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ARTICLE

Multidimensional Vulnerability Assessment of Flood-Prone Rural Communities of Pakistan

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Abstract

Rural settlements have experienced a noticeable increase in extreme weather events and associated disasters in recent years. Pakistan is consistently ranked as one of the most affected regions globally, and the catastrophic floods of 2022 further underscored its vulnerability to floods, causing unprecedented human, economic, and environmental losses. This study conducted a multidimensional vulnerability assessment of flood-prone rural areas in Dera Ismail Khan, Pakistan, using a composite index approach informed by principal component analysis (PCA). Principal component analysis was employed to assign statistically robust weights to selected indicators, ensuring an objective aggregation of vulnerability components. A questionnaire with a mix of closed-ended and open-ended items was used to collect data through a household survey. The findings revealed that a substantial proportion (40%) of respondents experienced high multidimensional vulnerability, while approximately 30% exhibited moderate vulnerability. Factors such as age distribution, household income, infrastructure quality, and risk perception significantly contributed to overall vulnerability. This study developed a scalable and replicable model for assessing rural flood vulnerability, offering practical insights for policymakers, planners, and disaster management authorities.

Keywords Developing countries · Pakistan · Principal component analysis · Rural flooding · Vulnerability

1 Introduction

Floods are among the most frequent and devastating natural hazards worldwide, causing extensive loss of life, damage to infrastructure, and disruption of livelihoods (Doocy et al. 2013; Shah et al. 2018). Climate change has further intensified their magnitude by altering rainfall patterns and accelerating glacier melt, particularly in river basins (Aslam et al. 2022; Wang et. al. 2025). These hydrological shifts make floods one of the most costly disasters globally (D'Silva et al. 2025; Waseem and Rana 2025; Zhang and Wu 2025). While the hazard itself is natural, the extent of destruction largely depends on the vulnerability of exposed communities, shaped by environmental conditions, development patterns, governance structures, and socioeconomic capacities (Khalid et al. 2021; Li et al. 2025).

Pakistan is consistently ranked among the most flood-prone countries due to its geographical setting and reliance on monsoon systems, combined with glacier-fed rivers (Ashraf et al. 2021). The catastrophic floods of 2010 affected more than 24 million people, devastated 2 million ha of cropland, and caused damages exceeding USD 10 billion (Mahmood et al. 2019). More recently, the 2022 floods displaced millions, highlighting once again the fragility of rural communities whose livelihoods and housing are closely tied to natural systems (Ndue et al. 2023). These recurrent disasters underscore the urgency of understanding not only flood hazards but also the vulnerabilities that exacerbate their impacts (Hamidi et al. 2022).

Although numerous studies have examined flood vulnerability across different contexts (Ding et al. 2016; Waseem

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and Rana 2023; Rasool et al. 2024), there is no consensus on a specific method, as each assessment is accurate within certain assumptions and defined contexts. However, dimension-based vulnerability assessment is one of the most common methods. Building on the existing literature, this study developed a comprehensive method for assessing the vulnerability of rural communities prone to fluvial and pluvial floods using principal component analysis (PCA). The insights gained from the study are critical for policymakers, development practitioners, and researchers to understand the state of vulnerability across multiple dimensions.

2 Vulnerability

The vulnerability to flooding can cause widespread devastation, the spread of waterborne illnesses, agricultural disruptions, and structural damage (Lan et al. 2022; Sarwar et al. 2024). Moreover, vulnerability is higher among children and women. The extent of connectivity significantly influences policy implementation, as the dynamics of social vulnerabilities vary across geographical locations (Gurney et al. 2017). Hence, identifying flood-prone areas is a crucial prerequisite for effectively mitigating vulnerabilities. Equally significant is assessing the community's capacity to cope with floods (Few 2003). Researchers have investigated various dimensions related to vulnerabilities, with a primary focus on the social-ecological systems (SES). Their efforts have explored diverse vulnerabilities and developed robust models to assess them across different social-ecological systems (Polsky et al. 2007).

In recent years, there has been a notable shift in focus within the scientific community from sustainability and global environmental change to vulnerabilities. The definition of vulnerability, as articulated in the Intergovernmental Panel on Climate Change (IPCC) Assessment Report, is "the degree to which a system is susceptible to, and unable to cope with, adverse effects of climate change, including climate variability and extremes" (IPCC 2007). Over the past three decades, scholars have developed a wide range of frameworks and models to conceptualize, measure, and assess vulnerability, reflecting the complexity and multidimensionality of the concept. Early contributions emphasized place-based and hazard-oriented perspectives, such as Cutter's hazards of place model (Cutter et al. 2003), which linked biophysical exposure with social conditions. Subsequent models expanded this scope by highlighting social and structural drivers of vulnerability, including the double structure of vulnerability (Bohle 2001), the pressure and release model (Wisner 2011), and Birkmann's five spheres approach (Birkmann and Wisner 2006). These foundational vulnerability frameworks shifted the focus from hazards alone to the social, institutional, and livelihood dimensions that shape community vulnerability.

Building on these foundations, other approaches have emphasized multidimensionality. The MOVE framework (Birkmann et al. 2013), the livelihood vulnerability index (Hahn et al. 2009), and subsequent multidimensional vulnerability indices represent efforts to operationalize vulnerability across social, economic, infrastructure, and attitudinal dimensions (Rana and Routray 2018; Khalid et al. 2021; Rana et al. 2023; Rasool et al. 2024). Similarly, the IPCC's vulnerability framework has been widely adopted, underscoring the dynamic interplay between exposure, sensitivity, and adaptive capacity in the context of climate change (IPCC 2022).

Despite these advances, no single framework has achieved universal acceptance, as each remains shaped by contextual assumptions, methodological choices, and data availability (Ali et al. 2024; Islam et al. 2024). As such, certain scholars emphasize the importance of attaining a comprehensive understanding of vulnerability by employing indicators to combine dimensions of vulnerability within the overarching framework (Birkmann et al. 2013; Godfrey et al. 2015). The indicator-based approach is clear, straightforward, and simple (Ciurean et al. 2013). Flood vulnerability indicators include socioeconomic and infrastructural factors (Fekete 2009; Kienberger et al. 2009; Frigerio and De Amicis 2016). The diversity of approaches highlights both the richness and the challenges of vulnerability research. On the one hand, it demonstrates the evolution from narrow, hazard-based assessments to holistic, multidimensional perspectives. On the other hand, it highlights the ongoing need for context-specific, empirically grounded methods that can effectively capture the complex vulnerabilities of flood-prone communities, such as those in Pakistan. The concept of multidimensional vulnerability encompasses various dimensions, including social, economic, infrastructure, and attitudinal factors. This research employed a conceptual framework delineating vulnerability across these dimensions, as illustrated in Fig. 1. Leveraging principal component analysis (PCA), the study constructed a comprehensive multidimensional vulnerability index tailored to flood-prone rural areas, facilitating risk assessment within these regions.

3 Principal Component Analysis

Weighting methods can be classified into three categories: (1) equivalent weighting; (2) weighting based on statistical techniques; and (3) weighting based on public or expert opinion. Equivalent weighting could be employed if all variables are considered equally significant or if no empirical or statistical evidence is available (Nardo et al. 2005). It is also the most straightforward method and is simple for others to

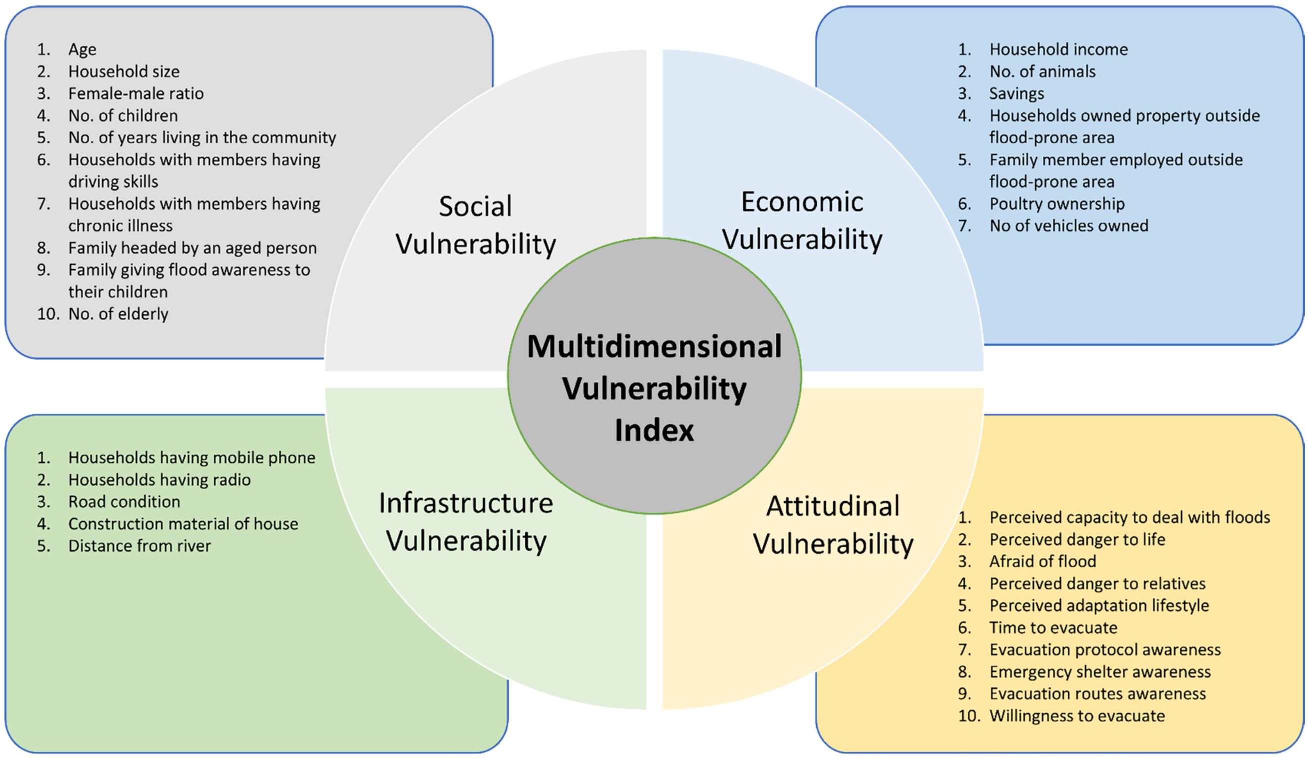

Fig. 1 A framework of multidimensional vulnerability (MDV) assessment

replicate (Lamb and Land 2013). On the other hand, with PCA, orthogonal (perpendicular) components are extracted from the correlation structure of the original dataset, with the expectation that indicators that are strongly related share underlying common variance representing latent constructs. Less informative elements are disregarded, while those that contribute the most to the variance are maintained (Smith 2002). Since these preserved factors have been rotated, only one of the new main factors is loaded with each of the original indicators. The new factors are defined by several characteristics (or components) to be used as a sub-index, including data from one or more indicators. The factor loadings, which show the proportion of the indicator's overall fluctuation that can be accounted for by the factors, may then be used to establish the relative significance of each dimension (Riedler et al. 2015; Vitunskiene and Dabkiene 2016).

Due to its empirical and data-driven characteristics, in this study PCA was selected over alternative weighting methods, including the analytic hierarchy process (AHP), equal weighting, and expert judgment. The AHP and expert-based methodologies, however beneficial, incorporate subjectivity and frequently rely on the availability and credibility of expert panels, which can differ between situations. Equal weighting assumes that all indicators have identical significance, which may not accurately represent their influence on vulnerability. Conversely, PCA establishes weights according to the variance contributed by each indicator to the dataset, which is more statistically robust and reproducible. However, a disadvantage of PCA is its susceptibility to outliers and data scaling, which was mitigated in this study using comprehensive normalization and validation protocols (Kurek et al. 2022; Ajtai et al. 2023; Wehbe and Baroud 2024).

4 Material and Methods

This section provides insight into the selected study area, sampling and data collection procedures, data transformation, indicator selection, index construction, and the analytical technique used to generate results.

4.1 Study Area

One of Khyber Pakhtunkhwa (KPK)'s largest districts is Dera Ismail Khan, situated in the southern part of the province. The area of this district is 7326 km^2. The elevation from the sea level is 178 m. Five tehsils make up the region: D.I. Khan, Daraban, Paharpur, Paroa, and Kulachi. The maps of selected tehsils are shown in Fig. 2. The overall population of District Dera Ismail Khan is 1,829,811, among which the population of rural D.I. Khan tehsil is 767,979, and the population of rural Paroa is 320,937. Rural Paharpur has 406,467 residents, rural Daraban has 149,447 residents,

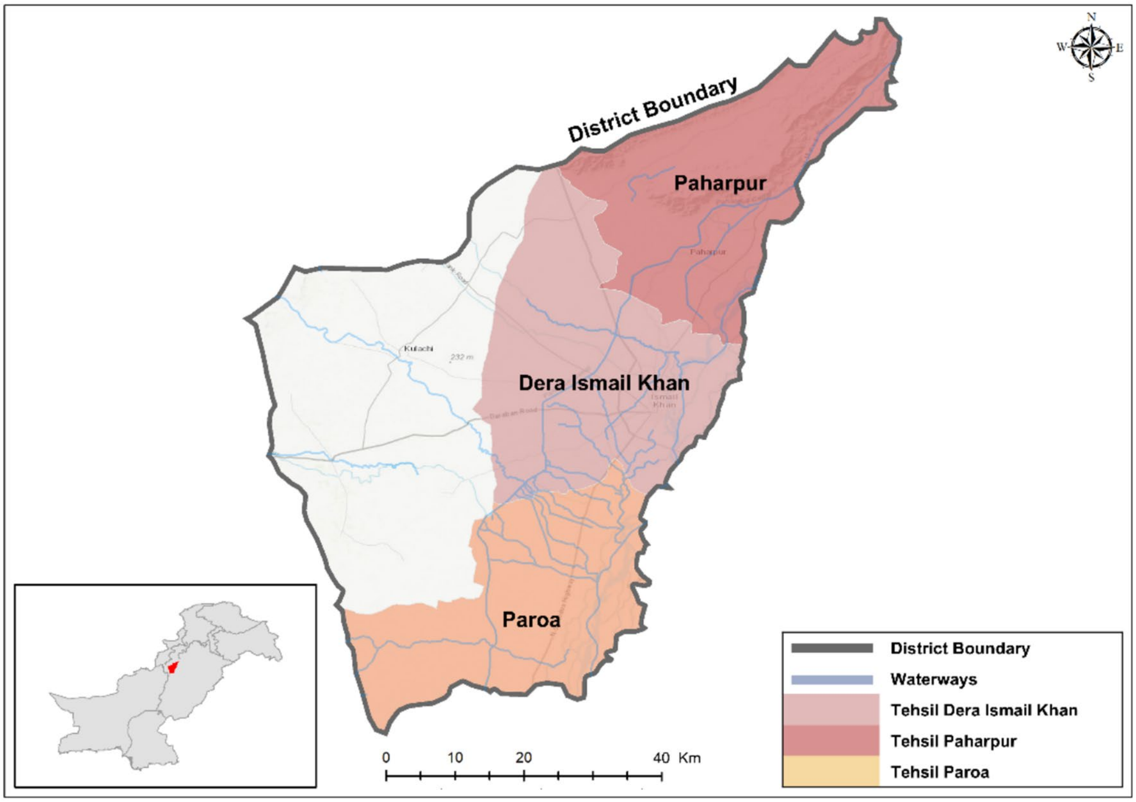

Fig. 2 Location of the study area

and rural Kulachi has 102,595 residents (PBS 2023). This region is prone to hydrological hazards, including riverine and flash floods.

4.2 Sampling and Data Collection

The data for the study were collected using a household questionnaire survey during March-April 2021. The survey was carried out by the first author through face-to-face interviews. The data were collected from the households residing in flood-prone areas of Dera Ismail Khan District, including Tehsil Dera Ismail Khan, Teshil Paharpur, and Tehsil Paroa. All ethical procedures and standards were followed. Consent forms were duly obtained from all respondents. The ethical approval was obtained from the Departmental Ethics Review Committee, School of Civil & Environmental Engineering, NUST, Islamabad. The respondents voluntarily participated in the survey. Before recording a response, the purpose of the questionnaire and academic use of the data was briefed to the respondent, and anonymity was ensured with no personal information involved. Simple random sampling was applied to collect the data.

According to the Census report, the total number of rural households in the tehsils of D.I. Khan, Paharpur, and Paroa was 57,717, 39,254, and 29,420. The minimum number of samples needed was determined by using Yamane's sampling technique (Yamane 1967; Liu et al. 2017), as shown in Eq. 1. With a 95% confidence interval, and e = 0.05, 384 samples were required. However, a total of 500 questionnaires were distributed. After scrutiny and discarding incomplete and invalid questionnaires, 465 questionnaires were collected and used for the data analysis. In D.I. Khan Tehsil, 110 responses were recorded from Mandhran and 101 from Jhok Basharat. In Paharpur Tehsil, 76 responses were recorded from Thatta Balochan and 76 from Shah Dau. Whereas, 35 responses from Chah Khan Wala, 33 from Miali, and 34 from Jhok Pechani were recorded from Paroa Tehsil.

To mitigate sample bias, measures were implemented to guarantee proportional representation of families in the most flood-affected tehsils, taking into account population size and geographic susceptibility. Nonetheless, possible constraints include the reliance on self-reported data, which may lead to recall bias or subjective interpretation of flood effects. Moreover, access to certain regions was limited by seasonal or logistical constraints, potentially excluding some of the most remote or adversely affected households. These constraints are recognized and incorporated into the analysis of results.

$$n = \frac{N}{1 + Ne^2} \quad (1)$$

where N = size of the populace, e = margin of error, n = sample taken.

4.3 Construction of an Index for Multidimensional Vulnerability

Urban flooding issues are covered by disaster risk science and climate change research, and they involve a wide range of professionals, including urban engineers, architects, ecologists, planners, and economists. The multifaceted and extensive dynamics of urban flooding necessitate a thorough vulnerability assessment that incorporates the factors influencing these complexities (Rana and Routray 2018). This study's index-based approach assessed four dimensions of vulnerability: economic, social, attitudinal, and physical/infrastructural vulnerability. The multidimensional vulnerability index was created in the following steps (Fig. 3).

4.3.1 Selection of Indicators and Data Normalization

After a thorough review of the literature, indicators were selected for each vulnerability dimension using empirical research in disaster risk science and climate change studies. The indicators were examined and modified in light of the local context (Kienberger et al. 2009; Fuchs et al. 2011; Birkmann et al. 2013; Ciurean et al. 2013; Godfrey et al. 2015) and social vulnerability (Fekete 2009; Frigerio and De Amicis 2016). The social, economic, infrastructure, and attitudinal vulnerability sub-indices were constructed using 10, 7, 5, and 10 indicators, respectively. The indicators for the diverse dimensions, classifications, and values are presented in Table 1, along with the empirical studies that used them.

The indicators have different units of measurement. Hence, normalization is required to make the data comparable (Saisana and Tarantola 2002). For any aggregate and weighting procedure, the measurement units and range determine the effective weight of the indicators. As a result, the decision regarding normalization affects the final result (Ebert and Welsch 2004). Minimum-maximum normalization, also known as rescaling, was used in this study (Eq. 2).

$$X' = \frac{x - \min_{(x)}}{\max_{(x)} - \min_{(x)}} \quad (2)$$

The normalized indicators were scaled to a standard range of 0–1 based on their degree of vulnerability, and this range was used to compute the sub-indices. Within this framework, a value of 0 represents the lowest possible vulnerability for a given indicator, and a value of 1 represents the highest. The variables were then categorized according to their characteristics. Responses were grouped into two, three, four, or five

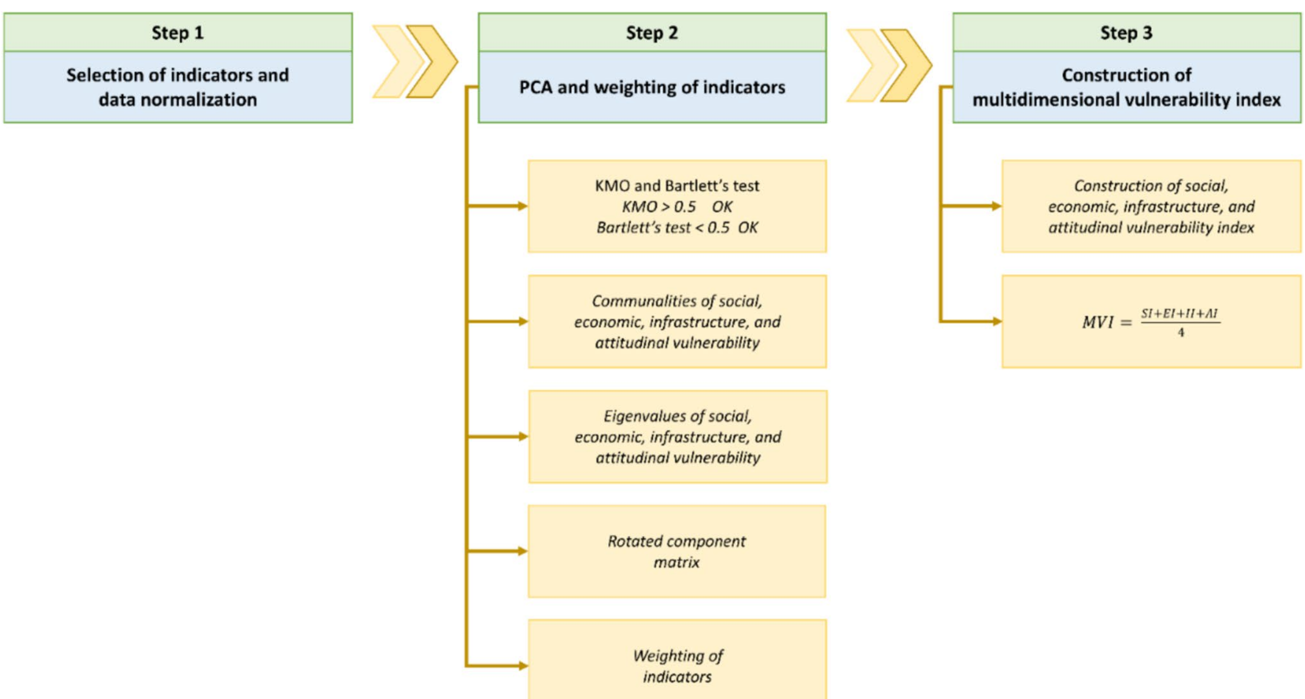

Fig. 3 Methodological framework for the development of the multidimensional vulnerability index (MVI) by principal component analysis (PCA)

Table 1 Indicators and value assignment of indicator classes

Serial No.	Indicator	Classes	Transformed values
Social vulnerability			
1	Age (AGE)	≤ 30	0.25
		31–39	0.5
		40–47	0.75
		48+	1
2	Household size (HHS)	≤ 7	0.25
		8–9	0.5
		10–12	0.75
		13+	1
3	Female-male ratio (FMR)	< 1	0.2
		1–2	0.4
		2–3	0.6
		3–4	0.8
		> 4	1
4	Number of children (NC)	≤ 2	0.25
		3–4	0.5
		5–6	0.75
		7+	1
5	Number of years living in the community (YLC)	≤ 50	1
		51–57	0.75
		58–64	0.5
		65+	0.25
6	Households with members having driving skills (DS)	= 0	1
		1–2	0.66
		3+	0.33
7	Households with members having chronic illness (CI)	Yes	1
		No	0
8	Family headed by an aged person (APH)	Yes	0
		No	1
9	Family giving flood awareness to their children (CA)	Very high	0.2
		High	0.4
		Medium	0.6
		Low	0.8
		Very low	1
10	Number of elderly persons in a household (NE)	0	0.33
		1	0.66
		2	1
Economic vulnerability			
1	Household income (HHI) in PKRs	≤ 30,000	1
		30,001–39,000	0.75
		39,001–48,000	0.5
		48,001+	0.25
2	Number of animals (NA)	≤ 5	0.25
		6–9	0.5
		10–13	0.75
		14+	1

Table 1 (continued)

Serial No.	Indicator	Classes	Transformed values
3	Savings (SV) in PKRs	≤ 1,000	1
		1,001–3,500	0.75
		3,501–6,000	0.5
		6,000+	0.25
4	Households owned property outside a flood-prone area (PO)	Yes	0
		No	1
5	Family member employed outside flood-prone area (FME)	Yes	0
		No	1
6	Poultry ownership (POUL)	≤ 5	0.25
		6–9	0.5
		10–13	0.75
		14+	1
7	Number of vehicles owned (NV)	= 0	1
		1–2	0.66
		3+	0.33
Infrastructure vulnerability			
1	Households having mobile phone (MP)	Yes	0
		No	1
2	Households having radio (RAD)	Yes	0
		No	1
3	Road condition (RC)	Excellent	0.33
		Good	0.66
		Poor	1
4	Construction material of the house (CM)	Pakka	0
		Kacha	1
5	Distance from river (DFR) in km	≤ 1	1
		2–3	0.66
		4+	0.33
Attitudinal vulnerability			
1	Perceived capacity to deal with floods (PC)	Very high	0.2
		High	0.4
		Medium	0.6
		Low	0.8
		Very low	1
2	Perceived danger to life (PDL)	Very high	0.2
		High	0.4
		Medium	0.6
		Low	0.8
		Very low	1
3	Afraid of flood (AF)	Very high	0.2
		High	0.4
		Medium	0.6
		Low	0.8
		Very low	1

Table 1 (continued)

Serial No.	Indicator	Classes	Trans-formed values
4	Perceived danger to relatives (PDR)	Very high	0.2
		High	0.4
		Medium	0.6
		Low	0.8
		Very low	1
5	Perceived adaptation lifestyle (PAL)	Very high	0.2
		High	04
		Medium	0.6
		Low	0.8
		Very low	1
6	Time to evacuate (TTE) in hours	≤ 2	0.25
		3–5	0.5
		6–8	0.75
		9+	1
7	Evacuation protocol awareness (EPA)	Very high	0.2
		High	0.4
		Medium	0.6
		Low	0.8
		Very low	1
8	Emergency shelter awareness (ESA)	Very high	0.2
		High	0.4
		Medium	0.6
		Low	0.8
		Very low	1
9	Evacuation routes awareness (ERA)	Very high	0.2
		High	0.4
		Medium	0.6
		Low	0.8
		Very low	1
10	Willingness to evacuate (WE)	Yes	0
		No	1

classes depending on the context. Binary (yes/no) indicators were assigned values of 0 and 1. Three-class indicators were given values of 0.33, 0.66, and 1; four-class indicators received values of 0.25, 0.5, 0.75, and 1; and five-class indicators were assigned values of 0.2, 0.4, 0.6, 0.8, and 1. The subsequent composite sub-indices and the overall multidimensional vulnerability index (MVI), which result from aggregating these normalized indicators, were interpreted as follows: values close to 0 indicate low vulnerability, while values close to 1 indicate severe vulnerability.

4.3.2 Principal Component Analysis and Weighting of Indicators

Principal component analysis (PCA) was conducted using SPSS. First, the association between the various indicators was examined. Principal component analysis, developed for correlations, is inappropriate if the indicators are uncorrelated. The selection of principal components with an eigenvalue of 1 or more, exclusive representation of 10% or more of the overall variation, and at least 60% of the total variance explained are standard practices (Nardo et al. 2005). A loading pattern and a more straightforward structure of the main components were produced by rotating the chosen principal components. The weights are built using Eq. 3.

$$w_{kj} = \frac{(\text{Roated factor loading}_{kj})^2}{\text{Eigenvalue}_j} \quad (3)$$

where rotational factor loading kj is the value of the loading of the indicator, eigenvalue j is the eigenvalue of the jth principal component, and k is the jth principal component.

Principal component analysis was employed in this study to reduce dimensionality and address multicollinearity among indicators, which is a common issue in vulnerability assessments that involve social, economic, and infrastructural factors. By transforming correlated variables into uncorrelated principal components, PCA enables a more objective weighing process based on statistical variance rather than arbitrary or expert judgment, thereby enhancing the reliability and consistency of the index. The use of rotation further improves interpretability, ensuring that the weight assigned to each indicator reflects the proportion of information it explains within the dataset. The PCA-based weighing method has been applied in many other contexts (Žurovec et al. 2017). This study extends its application to rural, flood-prone communities that are often underrepresented in vulnerability research. Unlike previous approaches that focus narrowly on socioeconomic or infrastructural dimensions, this study incorporates social, economic, infrastructural, and attitudinal vulnerability dimensions. It applies PCA at the sub-index level, offering a more comprehensive and nuanced understanding of vulnerability.

4.3.3 Construction of the Multidimensional Vulnerability Index

There are several methods for creating a multidimensional vulnerability index (MVI), including the gap approach, the matrix approach, the time analysis strategy, and the composite index technique (Senna et al. 2019). Due to its primary benefit of addressing the multifaceted character of vulnerability, the composite index technique was chosen for this study. This technique used the four sub-indices of social, economic, infrastructural, and attitudinal vulnerability (SI, EI, II, and AI, respectively) to construct the MVI. Weights for the indicators were assigned using PCA, and the weights were multiplied by the indicator values to form an index before being added to the other indicators to determine social, economic, infrastructural, or attitudinal vulnerability. The multidimensional vulnerability index was computed using Eq. 4 (Rana and Routray 2018).

$$\text{MVI} = \frac{\text{SI} + \text{EI} + \text{II} + \text{AI}}{4} \quad (4)$$

5 Results and Discussion

This section highlights findings extracted using the selected analytical techniques and equations to assess the vulnerability across multiple dimensions, including social, economic, institutional, and attitudinal.

5.1 Bartlett's Test and Kaiser-Meyer-Olkin Test

The sample size and the strength of correlations among variables are the two primary factors to consider when determining whether a dataset is suitable for exploratory factor analysis (EFA) (Pallant 2020). Sampling adequacy is assessed using the Kaiser-Meyer-Olkin (KMO) test (Kaiser 1970, 1974), while Bartlett's test of sphericity evaluates the strength of relationships among variables (Bartlett 1954). These tests require interval-scaled variables. A KMO value greater than 0.5 indicates that sampling adequacy is acceptable (Andy 2009).

Barlett's test, on the other hand, examines the null hypothesis that the correlation matrix is an identity matrix. A significance level below 0.05 rejects the null hypothesis, confirming sufficient correlations among variables and justifying the use of EFA (Andy 2009; Pallant 2020). Table 2 presents the results of KMO and Bartlett's tests for the four vulnerability sub-indices, including social, economic, infrastructure, and attitudinal. For all indices, the KMO values exceed 0.5, indicating adequate sampling. Similarly,

Table 2 Bartlett's test and Kaiser-Meyer-Olkin (KMO) test

Tests		Social vulnerability	Economic vulnerability	Infrastructure vulnerability	Attitudinal vulnerability
Kaiser-Meyer-Olkin measure of sampling adequacy		0.691	0.518	0.540	0.775
Bartlett's test of sphericity	Approx. Chi-square	1,167.036	368.660	356.256	3,600.191
	df	45	21	10	45
	Sig.	0.000	0.000	0.000	0.000

Barlett's test results were significant at $p < 0.05$, confirming that the data were suitable for further factor analysis.

Communality indicates the proportion of variance in each variable explained by the extracted components. In PCA, it is assumed that all variance is common and standardized to 1 before extraction. After extraction, communalities reveal how well each variable is represented by the factor solution, with values below 0.3 suggesting a poor fit (Hadi et al. 2016). For instance, the indicator households with access to a vehicle (number of vehicles owned greater than 0) has a communality of 0.459, meaning that the retained components explain 45.9% of its variance. As weaker factors are excluded during extraction and rotation, the communalities reflect only the proportion of variance accounted for by the final solution. Table 3 presents the communalities of indicators for sub-indices.

The core mathematical basis of PCA is eigenvalue decomposition, which breaks down the dataset's correlation matrix into eigenvalues and eigenvectors. An eigenvalue represents the amount of variance explained by a principal component, with larger values indicating greater importance. The corresponding eigenvector defines the direction in variable space along which the data varies most, showing how the original variables combine to form each component (Abdi and Williams 2010). Together, eigenvalues and eigenvectors provide the eigenmatrix decomposition that reveals the structure of the data. In practice, principal components are retained if their eigenvalues are at least 1 and, collectively, they explain around 60% or more of the dataset's total variance.

Table 4 presents the principal components of the social, economic, infrastructure, and attitudinal vulnerability indices. The results indicate that social vulnerability comprises four components, with eigenvalues of 2.850, 1.400, 1.219, and 1.054, accounting for 28.5%, 14.0%, 12.19%, and 10.54% of the variance, respectively. Together, these components account for 65.24% of the total variance in the social vulnerability index. Similarly, the economic, infrastructure, and attitudinal vulnerability indices consist of three, two, and three components, explaining total variances of 63.89%, 61.81%, and 71.42%, respectively.

After extracting the principal components, interpretation can be challenging because each component often represents a mixture of variables. To address this issue, varimax rotation is applied to simplify interpretation by making factor loadings

Table 3 Communalities of indicators for sub-indices

Social vulnerability		Economic vulnerability		Infrastructure vulnerability		Attitudinal vulnerability	
Indicator	Extraction	Indicator	Extraction	Indicator	Extraction	Indicator	Extraction
Age (AGE)	0.672	Household income (HHI)	0.507	Households with a mobile phone (MP)	0.590	Perceived capacity to deal with floods (PC)	0.516
Household size (HHS)	0.618	No. of animals (NA)	0.701	Households having radio (RAD)	0.523	Perceived danger to life (PDL)	0.678
Female-male ratio (FMR)	0.736	Savings (SV)	0.625	Road condition (RC)	0.775	Afraid of flood (AF)	0.801
No. of children (NC)	0.641	Households owned property outside a flood-prone area (PO)	0.586	Construction material of the house (CM)	0.393	Perceived danger to relatives (PDR)	0.856
No. of years living in the community (YLC)	0.609	Family member employed outside a flood-prone area (FME)	0.666	Distance from river (DFR)	0.810	Perceived adaptation lifestyle (PAL)	0.629
Households with members having driving skills (DS)	0.459	Poultry ownership (POUL)	0.750			Time to evacuate (TTE)	0.347
Households with members having chronic illness (CI)	0.617	No. of vehicles owned (NV)	0.637			Evacuation protocol awareness (EPA)	0.948
Family headed by an aged person (APH)	0.851					Emergency shelter awareness (ESA)	0.955
Family giving flood awareness to their children (CA)	0.528					Evacuation routes awareness (ERA)	0.950
No. of elderly (NE)	0.793					Willingness to evacuate (WE)	0.463

Table 4 Principal components (PCs) of the social, economic, infrastructure, and attitudinal vulnerability indices

Component	Eigenvalue	Percentage of variance	Cumulative percentage
Social vulnerability			
PC1	2.850	28.504	28.504
PC2	1.400	14.004	42.508
PC3	1.219	12.190	54.698
PC4	1.054	10.542	65.240
Economic vulnerability			
PC1	1.896	27.085	27.085
PC2	1.400	20.000	47.085
PC3	1.177	16.809	63.894
Infrastructure vulnerability			
PC1	1.888	37.754	37.754
PC2	1.203	24.060	61.813
Attitudinal vulnerability			
PC1	3.684	36.845	36.845
PC2	2.394	23.935	60.780
PC3	1.064	10.635	71.415

more distinct and clear. High loadings (for example, above 0.4) indicate strong relationships between variables and components. Rotation enhances interpretability by emphasizing these relationships, making it easier to identify defining variables. Without rotation, a component may show moderate loadings across many variables, which complicates labeling. With rotation, however, loadings become clearer and more polarized, allowing for straightforward interpretation (Hadi et al. 2016).

In this study, varimax rotation was applied to the components of the four vulnerability dimensions (social, economic, infrastructure, and attitudinal) to improve interpretability and derive meaningful weights for the composite vulnerability indices. The selected principal components were rotated to achieve a simpler and more precise loading pattern. Table 5 presents the PCA results after varimax rotation, with only factor loadings greater than 0.4 retained for further analysis.

The weights for each indicator were calculated based on the rotated factor loadings from Table 5 and the eigenvalues of the corresponding principal components (from Table 4), following Eq. 3. This process generated a final set of weights for each individual indicator within the four vulnerability dimensions. These weights reflect the proportion of the total variance explained by each indicator within its respective principal component structure. The resulting weights for all indicators are presented in Table 6.

The social, economic, infrastructure, and attitudinal vulnerability indices has the following composition.

$$\begin{aligned} SVI = {} & 0.4537(AGE) + 0.321(HHS) + 0.326(FMR) + 0.492(NC) + 0.362(YLC) \\ & + 0.381(DS) + 0.164(CI) + 0.289(APH) + 0.265(CA) + 0.273(NE) \end{aligned} \tag{5}$$

$$\begin{aligned} EVI = {} & 0.130(HHI) + 0.362(NA) + 0.437(SV) + 0.444(PO) \\ & + 0.480(FME) + 0.383(POUL) + 0.444(NV) \end{aligned} \tag{6}$$

$$\begin{aligned} IVI = {} & 0.466(MP) + 0.238(RAD) + 0.388(RC) \\ & + 0.313(CM) + 0.412(DFR) \end{aligned} \tag{7}$$

$$\begin{aligned} AVI = {} & 0.386(PC) + 0.254(PDL) + 0.293(AF) + 0.339(PDR) + 0.236(PAL) \\ & + 0.294(TTE) + 0.252(EPA) + 0.254(ESA) + 0.252(ERA) + 0.318(WE) \end{aligned} \tag{8}$$

The PCA-derived weights reveal the most influential indicators within each vulnerability dimension. The social vulnerability index (SVI) is primarily driven by the number of children (NC = 0.492) and age (AGE = 0.4537). The economic vulnerability index (EVI) is most influenced by having a family member employed outside the flood-prone area (FME = 0.480) and owning property outside the area (PO = 0.444). For infrastructural vulnerability (IVI), access to a mobile phone (MP = 0.466) and distance from the river (DFR = 0.412) are the key factors. The attitudinal vulnerability index (AVI) is shaped by perceived capacity to cope (PC = 0.386), perceived danger to relatives (PDR = 0.339), and willingness to evacuate (WE = 0.318). These results confirm that vulnerability is multidimensional, with social and attitudinal factors being as critical as economic and infrastructural ones. Each dimension is explored in detail in the subsequent sections.

5.2 Multidimensional Vulnerability Assessment

Following the calculation of sub-indices for each of the 465 surveyed households, the resulting vulnerability scores for each dimension and the overall multidimensional vulnerability index (MVI) were classified into discrete levels to facilitate interpretation. The classification into low, medium, high, and very high vulnerability was performed using the natural breaks (Jenks) method, which optimally arranges data by minimizing variance within classes and maximizing variance between classes. The quantitative distribution of households across these vulnerability levels is presented in Fig. 4. The detailed results for each vulnerability dimension are discussed separately in the subsequent sections.

Table 5 Rotated component matrix for social, economic, infrastructure, and attitudinal vulnerability

Indicator	Components			
	PC1	PC2	PC3	PC4
Social vulnerability				
Age (AGE)	0.035	**– 0.797**	– 0.042	0.180
Household size (HHS)	0.418	– 0.022	**0.626**	0.228
Female-male ratio (FMR)	0.362	0.266	– 0.435	**0.587**
No. of children (NC)	0.139	0.141	**0.775**	0.043
No. of years living in the community (YLC)	– 0.245	**0.712**	0.060	0.197
Households with members having driving skills (DS)	– 0.002	– 0.005	– 0.240	**-0.634**
Households with members having chronic illness (CI)	**0.685**	– 0.153	0.340	0.094
Family headed by an aged person (APH)	**-0.909**	0.090	– 0.124	0.039
Family giving flood awareness to their children (CA)	0.325	0.379	– 0.012	**-0.529**
Number of elderly (NE)	**0.883**	– 0.068	0.062	– 0.073
Economic vulnerability				
Household income (HHI)	**-0.497**	0.335	0.385	
No. of animals (NA)	**0.829**	– 0.084	0.084	
Savings (SV)	– 0.088	**0.783**	– 0.070	
Households owned property outside flood-prone area (PO)	– 0.213	0.135	**0.723**	
Family member employed outside flood-prone area (FME)	0.283	– 0.143	**0.752**	
Poultry ownership (POUL)	**0.853**	0.148	– 0.021	
No. of vehicles owned (NV)	0.079	**0.787**	0.104	
Infrastructure vulnerability				
Households having mobile phone (MP)	0.169	**0.749**		
Households having radio (RAD)	0.486	**-0.536**		
Road condition (RC)	**-0.856**	0.205		
Construction material of house (CM)	– 0.128	**0.614**		
Distance from river (DFR)	**0.883**	0.173		
Attitudinal vulnerability				
Perceived capacity to deal with floods (PC)	0.162	0.282	**0.641**	
Perceived danger to life (PDL)	– 0.028	**0.781**	– 0.258	
Afraid of flood (AF)	– 0.308	**0.838**	0.059	
Perceived danger to relatives (PDR)	– 0.198	**0.902**	0.060	
Perceived adaptation lifestyle (PAL)	0.082	**0.753**	0.234	
Time to evacuate (TTE)	0.161	0.085	**-0.560**	
Evacuation protocol awareness (EPA)	**0.965**	– 0.103	0.071	
Emergency shelter awareness (ESA)	**0.968**	– 0.112	0.077	
Evacuation routes awareness (ERA)	**0.965**	– 0.129	0.051	
Willingness to evacuate (WE)	0.351	– 0.034	**0.582**	

5.2.1 Social Vulnerability

Social vulnerability varies across locations, with the degree of connectivity directly influencing how policies are implemented (Gurney et al. 2017). In this study, the assessment is based on data from 465 surveyed households in the flood-prone rural areas of Dera Ismail Khan. The results indicate that 15.3% of these households exhibit low social vulnerability, 36.8% fall within the medium category, while 32.7% and 15.3% face high and very high vulnerability, respectively (Fig. 4). This outcome is strongly supported by the quantitative model. The social vulnerability index (SVI) reveals that the most influential drivers are the number of children (weight = 0.492) and the age of household members (weight = 0.454), confirming that dependency structure is a primary factor. This is further substantiated by the finding that limited awareness provided to children about floods and evacuation, as well as gender dynamics reflected in the male-to-female ratio, also contributed significantly to household vulnerability.

These results align with the established literature. Both children and elderly populations face significant challenges in disaster response without external assistance (Ngo 2001; Phillips and Hewett Jr 2005; Kar 2009; Smith

Table 6 Weights of the vulnerability indicators

Indicator	Components			
	PC1	PC2	PC3	PC4
Social vulnerability				
Age (AGE)	0	0.4537	0	0
Household size (HHS)	0	0	0.321	0
Female-male ratio (FMR)	0	0	0	0.326
No. of children (NC)	0	0	0.492	0
No. of years living in the community (YLC)	0	0.362	0	0
Households with members having driving skills (DS)	0	0	0	0.381
Households with members having chronic illness (CI)	0.164	0	0	0
Family headed by an aged person (APH)	0.289	0	0	0
Family giving flood awareness to their children (CA)	0	0	0	0.265
Number of elderly (NE)	0.273	0	0	0
Economic vulnerability				
Household income (HHI)	0.130	0	0	
No. of animals (NA)	0.362	0	0	
Savings (SV)	0	0.437	0	
Households owned property outside flood-prone area (PO)	0	0	0.444	
Family member employed outside flood-prone area (FME)	0	0	0.480	
Poultry ownership (POUL)	0.383	0	0	
No. of vehicles owned (NV)	0	0.444	0	
Infrastructure vulnerability				
Households having mobile phone (MP)	0	0.466		
Households having radio (RAD)	0	0.238		
Road condition (RC)	0.388	0		
Construction material of house (CM)	0	0.313		
Distance from river (DFR)	0.412	0		
Attitudinal vulnerability				
Perceived capacity to deal with floods (PC)	0	0	0.386	
Perceived danger to life (PDL)	0	0.254	0	
Afraid of flood (AF)	0	0.293	0	
Perceived danger to relatives (PDR)	0	0.339	0	
Perceived adaptation lifestyle (PAL)	0	0.236	0	
Time to evacuate (TTE)	0	0	0.294	
Evacuation protocol awareness (EPA)	0.252	0	0	
Emergency shelter awareness (ESA)	0.254	0	0	
Evacuation routes awareness (ERA)	0.252	0	0	
Willingness to evacuate (WE)	0	0	0.318	

et al. 2009). Children lacking adequate parental support are at particular risk (Fothergill 2004; Phillips and Hewett Jr 2005), and disasters can impose long-lasting psychological and physical impacts on them (Kar 2009). Elderly individuals often face limited access to resources, heightened health issues, and extended recovery periods (Ngo 2001), with many showing reluctance to evacuate, compounding their vulnerability. Within social vulnerability, age and the presence of dependent children emerged as the most critical indicators. Households with multiple children and older adults were found to be more vulnerable due to dependency, limited mobility, and slower response capacity, a finding supported by prior research showing that natural hazards disproportionately affect older adults (Schmidtlein et al. 2008).

5.2.2 Economic Vulnerability

The results of index construction, based on data from the 465 surveyed households, show that 18.9% experience low economic vulnerability, 26.5% have moderate vulnerability, while 37.8% and 16.8% fall into the high and

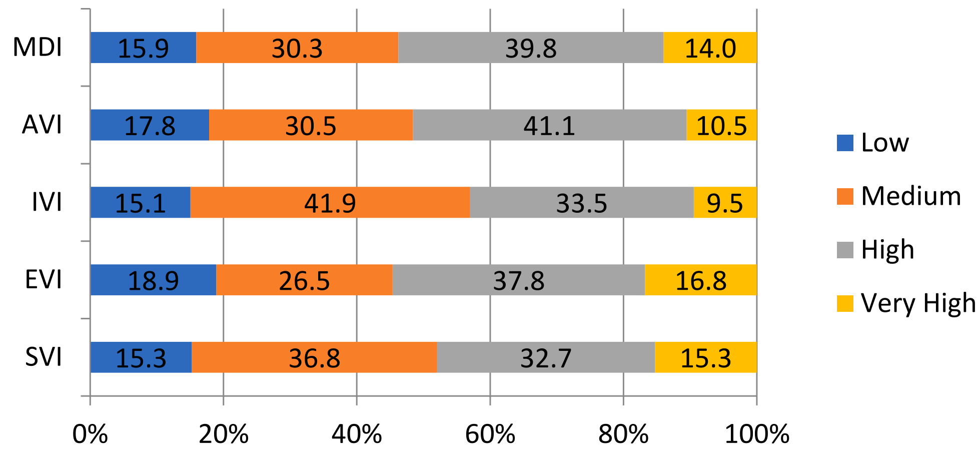

Fig. 4 Multidimensional vulnerability assessment results. *MDI* Multidimensional vulnerability index, *AVI* Attitudinal vulnerability index, *IVI* Infrastructural vulnerability index (IVI), *EVI* Economic vulnerability index, *SVI* Social vulnerability index

very high vulnerability categories, respectively (Fig. 4). This distribution is strongly supported by the economic vulnerability index (EVI), where limited income and lack of financial reserves were confirmed as key drivers of vulnerability. The quantitative analysis specifically identifies the most influential indicators through their PCA weights. Households with family members employed outside flood-prone areas (weight = 0.480) and those owning property outside these areas (weight = 0.444) had the most substantial impact on economic vulnerability. These results validate that while ownership of property outside the flood zone may provide some security, it can also create a false sense of protection, leading to under-preparedness. Similarly, households reliant on members working outside flood-prone areas are particularly exposed to disaster consequences, as dependence on external income reduces capacity for independent and timely decisions. The presence or absence of other economic buffers, such as savings (weight = 0.437) and vehicle ownership (weight = 0.444), further differentiates vulnerability levels. This combination of financial insecurity, external dependence, and risk misperception, as quantified by the EVI model, underscores the complex drivers of economic vulnerability in rural flood-prone communities.

5.2.3 Infrastructure Vulnerability

The results of the infrastructure vulnerability index (IVI), calculated for the 465 surveyed households, indicate that 15.1% experience low vulnerability, primarily attributed to access to mobile phones. While mobile phones are integral to daily life, their importance becomes more pronounced during floods for receiving warnings and communication. The survey revealed that 41.9% of households face a moderate level of infrastructural vulnerability, while 33.5% experience high vulnerability. This is primarily linked to the use of substandard building materials for houses and roads, as confirmed by the quantitative model where construction material (weight = 0.313) and road condition (weight = 0.388) were significant indicators. Economic constraints further exacerbate housing quality issues, while limited access to communication tools contributes to heightened vulnerability. Consequently, 9.5% of households fall into the very high vulnerability category.

The PCA weighting confirms that access to mobile phones (weight = 0.466) and distance from rivers (weight = 0.412) exert the strongest influence on infrastructural vulnerability. This statistical finding validates the field observations that many households resided in poorly constructed homes built with inferior materials, often situated dangerously close to rivers. The critical role of mobile phones is demonstrated by their dual impact: households with access experience lower vulnerability, while those without face significantly higher vulnerability due to restricted dissemination of early warnings and reduced disaster preparedness. Additionally, inadequate road infrastructure, reflected in its substantial weight, severely hampered evacuation efforts, particularly in the most flood-affected areas.

5.2.4 Attitudinal Vulnerability

Attitudinal vulnerability plays a critical role in shaping disaster outcomes. The results from the attitudinal vulnerability index (AVI), calculated for the 465 surveyed households, show that 17.8% exhibit low attitudinal vulnerability, 30.5% face a medium level of vulnerability, and 41.1% fall into the high vulnerability category. An additional 10.5% demonstrate very high attitudinal vulnerability (Fig. 4). These outcomes are strongly supported by the quantitative AVI model, which reveals that limited awareness and perceptions are driven by specific weighted indicators. The analysis confirms that perceived capacity to cope (weight = 0.386), perceived danger to relatives (weight = 0.339), and willingness to evacuate (weight = 0.318) collectively exert the strongest influence on attitudinal vulnerability. These three indicators substantially outweigh other variables in the model, validating that diminished perceptions of personal coping ability, safety concerns for family members, and reluctance to evacuate are the primary drivers of high attitudinal vulnerability in the study area.

The study highlighted the role of individual perceptions in shaping disaster vulnerability. Many respondents expressed low confidence in their ability to respond effectively and demonstrated limited knowledge of evacuation procedures, emergency shelters, and official guidance. This lack of preparedness was often compounded by fatalistic attitudes, emotional attachment to property, and reluctance to evacuate due to skepticism about the severity of the flood.

Reducing attitudinal vulnerability requires targeted interventions by authorities, nongovernmental organizations, and civil society. Seminars, community drills, and awareness campaigns can play a pivotal role in enhancing preparedness. In addition, participatory risk and needs assessment at the community level has proven effective in fostering engagement and building resilience. However, the study revealed that awareness of such initiatives remains minimal in the surveyed areas, underscoring the urgent need for systematic outreach and education.

5.2.5 Multidimensional Vulnerability

This article argues that vulnerability of rural communities to floods and related hazards should not be understood as a singular concept but rather as the outcome of multiple interrelated social, economic, infrastructure, and attitudinal dimensions. These elements of vulnerability can be assessed collectively within an integrated framework. Social vulnerability, for instance, is closely tied to the limited capacity of groups or communities to cope with and recover from disasters. Disadvantaged segments of society are typically more susceptible to floods and other environmental risks (Rehman et al. 2019). Earlier work by Kumpulainen (2006) emphasized the need to expand the understanding of flood vulnerability in relation to natural hazards. In this study, indicators were compiled based on their significance to construct vulnerability maps that highlight regions most exposed to flood hazards. By identifying four distinct dimensions of vulnerability and examining the factors shaping each, this research demonstrated that a multidimensional approach provides a deeper and more comprehensive understanding of flood vulnerability. Such an approach also offers robust evidence for designing and implementing effective flood prevention and mitigation policies.

The case study of Dera Ismail Khan District illustrated these dynamics clearly. The results from the 465 surveyed households reveal that approximately 15.9% experience low multidimensional vulnerability, 30.3% medium, while 39.8% and 14.0% face high and very high levels of vulnerability, respectively (Fig. 4). The vulnerability patterns presented in Fig. 4 further underscore the significance of each dimension, showing distinct distributions for social, economic, infrastructural, and attitudinal vulnerabilities. Critically, the aggregated MVI reveals that a substantial majority of the community (54%) faces high to very high levels of overall vulnerability, highlighting the severe and widespread nature of the risk.

These findings emphasize the importance of strengthening awareness programs and developing effective risk communication strategies to enhance community understanding of flood hazards. Equally crucial is the active participation of local institutions and communities in disaster risk reduction initiatives. Taken together, the results underscore the necessity for comprehensive, multidimensional approaches to address the complex drivers of flood vulnerability in rural areas.

6 Conclusion

This study proposed a multidimensional framework for assessing rural vulnerability to floods, rather than treating vulnerability as a separate entity independent of economic, social, physical/infrastructural, behavioral, and institutional aspects. It provides a precise and practical method for measuring the various dimensions and overall magnitude of vulnerability. Regardless of their expertise, disaster risk experts may apply this basic, quick, and straightforward method. This model helps identify the most vulnerable residents and the dimensions that make them vulnerable. The normalized value of each indicator, along with its PCA-derived weight, helps pinpoint the underlying causes of vulnerability for a given household or community. This will help local organizations create awareness campaigns, recovery plans, and emergency and disaster risk reduction methods tailored to each vulnerability. This adaptable model may be applied at various urban or rural geographic scales by utilizing a customized sample design. Additional indicators may be included or excluded from the vulnerability dimensions, depending on data availability, to enhance and better represent local requirements. This approach can be enhanced by integrating statistical prototypes of weight assignments that may vary across different spatial scales.

This study, while comprehensive, has several limitations that should be acknowledged. The data collection relied heavily on self-reported responses. While principal component analysis offers a statistically robust method for weighting indicators, it is sensitive to outliers and assumes linear relationships, which may oversimplify complex social dynamics. The interpretation of components and rotated loadings can also be subjective, potentially affecting the consistency of variable classification. The cross-sectional nature of the data limits the ability to capture temporal changes in vulnerability, underscoring the need for longitudinal studies to assess evolving vulnerability patterns over time. Lastly, this study does not develop vulnerability maps. Future studies can conduct extensive vulnerability mapping to provide a more comparative visualization of vulnerability. To reduce multidimensional flood vulnerability in rural Dera Ismail Khan District, interventions should prioritize improving social awareness, economic resilience, infrastructure, and attitudinal preparedness. Awareness programs targeting child and elderly protection, evacuation protocols, and early warning systems should be expanded. Economically, households must be supported through income diversification, financial literacy, and access to savings and credit, particularly for families relying on off-site income. Infrastructure investments should focus on improving housing quality, road connectivity, and access to communication. Attitudinal change can be done through regular drills, participatory risk assessments, and community education.

References

Abdi, H., and L.J. Williams. 2010. Principal component analysis. *Wiley Interdisciplinary Reviews: Computational Statistics* 2(4): 433–459.

Ajtai, I., H. Ştefănie, C. Maloş, C. Botezan, A. Radovici, M. Bizău-Cârstea, and C. Baciu. 2023. Mapping social vulnerability to floods. A comprehensive framework using a vulnerability index approach and PCA analysis. *Ecological Indicators* 154: Article 110838.

Ali, A., W. Ullah, U.A. Khan, S. Ullah, A. Ali, M.A. Jan, A.S. Bhatti, and Q. Jan. 2024. Assessment of multi-components and sectoral vulnerability to urban floods in Peshawar – Pakistan. *Natural Hazards Research* 4(3): 507–519.

Andy, F. 2009. *Discovering statistics using SPSS*. London: SAGE.

Ashraf, A., M.B. Iqbal, N. Mustafa, R. Naz, and B. Ahmad. 2021. Prevalent risk of glacial lake outburst flood hazard in the Hindu Kush-Karakoram-Himalaya region of Pakistan. *Environmental Earth Sciences* 80(12). https://doi.org/10.1007/s12665-021-09740-1.

Aslam, A.B., I.A. Rana, S.S. Shah, and G. Mohuddin. 2022. Climate change and glacial lake outburst flood (GLOF) risk perceptions: An empirical study of Ghizer District, Gilgit-Baltistan Pakistan. *International Journal of Disaster Risk Reduction* 83: Article 103392.

Bartlett, M.S. 1954. A note on the multiplying factors for various χ 2 approximations. *Journal of the Royal Statistical Society: Series B (Methodological)* 6(2): 296–298.

Birkmann, J., and B. Wisner. 2006. Measuring the un-measurable: The challenge of vulnerability. Bonn: United Nations University Institute for Environmentand Human Security (UNU-EHS).

Birkmann, J., O.D. Cardona, M.L. Carreño, A.H. Barbat, M. Pelling, S. Schneiderbauer, S. Kienberger, and M. Keiler et al. 2013. Framing vulnerability, risk and societal responses: The MOVE framework. *Natural Hazards* 67(2): 193–211.

Bohle, H.G. 2001. Vulnerability and criticallity: Perspectives from social geography. Newsletter of the International Human Dimensions Programme on Global Environmental Change, 2/01.

Ciurean, R.L., D. Schröter, and T. Glade. 2013. Conceptual frameworks of vulnerability assessments for natural hazards reduction. In *Approaches to disaster management – Examining the implications of hazards, emergencies and disasters*, ed. J.P. Tiefenbacher. London: IntechOpen Limited.

Cutter, S.L., B.J. Boruff, and W.L. Shirley. 2003. Social vulnerability to environmental hazards. *Social Science Quarterly* 84(2): 242–261.

Ding, T., L. Liang, M. Yang, and H. Wu. 2016. Multiple attribute decision making based on cross-evaluation with uncertain decision parameters. *Mathematical Problems in Engineering*. https://doi.org/10.1155/2016/4313247.

D'Silva, S., B.P. Mathew, V.K. Vijesh, A. Bhadran, D. Girishbai, and G. Gopinath. 2025. Geomorphic evolution of a tropical river basin in the Deccan Volcanic Province: A critical water supply source to Mumbai Metropolitan Region (MMR), India. *Geology, Ecology, and Landscapes* 9(3): 988–999.

Doocy, S., E. Leidman, T. Aung, and T. Kirsch. 2013. Household economic and food security after the 2010 Pakistan floods. *Food and Nutrition Bulletin* 34(1): 95–103.

Ebert, U., and H. Welsch. 2004. Meaningful environmental indices: A social choice approach. *Journal of Environmental Economics and Management* 47(2): 270–283.

Fekete, A. 2009. Validation of a social vulnerability index in context to river-floods in Germany. *Natural Hazards and Earth System Sciences* 9(2): 393–403.

Few, R. 2003. Flooding, vulnerability and coping strategies: Local responses to a global threat. *Progress in Development Studies* 3(1): 43–58.

Fothergill, A. 2004. *Heads above water: Gender, class, and family in the Grand Forks flood*. Albany, NY: State University of New York Press.

Frigerio, I., and M. De Amicis. 2016. Mapping social vulnerability to natural hazards in Italy: A suitable tool for risk mitigation strategies. *Environmental Science & Policy* 63: 187–196.

Fuchs, S., C. Kuhlicke, and V. Meyer. 2011. Vulnerability to natural hazards?. *The challenge of integration. Natural Hazards* 58(2): 621–840.

Godfrey, A., R. Ciurean, C. Van Westen, N. Kingma, and T. Glade. 2015. Assessing vulnerability of buildings to hydro-meteorological hazards using an expert based approach – An application in Nehoiu Valley, Romania. *International Journal of Disaster Risk Reduction* 13: 229–241.

Gurney, G.G., J. Blythe, H. Adams, W.N. Adger, M. Curnock, L. Faulkner, T. James, and N.A. Marshall. 2017. Redefining community based on place attachment in a connected world. *Proceedings of the National Academy of Sciences* 114(38): 10077–10082.

Hadi, N.U., N. Abdullah, and I. Sentosa. 2016. An easy approach to exploratory factor analysis: Marketing perspective. *Journal of Educational and Social Research* 6(1): Article 215.

Hahn, M.B., A.M. Riederer, and S.O. Foster. 2009. The livelihood vulnerability index: A pragmatic approach to assessing risks from climate variability and change – A case study in Mozambique. *Global Environmental Change* 19(1): 74–88.

Hamidi, A.R., L. Jing, M. Shahab, K. Azam, M.A.U.R. Tariq, and A.W.M. Ng. 2022. Flood exposure and social vulnerability analysis in rural areas of developing countries: An empirical study of Charsadda District, Pakistan. *Water* 14(7): Article 1176.

IPCC (Intergovernmental Panel on Climate Change). 2007. AR4 climate change 2007: Synthesis report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Geneva: IPCC.

IPCC (Intergovernmental Panel on Climate Change). 2022. Climate change 2022: Impacts, adaptation, and vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, UK: Cambridge University Press.

Islam, M.B., T. Sultana, I.A. Rana, H.B. Waseem, P. Murray-Tuite, T. Tingsanchali, and M. Mahfuz. 2024. Assessing the vulnerability of selected coastal informal settlements to floods in the Old Brahmaputra River floodplain, Bangladesh. *Urban Climate* 56: Article 102078.

Kaiser, H.F. 1970. A second generation little jiffy. *Psychometrika* 35: 401–415.

Kaiser, H.F. 1974. An index of factorial simplicity. *Psychometrika* 39(1): 31–36.

Kar, N. 2009. Psychological impact of disasters on children: Review of assessment and interventions. *World Journal of Pediatrics* 5: 5–11.

Khalid, Z., X. Meng, I.A. Rana, M. u. Rehman, and X. Su. 2021. Holistic multidimensional vulnerability assessment: An empirical investigation on rural communities of the Hindu Kush Himalayan region, northern Pakistan. *International Journal of Disaster Risk Reduction* 62: Article 102413.

Kienberger, S., S. Lang, and P. Zeil. 2009. Spatial vulnerability units – Expert-based spatial modelling of socio-economic vulnerability in the Salzach catchment, Austria. *Natural Hazards and Earth System Sciences* 9(3): 767–778.

Kumpulainen, S. 2006. Vulnerability concepts in hazard and risk assessment. *Special Paper-Geological Survey of Finland* 42: Article 65.

Kurek, K.A., W. Heijman, J. van Ophem, S. Gędek, and J. Strojny. 2022. Measuring local competitiveness: Comparing and integrating two methods PCA and AHP. *Quality & Quantity* 56(3): 1371–1389.

Lamb, V.L., and K.C. Land. 2013. Methodologies used in the construction of composite child well-being indices. In *Handbook of child well-being: Theories, methods and policies in global perspective*, ed. A. Ben-Arieh, F. Casas, I. Frønes, and J.E. Korbin, 2739–2755. Dordrecht: Springer.

Lan, T., Y. Hu, L. Cheng, L. Chen, X. Guan, Y. Yang, Y. Guo, and J. Pan. 2022. Floods and diarrheal morbidity: Evidence on the relationship, effect modifiers, and attributable risk from Sichuan Province, China. *Journal of Global Health* 12: Article 11007.

Li, R., G. Zhu, S. Lu, G. Meng, L. Chen, Y. Wang, E. Huang, Y. Jiao, and Q. Wang. 2025. Effects of cascade hydropower stations on hydrologic cycle in Xiying River basin, a runoff in Qilian Mountain. *Journal of Hydrology* 646: Article 132342.

Liu, D.L., Y. Li, S. Fang, and Y. Zhang. 2017. Influencing factors for emergency evacuation capability of rural households to flood hazards in western mountainous regions of Henan Province, China. *International Journal of Disaster Risk Reduction* 21: 187–195.

Mahmood, S., A.-u. Rahman, and A. Sajjad. 2019. Assessment of 2010 flood disaster causes and damages in district Muzaffargarh, Central Indus Basin, Pakistan. *Environmental Earth Sciences* 78(3): Article 63.

Nardo, M., M. Saisana, A. Saltelli, and S. Tarantola. 2005. Tools for composite indicators building. Ispra. Italy: European Comission.

Ndue, K., M.M. Baylie, and P. Goda. 2023. Determinants of rural households' intensity of flood adaptation in the Fogera Rice Plain, Ethiopia: Evidence from generalised Poisson regression. *Sustainability* 15(14): Article 11025.

Ngo, E.B. 2001. When disasters and age collide: Reviewing vulnerability of the elderly. *Natural Hazards Review* 2(2): 80–89.

Pallant, J. 2020. *SPSS survival manual: A step by step guide to data analysis using IBM SPSS*. New York: Routledge.

PBS (Pakistan Bureau of Statistics). 2023. *7th population and housing census – 2023*. Government of Pakistan.

Phillips, B.D., and P.L. Hewett Jr. 2005. Home alone: Disasters, mass emergencies, and children in self-care. *Journal of Emergency Management* 3(2): 31–35.

Polsky, C., R. Neff, and B. Yarnal. 2007. Building comparable global change vulnerability assessments: The vulnerability scoping diagram. *Global Environmental Change* 17(3–4): 472–485.

Rana, I.A., and J.K. Routray. 2018. Multidimensional model for vulnerability assessment of urban flooding: An empirical study in Pakistan. *International Journal of Disaster Risk Science* 9(3): 359–375.

Rana, I.A., M.M. Khan, R.H. Lodhi, S. Altaf, A. Nawaz, and F.A. Najam. 2023. Multidimensional poverty vis-à-vis climate change vulnerability: Empirical evidence from flood-prone rural communities of Charsadda and Nowshera Districts in Pakistan. *World Development Sustainability* 2: Article 100064.

Rasool, S., I.A. Rana, and H.B. Waseem. 2024. Assessing multidimensional vulnerability of rural areas to flooding: An index-based approach. *International Journal of Disaster Risk Science* 15(1): 88–106.

Rehman, S., M. Sahana, H. Hong, H. Sajjad, and B.B. Ahmed. 2019. A systematic review on approaches and methods used for flood vulnerability assessment: Framework for future research. *Natural Hazards* 96: 975–998.

Riedler, B., L. Pernkopf, T. Strasser, S. Lang, and G. Smith. 2015. A composite indicator for assessing habitat quality of riparian forests derived from Earth observation data. *International Journal of Applied Earth Observation and Geoinformation* 37: 114–123.

Saisana, M., and S. Tarantola. 2002. State-of-the-art report on current methodologies and practices for composite indicator development. Ispra, Italy: Joint Research Center, European Commission.

Sarwar, A., M. Ali, M. Israr, S. Gulzar, M.I. Khan, M.A.S. Ali, A. Majid, and S. Rukh. 2024. Mapping annual soil loss in the southeast of Peshawar Basin, Pakistan, using RUSLE model with geospatial approach. *Geology, Ecology, and Landscapes* 9(3): 1102–1113.

Schmidtlein, M.C., R.C. Deutsch, W.W. Piegorsch, and S.L. Cutter. 2008. A sensitivity analysis of the social vulnerability index. *Risk Analysis* 28(4): 1099–1114.

Senna, L.D.d., A.G. Maia, and J.D.F.d. Medeiros. 2019. The use of principal component analysis for the construction of the water poverty index. *Brazilian Journal of Water Resources* 24: Article e19.

Shah, A.A., J. Ye, M. Abid, J. Khan, and S.M. Amir. 2018. Flood hazards: Household vulnerability and resilience in disaster-prone districts of Khyber Pakhtunkhwa Province. *Pakistan. Natural Hazards* 93(1): 147–165.

Smith, L.I. 2002. A tutorial on principal components analysis. arXiv: 1404.1100v1.

Smith, S.M., M.J. Tremethick, P. Johnson, and J. Gorski. 2009. Disaster planning and response: Considering the needs of the frail elderly. *International Journal of Emergency Management* 6(1): 1–13.

Vitunskiene, V., and V. Dabkiene. 2016. Framework for assessing the farm relative sustainability: A Lithuanian case study. *Agricultural Economics* 62(3): 134–148.

Wang, Q., Y. Liu, G. Zhu, S. Lu, L. Chen, Y. Jiao, W. Li, W. Li, and Y. Wang. 2025. Regional differences in the effects of atmospheric moisture residence time on precipitation isotopes over Eurasia. *Atmospheric Research* 314: Article 107813.

Waseem, H.B., and I.A. Rana. 2023. Floods in Pakistan: A state-of-the-art review. *Natural Hazards Research* 3(3): 359–373.

Waseem, H.B., and I.A. Rana. 2025. A meta-review of disaster research. *Natural Hazards* 121: 12427–12460.

Wehbe, C., and H. Baroud. 2024. Limitations and considerations of using composite indicators to measure vulnerability to natural hazards. *Scientific Reports* 14(1): Article 19333.

Wisner, B. 2011. Are we there yet? Reflections on integrated disaster risk management after ten years. *Journal of Integrated Disaster Risk Management* 1(1): 1–14.

Yamane, T. 1967. *Statistics: An introductory analysis*, 2nd edn. New York: Harper and Row.

Zhang, Y., and X. Wu. 2025. Global space-time patterns of sub-daily extreme precipitation and its relationship with temperature and wind speed. *Environmental Research Letters* 20: Article 085009.

Žurovec, O., S. Čadro, and B.K. Sitaula. 2017. Quantitative assessment of vulnerability to climate change in rural municipalities of Bosnia and Herzegovina. *Sustainability* 9(7): Article 1208.