role of flood control in addressing adaptation needs [24]. The estimation of flood risk can provide valuable support for decision-making in both land use planning and flood area management [25]. In previous studies, the quantification of disaster risks can be categorized into two main aspects: damage to infrastructure or buildings, also referred to as "asset damage," and the loss of business opportunities resulting from business interruption [23]. The literature shows that the flood damages on macro level [4,10]. Some studies have calculated the business damages through questionnaire surveys, i.e Thieken, Bessel [26] estimated the loss to business in Germany of 2013 floods, Yang, Kajitani [27] estimated for 2000 heavy rains in Japan. However, to study the linkages between the actual risk of the community and economic losses, studies are limited [28]. Therefore, this study explores the relationship between household-level risk and post-flood losses in Pakistan.

In Pakistan's context, scholars have noted that disasters pose particularly pronounced challenges for minority ethnic communities, given that their adaptive capacity tends to be low and their risk assessments are high. High risk assessments are mainly due to a lack of early warning systems and poor awareness of disaster risks and adaptation measures [29]. These conditions tend to result in low preparedness and, thus, poor responses to disasters. Furthermore, minority ethnic communities often reside in rural environments in Pakistan, where households' vulnerabilities and damage potential following floods and other disasters tend to be much higher than in urban areas [15]. To improve the preparedness of rural communities facing potential disasters, national and international agencies have begun to focus on building communities' resilience to risk and their adaptation capacities [17]. The literature stresses that managing risk and developing adaptative capacity, in whatever form is available to community members, are of paramount significance for reducing households' vulnerability in the face of disaster [21].

This study contributes to the literature in several respects. First, we focus on variations in risk levels and losses within rural, minority communities that are generally more vulnerable to flooding. While the existing literature explores the effects of flooding on the agriculture sector [6,30–32]; in rural, non-mountainous areas [33,34]; in mountainous areas [21,35]; and in urban regions [20,36], fewer studies explicitly evaluate the impact of flooding on minority ethnic households within flood-prone areas.

Second, this study presents a hard case for identifying patterns in the association between risk levels and loss. Most households in the study area are relatively vulnerable and face high levels of risk, owing to numerous sociopolitical factors associated with their minority status. The study region is also particularly susceptible to flooding; the Provincial Disaster Management Authority (PDMA) termed the province highly exposed to flood risks in its annual report [37]. Given that both household risk and potential flood damage are high in the study area, the likelihood of finding variation that reveals patterns across households within the study area are reduced, lending greater credibility to the patterns that we do identify.

Third, this study aims to assess the actual vulnerability of households, using a set of questions that produce a composite vulnerability index. Prior studies more frequently rely on subjective weightings to assess vulnerability (see, for example, Rana and Routray [20]. In this study, we employ a vulnerability measurement based on more objective indicators rather than on the perceptions of household members. We also include multiple factors in the index for vulnerability, recognizing the complexity of the concept.

Finally, this study adds empirical evidence to support the understanding that preventative measures and policies are crucial for protecting households against natural disasters. Existing studies have recognized that understanding rural households' vulnerability, risk, and adaptive capacity over time is crucial for building effective mitigation plans to reduce flood damage [20,21]. Findings of this study further emphasize the importance of strategies that protect both agricultural and non-agricultural commodities, and that contribute to the resilience of households more generally to reduce the impact of natural disasters on people's lives and livelihoods. The study aims to assess the hazard, vulnerability, adaptive capacity, and actual risk of the households. Moreover, to link the actual risk of the households with the flood damages. Counter to the conceptualization that flood damage is an unpredictable consequence of nature that affects communities without discrimination; the study hypothesizes that communities at greater risk also suffer greater losses when floods hit.

2. Theoretical Framework

Exposure to floods, sensitivity, and household adaptive capacity are key factors that contribute to vulnerability [36]. Exposure refers to the degree to which a system, such as a household or community, is subjected to a particular hazard or stressor [14,21,36]. In the context of floods, exposure would involve the proximity and likelihood of being affected by flood events. The higher exposures lead to higher vulnerability of the households [33], illustrated in Fig. 1. Sensitivity refers to the extent to which a system or population is adversely affected by the hazard [4]. It considers the inherent characteristics, conditions, and susceptibilities that make the system more prone to suffering negative impacts from the flood [38]. This indicated that sensitivity is related to vulnerability [36]. Adaptive capacity, on the other hand, represents the ability of a system to adjust, cope with, and recover from the impacts of the hazard [19]. It encompasses various factors, including available resources, knowledge, technology, institutions, and social networks, that enable communities to respond effectively to floods and reduce their negative consequences [20,39]. The higher adaptive capacity leads to lower vulnerability of the households [21]. Once vulnerability is assessed and identified, it becomes a key determinant of the level of risk households may encounter. Higher vulnerability increases the likelihood and magnitude of potential risks and impacts [40]. Risk is a function of both the probability of a hazard occurrence and the vulnerability of the exposed system [41]. The process of risk assessment is a regular practice that involves the participation of various stakeholders. It is a comprehensive process that provides guidelines for identifying hazards and assessing vulnerabilities within a community [42]. Risk assessment aims to determine the scope and nature of potential hazards by evaluating existing vulnerabilities and capacities that pose a threat to the community [43]. This involves identifying the location, intensity, and probabilities of hazards, as well as analyzing social, physical, and economic factors [44]. In the context of households and floods, the risk faced by households is influenced by their vulnerability to flooding events. Higher vulnerability implies a greater likelihood of experiencing adverse effects and losses when a flood event occurs [23]. For example, households with limited resources, inadequate infrastructure, and low adaptive capacity are more vulnerable to flood-related risks. These households may face challenges in terms of evacuation, securing property, accessing clean water and sanitation facilities, and recovering from the damages caused by the flood [21]. Their overall risk is elevated due to their heightened vulnerability. Conversely, households with higher adaptive capacity, effective preparedness measures, and resilient infrastructure are likely to be less vulnerable and, therefore, face lower risks when confronted with flooding events and receive fewer economic losses [10].

3. Methodology

3.1. Selection of study area and sampling design

To determine the relationship between risk and flood-related losses, the study focuses on one Union Council area in Chitral District, located in the vulnerable and flood-prone province of Khyber Pakhtunkhwa [45]. In the month of July 2015, severe glacial lake outburst floods (GLOF) hit the region [46]. These floods washed away villages, roads, schools, and agricultural land, destroying standing crops extensively and thousands of homes and dozens of irrigation channels, shops, hotels, and buildings [37,47]. Communities in Chitral, comprised largely of farming families from ethnic minority groups who grow cash crops to meet their livelihood needs, have struggled to recover fully.

The province of KP was chosen purposively at the first stage of sampling, given its status as one of the most highly flood-prone provinces in Pakistan [30]. Major floods recorded in the province's history include the floods of 1976, 1982, 1988, 2005, 2006, 2007, 2010, and 2015 [46]. The historic floods of 2010 were the most catastrophic in the history of the province, with 24 of its districts badly affected [48]. In the second stage of sampling, we selected Chitral District based on the extensive impact of the 2015 floods. In addition, the Provincial District Management Authority indicates that Chitral is regularly exposed to flash flooding phenomena [46, 49–51]. The total population in the district affected by the 2015 floods was 253,321 across 200 villages [45]. In the third stage of sampling, we selected one union council (UC) among the most impacted union councils in the Chitral District, which also has a large minority ethnic community. Table 1 shows the most vulnerable areas in Chitral District, along with the water sources that contribute to water-related disasters. While Mastuj UC comprises the largest number of households, Ayun UC is home to the most diverse minority ethnic community. It also includes ample household-level variation in both risk and flood impact, despite extensive susceptibility

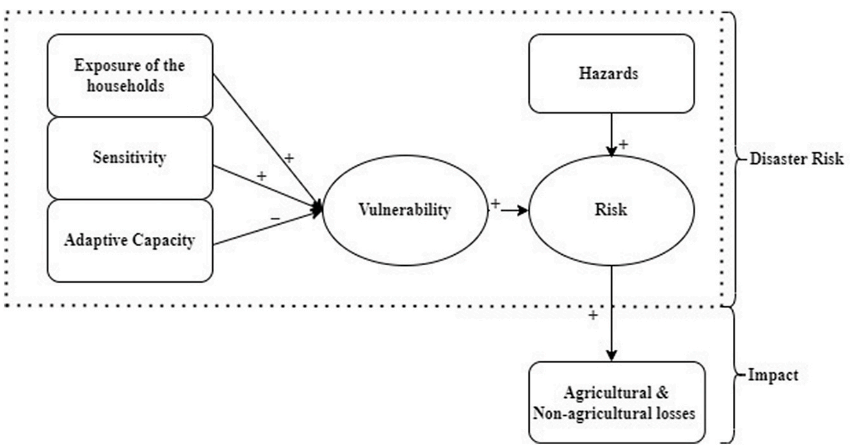

Fig. 1. Theoretical framework.

Table 1
Vulnerable Villages/UCs in district chitral.

Name of UC	Vulnerable Population (persons)	Vulnerable Household (Number)	Name of River/Stream/Nullah
Shishikoh	12511	1345	Shishikoh Nala
Mastuj	23030	2468	Risorlaspur Nala, Broke Nala, Raman Nala
Chitral 1	11282	1209	Chitral Ghol, Uchust Nala, Molen Ghol
Chitral 2	176013	18865	Jughoor Ghol, Mori Ghol, Bank Jutilast,
Ayun	17985	2398	Rumbor, Birir And Bumborate Nala, River Bank Ayun
Drosh 1,2	12500	1339	Drosh Ghol, Kaldam Ghol, Shishikoh Nala
Total	253321	27153	

Source: PDMA [37].

across the UC. Given our interest in understanding the impact of flooding on often neglected communities, we thus chose to draw the sample from Ayun.

3.2. Household selection from the most vulnerable areas

Ayun's community in the Chitral District exhibits one of the highest vulnerability rates, with 2,398 households and 17,985 individuals considered vulnerable. In Ayun, the average household size is 7.5 persons per household [52], and the minority ethnic communities in this area reside in three different valleys, Rumbor, Birir and Bumborate. These communities were purposively selected due to their high vulnerability to floods and heavy rains [45]. Data on total households was taken from 2015 PDMA's Monsoon Contingency Plan. Using Yamane [53] formula (Eq. 1) with a 5% error margin and 95% confidence interval, we targeted a sample size of 343 households, randomly selected from a total of 2,398 households.

$$n = \frac{N}{(1 + N\,e^2)} \tag{1}$$

where n is the sample size, N is the total number of vulnerable households, and e is the margin of error, set as 5% (0.05). The sample size for analysis remained 340 after removing incomplete questionnaires.

3.3. Data collection and questionnaire design

The data were collected through a structured questionnaire from May to June 2022. The intention is to empirically evaluate present-day losses as a function of the devastating floods in 2015, recognizing that households may also have incurred some loss as a result of more regular flash flooding in the interim period. Therefore, the questionnaire was designed to comprehensively cover all key questions and aspects of the study. The study was reviewed and approved by the research committee of the IMS Peshawar , Khyber Pakhtunkhwa, Pakistan. The participants provided their written informed consent to participate in this study. The questionnaire was tested on 30 households prior to data collection to remove any mistakes from its contents.

3.4. Data analysis techniques

In the literature, several methods are used to assess people's vulnerability, adaptive capacity, and risk levels. For instance, the "vulnerability curve method" can be used to investigate the relationship between flood risk and impact. This strategy is based primarily on data from well-documented case studies; hence it is often limited to households in certain well-studied locations [54]. This technique identifies component classes of objects, and each component class uses averaged data to generate step-damage curves. However, this method is less reliable than others because it cannot be easily applied to different geographic contexts, and it requires extensive time and resources, given that it is based on actual damage surveys [55]. Another method is the "disaster loss data method." This method is based on data gathered from actual flood hazards and their association to upcoming events. It is a straightforward approach, but the results tend to be somewhat inaccurate due to unevenly recorded data. Scholars thus recommend that the results be handled cautiously [55]. Furthermore, computer models can accurately assess the depth, elevation, and velocity of a flood by incorporating the frequency, size, and form of the hydrograph. One-dimensional (1D) or two-dimensional (2D) models based on the exact or approximate forms of the surface water equations can then be used to calculate flood inundation and impact [55]. For accuracy, these methods rely on comprehensive information about the topography, hydrographic, and economic data in the studied region, and the method can make information about economic loss understandable to the general population. Yet, due to insufficient data, models tend to exhibit considerable abnormalities that might impair assessment validity and confuse decision-makers [56].

The last is the "indicators-based approach." This method is designed to utilize currently available data to understand a location's vulnerability [57]. The method uses intricate indices, which may or may not be weighted, to assess vulnerability. However, the method faces significant challenges regarding standardization, weighing, and aggregation techniques [58]. The approach also entails a significant amount of uncertainty, as each layer of the assessment contains numerous variables that may be interdependent. To address this issue, researchers who employ the method suggest weighting factors to appropriately capture their influence on outcomes [21,36]. This approach is popular with policymakers because it provides a comprehensive view of a location's vulnerability, allowing them to prioritize actions and plan risk responses tailored to the particular location [55]. Considering the above methods, the indicators-based approach is most appropriate for our study's objective. We thus adopt this approach, using different indicators (mentioned in appendix A) for each of the key concepts that contribute to household-level risk (hazard, vulnerability, capacity, etc.).

Our approach is to first generate scores for the components that factor into risk. We then calculate the composite risk score for households in order to evaluate the correlation between risk and flood-related losses. Risk is defined as a function of vulnerability and hazard (see Birkmann, 2016). Vulnerability is itself determined by multiple composite factors, so we develop these indicators in what follows.

3.4.1. Vulnerability assessment

Scholars and disaster relief agencies use the concept of vulnerability to describe “the degree to which someone or something is susceptible to harm or damage from external factors or events, such as natural disasters, economic fluctuations, or social upheavals” [59]. Vulnerabilities have been studied at the local, regional, national, and international levels in the domain of hazard research, particularly with an eye toward developing mitigation measures [36]. As Shah, Ye [60] indicates, vulnerability can take on different meanings as a function of differential orientations such as spatial, political, physical, and ecological. It is a multidimensional phenomenon that can be assessed at different levels, from the international down to the household or individual.

We draw on work from Ref. [38] and numerous other studies to conceptualize vulnerability as a function of exposure, sensitivity, and capacity in the form presented in Eq. (2). Respondents were divided into four quartile categories [5,36] based on their vulnerability index score and labelled as lowest quartile, medium quartile, upper quartile, and highest quartile.This is further hypothesized that high exposure and sensitivity and low adaptive capacity lead to high vulnerability.

$$Vulnerability(V) = \frac{Exposure\ (E) \times Senstivity\ (S)}{Adaptive\ Capacity\ (C)} \tag{2}$$

i. Exposure assessment

In total, eight key indicators – including household location, household construction type, and access to any early warning information – were used in this study to determine the exposure of households to floods, using equation (3). Exposure was converted into index form and distributed into four categories, again labelled as lowest quartile, medium quartile, upper quartile, and highest quartile [36,61].

$$Exposure\ Index\ (EI) = \frac{\sum_{i=1}^{8} EW_i}{8} \tag{3}$$

where E represents Exposure, and W is the respective weight assigned.

ii. Sensitivity assessment

Another key component of the risk equation is sensitivity, which is calculated using the formula given in equation (4) below, drawing on 15 indicators to develop the composite index (see Appendix A). We categorize household sensitivity using the same quartile categories [21].

$$\text{Sensitivity Index (SI)} = \frac{\sum_{i=1}^{15} \text{SW}_\text{i}}{\text{n}} \tag{4}$$

iii. Adaptive capacity assessment

The third component of a vulnerability assessment is capacity analysis. The United Nations Development Group [62] defines adaptive capacity as a process of strengthening the abilities of societies, organizations, or individuals to achieve their own development goals using improved knowledge, skills, and resources [62]. Capacity development can involve a range of strategies and activities, including training and education, mentorship and coaching, access to resources and technology, and policy and institutional reforms [63]. The aim of adaptive capacity development is to empower individuals and communities to take control of their own development and to build resilience and sustainability in the face of economic, social, and environmental challenges. In the context of disaster risk reduction, capacity development is a critical aspect of building resilience and reducing vulnerability to natural hazards [64]. This can involve educating communities on disaster preparedness and response, building the capacity of emergency responders and local institutions, and investing in infrastructure and resources that enhance resilience and reduce risks [65]. Given the high levels of risk and the low adaptive capacity of rural and minority communities, capacity development in these environments is both critical and difficult [13]. The logic is that in building the capacity of individuals and communities to respond effectively to natural disasters, stakeholders can reduce the impact and long-term consequences of these events [65,66].For this purpose, a total of 15 indicators (Appendix A) were used to prepare a composite index using Eq. (5). Respondents were also divided into four quartile categories for adaptive capacity [61].

$$\text{Adaptive Capacity Index (ACI)} = \frac{\sum_{i=1}^{15} W_i}{15} \tag{5}$$

3.4.2. Hazard assessment

Hazard represents one of the core components of a risk assessment; it is measured directly with four indicators of flood frequency, duration, past damages, and future likelihood. Hazard – the "processes, phenomena, or human activities that have the potential to cause harm to human health and safety, the environment, or property" [59] – represents a component of risk. Hazards can be natural, such as earthquakes, floods, or hurricanes, or they can be anthropogenic, such as industrial accidents or pollution [67]. Typically, hazard is used to describe the potential impact of a disaster on a household or community. It is thus important to identify and assess hazards and hazard levels in order to take appropriate measures to reduce the risk and mitigate their potential impacts. For the hazard assessment, we followed the methodology of Ullah, Saqib [61], Shah, Shaw [65], shown in Eq. (6),

$$H = \frac{\sum_{i=1}^{4} XW_i}{n} \tag{6}$$

where X is the indicator, and W is the respective weight. The Hazard Assessment index ranges from 0 to 1. We again divided respondents into four approximately equal-sized categories, labelled as lowest quartile, medium quartile, upper quartile, and highest quartile.

3.4.3. Risk assessment

Gravley describes risk as "the probability or likelihood of a negative event occurring and the potential consequences or severity of that event" [41]. In other words, risk involves both the chance of something going wrong and the potential impact or harm that could result [61]. In this study, household-level risk represents the key factor of interest for understanding agricultural and non-agricultural losses associated with flooding. Having defined the components of vulnerability and described the measurement of hazard, we are in a position to present the equation for risk, shown in Eq. (8). Risk is the product of hazard and vulnerability, while the climate change adaptation approach defines vulnerability as a function of exposure, sensitivity, and adaptive capacity [40]. Thus,

$$\text{Risk (R)} = \text{Hazard (H)} \times \text{Vulnerability(V)} \tag{8}$$

and by substituting vulnerability from Equation (2) into Equation (8), the risk becomes a function of hazard, exposure, sensitivity, and adaptive capacity, as given in Equation (9). Households are then divided into the same four quartile categories as above. Furthermore,

Table 2
Household socioeconomic profile.

Variable	n	%
Gender		
Male	291	85.59
Female	49	14.41
Age of the household head		
<35	58	17.06
35–46	145	42.65
46–57	79	23.24
>57	58	17.06
Household Size		
Small Family (<5)	127	37.35
Medium Family (5-10)	187	55.00
Large Family (>10)	26	7.65
Family type		
Joint	225	66.20
Nuclear	115	33.80
Education		
Illiterate	106	31.18
Primary	61	17.94
Secondary	100	29.41
Higher Secondary and Above	73	21.47
Monthly income		
>40000	84	24.71
21000–40000	103	30.29
15000–21000	46	13.53
<15000	107	31.47
Employment status		
No	210	61.76
Yes	130	38.24
Occupation		
Government Service	60	17.65
Others	280	82.35
House ownership		
No	42	12.4
Yes	298	87.6

we can hypothesize that high level of hazards and high vulnerability causes high risk.

$$\text{Risk (R)} = \text{Hazard (H)} \times \frac{\text{Exposure (E)} \times \text{Senstivity (S)}}{\text{Adaptive Capacity (C)}} \tag{9}$$

3.4.4. Statistical tests

To evaluate the relationship between risk and loss, we first apply indicators from the literature on exposure, sensitivity, and adaptive capacity to generate actual vulnerability scores for households. We then determine household-level risk as a function of vulnerability and hazard. Finally, we employ Kruskal–Wallis one-way variance analysis to measure the association between household risk and flood impact, in terms of both agricultural and non-agricultural losses. The findings lend strong support to the hypothesis: households with higher levels of risk also face higher agricultural and non-agricultural losses. Regarding non-agricultural losses, high risk households experienced significantly greater losses in terms of food access and hotel-related livelihoods (in what is a prominent area for affordable local tourism). The link between risk and agricultural losses was most pronounced for pears and farm crops, though the correlation was evident across numerous agricultural commodities. We first examined household losses to check ANOVA assumptions. The assumption of normality was violated, so we employed the Kruskal–Wallis analysis, a non-parametric test that substitutes for a one-way ANOVA. We analyzed the data in SPSS-26 and presented outcomes based on four categories of risk level.

4. Results and discussion

4.1. Socioeconomic profile of the respondents

Table 2 presents the summary statistics of the independent variables used to predict household-level risk. The results reveal, first, that most households (85.59%) were male-headed, suggesting a traditional setting in which males generally represent the primary decision-makers regarding risk and adaptation responses in the study area [68]. The average age reported in the study area was 46.18 years, ranging from 25 to 85 years of age. The average household size, as mentioned, was 7.9; the smallest consisted of 2 members, whereas the largest household included 13 members. The majority of households (66.18%) included extended family members of the household head, followed by nuclear family households (28.82%) and single families (5%), respectively. These results are consistent with the findings of Shah, Ye [13] and Saqib, Ahmad [69], who demonstrate that in Khyber Pakhtunkhwa people tend to live in joint, extended family settings and to have large household sizes. A plurality of the household heads were illiterate with no formal education (31.18%), followed by those with a secondary level education (29.41%), higher secondary and above (21.47%), and primary level (17.94%). The average monthly income of households was reported to be 32,311 Pakistani Rupees (PKR), and 61.86% of household heads reported being employed in some capacity. A total of 15.59% of respondents were civil servants, and many household heads in the survey were employed in tourism-related activities. Most respondents (87.65%) owned their houses, and it was very common for families in the study to have resided in the community for long periods and to own land in the area. These results are consistent with findings from Ullah, Saqib [61] and Ullah, Jourdain [31] on rural communities, whereas families in urban areas would be more likely to have migrated there and to live in rented houses [20].

4.2. Exposure level

Before presenting the association between risk and losses, we provide descriptive statistics for each component and sub-component of risk. Table 3 shows details for exposure levels. The first column indicates the quartile, followed by the number of households in each quartile (F) and the percentage (%) of households falling within that quartile range. The last column provides descriptive statistics on the flood exposure levels for each quartile. The mean, standard deviation (SD), minimum, and maximum flood exposure levels are included in the table. The lowest quartile (<0.41) represents 25.9% of rural households in Chitral, and the mean flood exposure level for all quartiles is 0.52. The standard deviation is 0.167, indicating that household flood exposure levels are relatively consistent. The minimum flood exposure level for this quartile is 0.02, and the maximum is 0.96. This information can be useful for understanding the wide variation of flood exposure levels among rural households in Ayun and for developing strategies to mitigate the impact of floods on vulnerable communities. A study from the plain areas in Pakistan (Hamidi, Jing [70] revealed means between 0.77 and 0.94, but that study focused on households in low elevated areas. However, in our case, the study area is a mountainous zone with less exposure to water inundation. While Ullah, Saqib [61] reveal that communities in the mountainous region of Pakistan are exposed to numerous natural calamities, the flooding type varies. People living near rivers tend to be exposed to riverine flooding, while households living at higher elevations are often exposed to flash floods.

4.3. Level of sensitivity

Table 4 presents data on sensitivity, which includes factors such as access to safe drinking water, internet facilities, etc. (see

Table 3
Quartile distribution of exposure levels among rural households of Chitral.

Level	F	%	Descriptive Statistics	
Lowest quartile (<0.41)	88	25.9	Mean	0.52
Medium quartile (0.41–0.52)	85	25.0	SD	0.167
Upper quartile (0.52–0.64)	85	25.0	Minimum	0.02
Highest quartile (>0.64)	82	24.1	Maximum	0.96

Table 4
Frequency distribution of sensitivity levels among rural households of Chitral.

Level	F	%	Descriptive Statistics	
Lowest quartile (<0.27)	86	25.3	Mean	0.38
Medium quartile (0.27–0.36)	88	25.9	SD	0.15
Upper quartile (0.36–0.48)	84	24.7	Min	0.02
Highest quartile (>0.48)	82	24.1	Max	0.77

Table 5
Frequency distribution of adaptive capacity levels among rural households of Chitral.

Level	F	%	Descriptive Statistics	
Lowest quartile (<0.53)	88	25.9	Mean	0.46
Medium quartile (0.53–0.57)	84	24.7	SD	0.25
Upper quartile (0.57–0.70)	84	24.7	Minimum	0.02
Highest quartile (>0.70)	84	24.7	Maximum	0.97

Appendix A). The mean of 0.38 and standard deviation of 0.15 suggest considerable variation among households, likely owing to the fact that some households are located in remote hilly areas while other families reside in the main tourist areas. The sensitivity of households and communities largely depends on their livelihood conditions [36].

4.4. Level of adaptive capacity

Table 5 shows substantial variation across households in terms of adaptive capacity, which is determined by indicators such as education, income, access to insurance, networks outside of the home, and first aid knowledge (see Appendix A). Some studies from Pakistan suggest that the adaptive capacity of households is low because most households are involved in agriculture with limited off-farm income opportunities, skills, and access to basic amenities [30,71,72].

4.5. Level of vulnerability

Table 6 shows the frequency distribution of vulnerability levels among rural households in Chitral. The mean vulnerability level of all households is 0.39, while the standard deviation is 0.27, with notable variation from minimum to maximum. Recall that vulnerability is determined as a function of sensitivity, exposure and adaptive capacity. Ullah, Shah [21] note that most households in Chitral are in the high vulnerability range, but we stress that our study focuses on actual vulnerability. Furthermore, our distribution is quartile-based, having approximately equal numbers of households in each category, which allows us to identify patterns even if overall vulnerability levels may be relatively high compared to other contexts. Given the composite nature of the measure for vulnerability, numerous factors can affect households: those in low-lying areas are naturally more vulnerable, as are those lacking basic infrastructure [36]. Moreover, households lacking access to information on how to prepare for and respond to floods may be more vulnerable [67]. The results showed that the households were highly vulnerable due to low adaptive capacity and high exposure and sensitivity.

4.6. Hazard level

The results presented in Table 7 provide insights into the hazard assessment level for households in the study. Again, considerable variation exists. Overall, the results suggest that while many rural households may have fairly low hazard levels, some households still require attention and support in managing flood risks. Based on the hazard indicators (see Appendix A), high hazard levels may be attributed to factors such as flood frequency, long flood duration, past flood damage, and the high likelihood of future floods. The weights assigned to each indicator are based on established sources such as Cutter, Boruff [73], Kappes, Papathoma-Koehle [74], and Shah, Ajiang [29]. Ullah, Shah [21] find higher hazard levels than we find in our study, which may be a function of greater flood frequency in that study context. Nevertheless, that study also finds lower hazard levels in hilly areas [21].

4.7. Level of risk

Using the information on exposure, sensitivity, and adaptive capacity (together comprising vulnerability), along with hazard levels, we can determine household-level risk. The risk levels are categorized into four quartiles, with values ranging from 0 to 0.94 (Table 8). While we conduct our analyses based on quartiles in the data, we note that risk related to flooding is generally high among rural households in Chitral. The district is one of the more rural ones in Pakistan, with a population heavily dependent on the agricultural

Table 6
Frequency distribution of vulnerability levels among rural households of Chitral.

Level	F	%	Descriptive Statistics	
Lowest quartile (<0.18)	86	25.3	Mean	0.24
Medium quartile (0.18–0.33)	85	25.0	SD	0.19
Upper quartile (0.33–0.55)	86	25.3	Minimum	0.01
Highest quartile (>0.55)	83	24.4	Maximum	0.94

Table 7
Rural households hazard assessment.

Level	F	%	Descriptive Statistics
Lowest quartile (<0.51)	86	25.3	Mean = 0.62
Medium quartile (0.51–0.61)	91	26.8	S.D = 0.15
Upper quartile (0.61–0.74)	78	22.9	Min = 0.27
Highest quartile (>0.74)	85	25.0	Max = 1.00

Table 8
Frequency distribution of risk levels among rural households of Chitral.

Level	F	%	Descriptive Statistics	Level
Lowest quartile (<0.11)	89	26.2	Mean	0.24
Medium quartile (0.11–0.19)	86	25.3	SD	0.19
Upper quartile (0.19–0.34)	80	23.5	Minimum	0.00
Highest quartile (>0.34)	85	25.0	Maximum	0.94

sector and with limited access to government facilities. Shah, Ajiang [29] show that 66% of households perceive high risks due to flooding in rural areas in Pakistan. However, we stress that our risk levels are actual rather than perceived, and we focus on quartiles in order to illustrate correlations to loss even in an environment where most view themselves as facing high risk. Rana and Routray [20], meanwhile, argue that perceived and actual risks tend to be comparable. Another study from hilly areas conducted by Ullah, Saqib [61] shows that 50.52% of the respondents perceived a high risk due to floods in the study area. However, the Chitral district is more scattered and rural than the rest of the districts in Pakistan (Saqib, Panezai [75], so differences should be anticipated in any case. It implies that high hazards level and low adaptive capacity caused population in high risk, which is further linked with the agricultural and non-agricultural losses.

4.8. Association between risk and non-agricultural losses

With household-level risk defined, we can evaluate the association between the risk level of the households and their losses from previous floods. Table 9 begins by presenting the effects of risk on non-agricultural losses. The findings show that respondents who were at very low risk had low losses in terms of food. As the risk increases, the losses increase, with a difference that is significant at *p*-value <0.05. The floods from 2015 had manifold impacts on the households in the study area, and for high risk households, food insecurity was one of them. Reed, Anderson [76] similarly show using data from Africa, that flooding and the accompanying meteorological circumstances concurrently worsened local food security while improving it at regional geographical scales, resulting in significant changes in the results of overall food security. Likewise, Mavhura, Manyena [77] report that floods can impact food security both immediately and in the months after the flood event. In this study, the mean loss as a proportion of total assets is 0.19 for the very low-risk quartile, 0.15 for the medium-risk quartile, 0.22 for the upper-risk quartile, and 0.43 for the high-risk quartile. The *p*-value of 0.03 indicates that the relationship between food losses and risk is statistically significant. These results highlight the need to prioritize measures that reduce the vulnerability of households in the high-risk quartile, such as improving early warning systems, building flood-resistant homes, and providing access to emergency food supplies [65]. Additionally, they emphasize the importance of targeted interventions that address the specific needs and vulnerabilities of different communities, particularly those in higher-risk areas [17].

Losses in home appliances due to flooding did not differ significantly across low and high risk households. We calculated the losses in proportion to households' total assets. While Mukhtar [78] reports that recent floods in Pakistan made it difficult for many of the nation's underprivileged to start over, and while people living in high-risk areas may have lower incomes and fewer resources to invest in protecting their belongings from floods [79], we suspect that home construction does not differ significantly enough to allow for differential flood impacts on appliances within the home based on risk levels.

In the study area, tourism and hotels represent one of the main livelihood activities. Results from the hotel losses show that the respondents at very high risk had higher losses than respondents at low risk. The mean loss is 0.16 in the very low-risk quartile, 1.10 in the medium-risk quartile, 1.33 in the upper risk quartile, and 1.46 in the high-risk quartile. The results are supported by an OCHA [80] report from the same floods in Chitral. Flash floods also destroyed nine bridges and a hotel, a private institution, and a power station. Damage to hotels means that hoteliers have lost a source of revenue, and travelers are now limited in their options, a consequence that can persist for several years (Yousafzai [81].

Finally, health losses also show that low-risk respondents had fewer losses, while very high-risk households faced greater losses in terms of health, although the results do not reach conventional levels of statistical significance. The results are nevertheless important to consider from a public health standpoint since, as Mukhtar [78] reports, households in post-flood contexts often struggle to find dry patches of ground to create tarpaulin shelters and keep themselves and their remaining cattle safe, which invites a host of health risks. According to a report from OCHA (2015) following the 2015 floods, "We worry that there will be outbreaks of gastroenteritis, diarrhea, malaria, typhoid, dengue fever, scabies, and other diseases in Chitral, where it is hard to reach the people who are stuck and give them medical care." All households in the district faced these challenges, while very high-risk households may be of particular concern.

4.9. Association between risk and agricultural losses

We turn now to the correlation between household risk and agricultural losses. Table 10 shows the mean, standard deviation of the

Table 9
Non-Agricultural losses vs Risk.

Items	Lowest Risk Quartile (n = 89)		Medium Risk Quartile (n = 86)		Upper Risk Quartile (n = 80)		Highest Risk Quartile (n = 85)		*p*-value
	Mean (SD)	Mean Rank	Mean (SD)	Mean Rank	Mean (SD)	Mean Rank	Mean (SD)	Mean Rank	
a) Actual Losses									
Food Stock	24044.9 (35434.6)	145.3	36253.5 (42108.3)	174.4	46137.5 (74593.2)	186.7	34317.6 (33750.9)	177.8	0.02**
Home Appliances	16539.3 (30001.5)	177.2	22802.3 (39992.0)	180.5	25037.5 (74386.5)	167.0	16000.0 (33839.6)	156.7	0.22
Hotels	69213.5 (356549.8)	168.52	48255.8 (332764.5	164.84	90750.0 (318317.5)	178.12	133529.4 (707754.2)	171.12	0.635
Health	6224.7 (12837.9)	153.6	9360.5 (14639.1)	175.2	9787.5 (14956.2)	175.8	10705.9 (17122.7)	178.5	0.17
b) Losses as proportional to their total assets									
Food Stock	0.19	150.7	0.15	164.0	0.22	179.8	0.43	189.1	0.03**
Home Appliances	0.16	179.7	0.23	180.1	0.14	164.5	0.17	156.9	0.17
Hotels	0.16	168.7	1.10	164.7	1.33	178.2	1.46	170.9	0.29
Health	–	–	–	–	–	–	–	–	–

Note: ** = p-value$<$0.05.

actual losses incurred and the mean rank (kruskal wallis test) for different items, categorized into four quartiles of very low risk, medium risk, upper risk, and high risk. Results show that agricultural land damage increased as the risk level increased (p-value<0.05). The effects of risk are particularly pronounced for cattle loss, which is unsurprising given that many of the high risk households live in the lowlands near rivers and streams, where cattle would be most affected by flooding. Fruits represent common agriculture produce in Chitral [82], and various types of fruit loss, including grapes and apples, were made worse by household risk. Risk levels also affected the loss of agricultural products such as Chestnut and Mulberry, significant at p-value<0.05. Likewise, the monetary loss from crops was greater for high risk households, and the results were again significant at p-value<0.05. It is worth noting that the study area differs from the rest of Pakistan in its abundance of crops and both dry and fresh fruits [83]. Therefore, after flooding in Chitral District's hilly agricultural lands, farmers must spend much of their savings preparing these fields anew (Qasim et al., 2023). The findings of this study are consistent with reports of widespread damage to apple and apricot orchards as well as standing crops of wheat and barley [84]. However, we note that the crops of high risk households are particularly at risk.

Households in Chitral rely primarily on subsistence farming, livestock raising, and orchards as their primary sources of income [85]. Unfortunately, recent heavy rains and floods have caused significant damage to both agricultural and non-agricultural livelihood sources in the affected areas, leaving the population without a dependable source of food or income. The damage has not spared any household, and every household in the affected areas has suffered either from crop and orchard damage, livestock loss, or displacement [86]. Yet, those facing preexisting vulnerabilities and risks tend to be most severely affected. Overall, based on these results, stakeholders in the agriculture sector need to take measures to mitigate risks and protect vulnerable crops from potential losses, especially in the most vulnerable locations in communities [87]. This could involve implementing strategies such as crop insurance [88], diversifying crops [31], and taking measures to protect crops from weather events.

5. Conclusion

i. Summary of the key findings

Losses related to flooding constitute a critical threat across much of Pakistan. In this study, we evaluated how household-level risk may exacerbate those losses in a union council in the Chitral District of Khyber Pakhtunkhwa province. The study first underscores the importance of building on existing literature to include multiple measures of risk, as a single measure could prove misleading or too narrow. Thus, we used the accepted definition of risk as a function of hazard levels and vulnerability, which itself is determined by exposure, sensitivity, and adaptive capacity. The increased risk households face in the study area can be attributed to multiple hazards and a low adaptive capacity. The lack of inadequate infrastructure, early warning systems, and limited resources for preparedness and response, contributed to a higher level of risk. Households with higher risk levels experienced more significant losses, both in terms of agriculture and non-agriculture sectors. The vulnerabilities of these high-risk households, such as their location in flood-prone areas, limited access to protective measures, and lower socio-economic status, magnified the impact of the hazards. Results show that as the risk level increases, losses also increase, particularly in terms of food and hotels, and certain crops such as chestnut, mulberry, grapes, apples, and pears.

ii. Managerial/policy implications

The findings emphasize the importance of addressing underlying risk factors to reduce vulnerability to disasters rather than simply responding to immediate impacts. The vulnerability of households in high-risk areas can be prioritized by improving early warning systems, building flood-resistant homes, and providing access to emergency food supplies. Regarding the agricultural sector, the findings suggest that stakeholders may take measures to mitigate risks and protect vulnerable households and crops, by taking measures such as implementing crop insurance, diversifying crops, and introducing crop protection against weather events such as floods. In general, rural areas often have less developed infrastructure, such as inadequate roads, bridges, and drainage systems, which can make it more difficult for people to evacuate or access emergency services during a flood [8]. Therefore, the study suggests that policymakers should take a proactive stance in these areas, in order to reduce vulnerabilities and risk that will otherwise impose greater losses in the long run.

iii. Limitations of the study

The study is limited in the sense that it focused on a specific district in Khyber Pakhtunkhwa, Pakistan, which may not be representative of other areas in the region or country. The study also relied on self-reported data from households, which may be subject to bias or inaccuracies. The study was conducted at a single point in time and did not follow households over an extended period, which could limit a complete understanding of the effects of risk on long-term flood impacts. Finally, the study focused primarily on economic and environmental factors and did not fully consider the role of cultural and social factors in shaping vulnerability and risk in the area.

iv. Future studies' recommendations

Future studies could explore the effectiveness of various measures to reduce risk levels and the vulnerability of households to floods, such as early warning systems, flood-resistant homes, and emergency food supplies. Additionally, research could be conducted to examine the long-term impacts of floods on households and communities as a function of risk levels, including economic, social, and psychological effects. Studies could also investigate the role of government policies and interventions in mitigating the risks and reducing the impact of floods, particularly in vulnerable and marginalized areas. Finally, future research could explore the potential for

Table 10
Agricultural losses vs risk.

Items	Lowest Risk Quartile (n = 89)		Medium Risk Quartile (n = 86)		Upper Risk Quartile (n = 80)		Highest Risk Quartile (n = 85)		*p*-value
	Mean (SD)	Mean Rank	Mean (SD)	Mean Rank	Mean (SD)	Mean Rank	Mean (SD)	Mean Rank	
Agriculture Land Damages	204955.1 (432965.1)	150.4	273255.8 (497342.2)	158.8	422500.0 (631599.3)	193.3	335729.4 (516246.1)	181.9	0.04**
Cattles Loss	31460.7 (81709.68)	160.41	34883.7 (71154.3)	160.26	44557.0 (75630.6)	173.13	69186.0 (108510.9)	188.76	0.04**
Walnuts Loss	173033.7 (334736.7)	138.6	261627.9 (355765.5)	173.8	237500.0 (257360.0)	172.6	331764.7 (342856.3)	198.6	0.00***
Chestnut	10247.2 (42737.1)	161.5	42209.3 (243206.0)	160.9	55100.0 (132032.9)	181.0	78823.5 (229566.9)	179.8	0.02**
Mulberry	3089.9 (14011.1)	156.3	5755.8 (22036.3)	161.1	7312.5 (17912.3)	174.0	12117.6 (27531.1)	191.5	0.00***
Grapes	4213.5 (19304.7)	156.5	4011.6 (13213.6)	162.0	8493.8 (20549.0)	179.6	16823.5 (51268.7)	185.2	0.00***
Apples	12112.4 (32869.7)	159.9	13081.4 (34455.2)	159.5	25570.4 (46758.7)	192.8	16529.4 (33859.2)	171.8	0.00***
Pears	2730.3 (12305.5)	168.2	4209.3 (15755.6)	172.6	5937.5 (26458.6)	166.0	6658.8 (23971.0)	175.0	0.58
Apricot	6741.6 (37832.6)	161.8	5116.3 (20102.3)	165.8	9812.5 (32854.1)	177.0	19764.7 (77054.8)	178.2	0.08*
Crops	9325.8 (15670.5)	158.0	16476.7 (24954.4)	176.8	21458.2 (50815.0)	175.6	26294.1 (54194.1)	172.4	0.03**

Note: ** = p-value<0.05, and *** = p-value<0.01.

community-based disaster risk reduction and management approaches that target higher risk households within communities, perhaps by involving representatives of high-risk households in disaster preparedness and response activities.

Consent to participate

All participants' consent to participate in the study was obtained before the interview.

Consent to publish

All the participants were informed about the purpose of the study, its academic use, and its publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Indicators used in the study

Exposure Indicators

	Indicators	Classes	Weights	Source
1.	Household size	<5	0	[36,58]
		5–10	0.5	
		>10	1	
2.	Family Type	Extended	0	[36,89]
		Nuclear	0.5	
		Single	1	

(continued on next page)

(*continued*)

	Indicators	Classes	Weights	Source
3.	Deaths & injuries from the past floods	No	0	[20,90]
		Yes	1	
4.	Location of the house	Hillslope	0	[73]
		Flood Plain	0.5	
		Bank of the River	1	
5.	House/building age	<10	0	[20,91]
		10–17	.33	
		17–30	.67	
		>30	1	
6.	House construction composition	Pacca (brick/cement)	0	[20,91]
		Kacha (Adobe, mud)	1	
7.	Household level of Early warning Understanding	Very low	0	[92]
		Low	.25	
		Moderate	.5	
		High	.75	
		Very High	1	
8.	Household who received Early Warning Information in the last floods	Yes	0	[20,90]
		No	1	

Indicators Used for Assessment of Sensitivity.

S.No	Indicators	Class	Weights	Source
1.	Household Dependency Ratio (Dependent to total Household size	<0.1111	0	[89,93]
		0.1111–0.2500	.33	
		0.2500–0.6667	.67	
		>0.6667	1	
2.	Average Monthly Income of the Household	>40000	0	(Rana, 2017) (Khan, 2012)
		21000–40000	.33	
		15000–21000	.67	
		<15000	1	
3.	Household having a disability in their family members	0	0	[56,89,92]
		1	.33	
		2	.67	
		3	1	
4.	Household Head occupation	Government Service	0	[20,73]
		Transport & Commerce	0.33	
		Agriculture	0.67	
		Daily Wages/others	1.0	
5.	Number of years living in the community	>40	0	
		30–40	0.25	
		20–30	0.5	
		10–20	0.75	
		<10	1	
6.	Ownership of the house	No	1	
		Yes	0	
7.	Household distance to the nearest health facility	<1 Km	0	[20,61,94]
		1 - 10 Km	0.67	
		10- 12 Km	0.33	
		>12 Km	1	
8.	Household having access to safe drinking water	Yes	0	[61,92]
		No	1	
9.	Household having access to sanitation	Yes	0	
		No	1	
10.	Household having access to transportation	Yes	0	[21,61,89]
		No	1	
11.	Household having access to electricity	Yes	0	[21,61,89,92]
		No	1	
12.	Household having communication means (TV)	Yes	0	[21,36,58,61]
		No	1	
13.	Household having Radio	Yes	0	
		No	1	
14.	Household having mobile phones	Yes	0	
		No	1	
15.	Household having Internet	Yes	0	
		No	1	

~~Selected Indicators Used for Assessing Capacity.~~

(*continued on next page*)

(*continued*)

Selected Indicators for Capacity Assessment

Selected Indicators for Capacity Assessment
Indicators Classes Weights Source

	Indicators	Classes	Weights	Source
1)	The educational level of the household head	Illiterate	0	[36,95]
		Primary	.25	
		Secondary	.5	
		Higher Secondary and above	.75	
			1	
2)	Household have experienced floods in the past	No	0	[20,21,36,61,92,95]
		Yes	1	
3)	Household members who know about first aid	No	0	
		Yes	1	
4)	Household having any other source of income	No	0	
		Yes	1	
5)	Household having any kind of insurance	Yes	1	
		No	0	
6)	Household having any kind of savings	Yes	1	
		No	0	
7)	Household having taken a loan in the past	Yes	1	
		No	0	
8)	Household having land outside the community	No	0	
		Yes	1	
9)	Household having close relative outside the community	No	0	
		Yes	1	
10)	Household having members working outside the community	No	0	
		Yes	1	
11)	Level of community cooperation	Very poor	0	[36,89]
		Poor	.25	
		Moderate	.5	
		Good	.75	
		Very good	1	
12)	Household having knowledge of any emergency shelter in the community	No	0	[20]
		Yes	1	
13)	Household having knowledge of evacuation centre	No	0	[79]
		Yes	1	
14)	Household seek help from the government in the last 12 months	Yes	0	[36]
		No	1	
15)	The household who know about the DDMU flood awareness program in the community	No	0	
		Yes	1	

Indicators Used for Hazard Assessment.

	Indicators	Classes	Weights	Source
1)	Floods frequency	No Occurrence	0	[74,89]
		One time	.25	
		Two time	.5	
		Three times	0.75	
		Four time	1	
2)	Flood duration	No flood	0	[36,79]
		<1 day	.2	
		1–2 days	.4	
		2–4 days	.6	
		4–7 days	.8	
		>7 days	1	
3)	Past Flood damages	No Damage	0	[21,36]
		Very Low	.2	
		Low	.4	
		Moderate	.6	
		High	.8	
		Very High	1	
4)	Future flood likelihood	Nil	0	[61,79]
		Very Low	.2	
		Low	.4	
		Moderate	.6	
		High	.8	
		Very High	1	

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