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Assessment of vulnerability and resilience of smallholder farming households to flood risks: Insights from the Southern Punjab region of Pakistan

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ABSTRACT

The frequency and severity of flood hazards in Pakistan have remarkedly increased in recent decades, posing significant socio-economic and environmental challenges to affected areas, particularly among smallholder farming communities. The present study employs an updated vulnerability assessment framework based on the IPCC AR6 (sixth assessment report, 2023) guidelines, distinguishing exposure from vulnerability. It also develops and operationalizes multidimensional resilience indices to assess the resilience of 269 smallholder farming households across three flood-affected districts in Southern Punjab, Pakistan. This study advances beyond previous research by utilizing latent class analysis (LCA) approach to cluster surveyed households based on their resilience index scores and examine the impact of selected socio-demographic characteristics on their cluster membership. The results reveal high vulnerability and notable geographical disparities in flood vulnerability across the three districts. The findings show that resilience index scores are generally low and more or less homogenous across the studied districts, with some variations pertaining to specific components. Based on LCA analysis, the findings reveal that nearly half of the surveyed households exhibit low resilience, while the remaining households are classified as moderately or highly resilient. Regarding the role of demographic and socio-economic characteristics in shaping the resilience of farming households, income, education, and age stand out as primary determinants of resilience. The study highlights the need for effective interventions and an integrated approach to flood risk management that considers different components of vulnerability and resilience while being responsive to farming households' evolving needs and preparedness in face of intensifying climate change impacts.

1. Introduction

Climate change and its effects on natural and human systems are becoming an increasingly critical global issue (IPCC AR6, 2023). No country is exempt from the impacts of climate hazards, but low- and middle-income countries, which contributed the least to the problem and have a low capacity to adapt, are projected to be among the most affected by climate hazards [1,2]. The consequences of

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these climate hazards are expected to worsen livelihoods, food and water security, infrastructure, cities and built environments and threaten to derail efforts to achieve sustainable development goals (SDGs) in these countries [3,4].

Pakistan is recognized as a hotspot for climate change impacts, primarily due to recurring flood-related disasters [5]. In recent decades, the country has witnessed several major flood incidents, which caused extensive damage to infrastructure, housing, agriculture, industry, and livelihoods in various regions [6]. The destructive impact of these floods on humans, the economy, and the environment is often amplified by a mix of inadequate infrastructure and early warning systems, financial constraints, lack of capacity to design and implement proper mitigation measures, and high population density in flood-prone areas [7,8].

With the agriculture sector contributing approximately 23 % to the Pakistani economy, employing around 40 % of the labour force and responsible for 60 % of the total exports, the increasing severity and frequency of floods have far-reaching implications for agriculture-dependent communities and rural households [9,10]. For instance, the catastrophic floods in 2010 destroyed two million acres of crops, resulting in an estimated USD 10 billion in losses (Ahmad et al., 2021). More recently, another catastrophic flood struck the country in 2022, impacting over 33 million individuals in the most economically challenged regions, displacing nearly 8 million, destroying more than 2.3 million homes, claiming over 1700 lives and pushing over 8 million people into poverty [11,12]. In addition, the 2022 flood hazards and waterlogging have affected 45 % of Pakistani cropland, destructing 4.4 million acres of crops, resulting in a $2.3 billion loss in crop damage, and causing substantial physical and chemical changes that would have significant consequences for crop production and yield [13]. Rainfall-related flooding has severely affected livestock activities, while over 800 thousand cattle died, leading to higher prices and a shortage of meat, milk, and other dairy products [10,12].

A combination of factors encompassing inadequate infrastructure, constrained resources for disaster preparedness and response, and a high population density in flood-prone areas often exacerbate the destructive potential of floods in different regions of Pakistan, resulting in significant human, economic, and environmental losses [14]. A body of evidence highlights that the impacts of natural disasters including floods jeopardize sustainable development efforts in these vulnerable regions by rerouting financial resources that could otherwise be channeled into long-term development projects towards recovery and reconstruction efforts, hinder the progress towards sustainable economic growth, poverty reduction and the enhancement of overall living standards of the population [15]. Previous research suggests that effective adaptation to flood hazards involves identifying vulnerable communities, understanding the factors contributing to their susceptibility, and assessing their resilience capacity to mitigate the negative consequences [16]. Moreover, examining the aspects of vulnerability and resilience has been fundamental in transforming hazard research and contributed to more effective disaster management and risk reduction strategies (IPCC AR6, 2023; [4]). Therefore, in recent decades, successive Pakistani governments and their development partners have integrated the concepts of “vulnerability” and “resilience” into policy interventions aimed at enhancing preparedness and building the adaptive capacity of rural communities in the face of escalating flood risks [17]. In conjunction with this, assessing Pakistani households’ vulnerability and resilience to floods is critical for tailoring effective disaster management strategies and enhancing preparedness in flood-prone rural communities.

Drawing on a survey of 269 smallholder farming households from three flood-affected districts in Southern Punjab, this study evaluates the households’ vulnerability using the IPCC AR6 (2023), vulnerability assessment framework and introduces a multidimensional resilience framework to measure their resilience against flood hazards. In addition, a latent class analysis (LCA) approach is employed to cluster the surveyed households according to their flood resilience index scores. With this, the present study contributes to existing literature in several different ways. First, it is intuitive that communities with greater vulnerability typically exhibit lesser resilience to destructive consequences of flood hazards [18]. Therefore, our analysis covers both vulnerability and resilience to flood hazards, which contributes to a more comprehensive analysis of the natural (ecological-biophysical) and human (social-political) aspects of hazards and thereby provides relevant insights that can help strengthen the adaptive capacity of rural communities against flood hazards [8]. Second, our vulnerability assessment framework based on IPCC AR6 (2023) framework, which treats exposure as an external factor rather than a component of vulnerability, addresses the conceptual issue in vulnerability assessment where past studies often conflate exposure with vulnerability. Third, our multidimensional community-resilience index recognizes that understanding a community’s experience and responses to flood hazards requires a comprehensive approach that addresses these various components of vulnerability and resilience and their linkages and interplay [19]. By integrating multiple components of resilience, including social, economic, environmental, physical, institutional, and psychological indicators, our analysis provides deeper insights into the determinants of households’ resilience to flood impacts. Fourth, our analysis moves beyond mere resilience level assessments that can be found in previous studies by employing an LCA clustering approach to categorize the surveyed smallholder farming households into different classes (groups) according to their individual attributes and resilience mechanisms. This offers a deeper understanding of the determinants of household resilience that can help design more targeted interventions to enhance preparedness and mitigate the effects of flood hazards on different farming household groups. Fifth, while most of the previous studies derived their findings from the 2010 floods (e.g. Ref. [20]), our study focuses on community resilience against the most recent and unprecedented flood hazards of 2022, which renders our findings more relevant for today’s context and realities. Therefore, our findings offer fresh empirical evidence from selected rural areas of Southern Punjab, which have been severely affected by recurrent flooding events in recent years and are anticipated to face intensified flood events in the future due to climate change effects [21]. Hence, our findings should help to develop effective strategies and context-specific interventions to enhance resilience and reduce vulnerability among smallholder farming households in flood-prone areas within rural communities.

2. Conceptualization and literature review

2.1. Conceptualization

In this study, vulnerability is conceptualized according to the IPCC AR6 (2023), framework, which defines it as "the propensity or predisposition of a system, community, or household to be adversely affected by hazards, incorporating sensitivity or susceptibility to harm and limited capacity to cope and adapt." Hence, we frame vulnerability as a multidimensional construct, operationalized through two core components: sensitivity, and adaptive and coping capacity [22,23]. In this respect, sensitivity captures the inherent predisposition of farming households and weaknesses that increase inclination to flood implications, such as physical fragility (e.g., poor housing quality), and socio-economic dependence on flood-prone agriculture [24]. Adaptive and coping capacity reflects farmer households' ability to adjust to or mitigate flood-related damages, for example: access to coping mechanisms, familiarity with evacuation plans, financial resources, or disaster preparedness systems [25].

With regard to resilience, a consensus on a precise definition remains elusive. However, most of the existing definitions touch upon themes such as bounce-back and recovery, adaptive capacity, coping abilities, and risk acceptance [26]. In this study, resilience refers to "the capacity of social, economic, and environmental systems to cope with hazardous events, responding or reorganizing in ways that maintain their essential function, structure, and identity while sustaining the ability to adapt, learn, and transform", (IPCC AR6, 2023; [27]). Unlike vulnerability, which focuses on predisposition to harm, resilience emphasizes the ability to recover, transform, and thrive in the face of recurring risks [22]. We conceptualize resilience as a dynamic, multidimensional attribute encompassing social, economic, environmental, physical, institutional, and psychological components, reflecting the households' ability to withstand and bounce back from flood impacts [28]. Social resilience refers to the strength of social networks and community support systems that can aid in recovery [29]. Economic resilience pertains to the financial resources and strategies that enable farming households to recover from flood-induced losses [30]. Physical resilience refers to tangible measures and strategies employed to reduce vulnerability, such as using flood-resistant infrastructure [31]. Institutional resilience encompasses the governance structures, policies, and systems that facilitate effective response to floods [20]. Psychological resilience captures the mental and emotional fortitude influencing a farming household's ability to cope with and recover from flood events [32]. Lastly, environmental resilience describes the role of healthy ecosystems in mitigating flood impacts [28].

Theoretical debates have often led to confusion in defining vulnerability and resilience, as some frameworks integrate coping/adaptive capacity into both concepts. Cutter et al. [27] argue that reducing vulnerability does not necessarily lead to increased resilience, as resilience involves additional elements such as learning, transformation, and institutional adaptability. Birkmann et al. [33] further emphasizes that vulnerability focuses on negative predisposition, while resilience focuses on positive recovery and adaptability. To avoid conceptual ambiguity, this study maintains a clear distinction between vulnerability and resilience by framing vulnerability as a negative state (sensitivity and deficits) and resilience as a positive capacity (abilities to absorb, adapt, and transform). We recognize that vulnerability and resilience are distinct but interrelated, linked inversely through the capacity indicator. We examine the interplay between vulnerability and resilience, recognizing that reducing vulnerability (e.g., addressing sensitivity, enhancing adaptive and coping capacity) strengthens resilience, and building resilience (e.g., through economic diversification, institutional support) mitigates vulnerability.

2.2. Review of existing literature and contribution of the present study

The literature on flood vulnerability and resilience in Pakistan has evolved significantly, with a predominant focus on assessing socio-economic, institutional, and environmental factors that shape household susceptibility and adaptive capacity (e.g., Aslam et al. [34]; Abid et al. [35]; Ahmad & Afzal [36]; Khan et al. [37]; Nadeem et al. [38]. Several studies have employed composite indices to measure vulnerability, majority relying on the IPCC's exposure-sensitivity-adaptive capacity framework (e.g., Ref. [20,39]). Focusing on Punjab province, numerous studies have investigated vulnerability (e.g., Ref. [37–41]) and only few measured resilience in flood-prone districts [20,42] (detailed literature review is presented in Table S8 in Supplementary Material I). Many of these studies identify Southern Punjab as highly vulnerable due to socio-economic constraints and weak governance structures [20,42]. Specifically, studies in Southern Punjab, including Qaisrani et al. [40], Jamshed et al. [42], Aslam et al. [34], and Shahzad et al. [39], have examined regional variations in vulnerability, highlighting that communities in different regions of South Punjab face disproportionate flood risks due to high poverty rates, reliance on subsistence agriculture, and inadequate institutional support. Regarding resilience, previous research has emphasized the role of economic diversification, community cohesion, and institutional effectiveness in enhancing household capacity to recover from flood events (e.g., Ref. [43]). While past research has extensively examined flood vulnerability and resilience in Pakistan, and provide useful insights, key limitations remain in how these concepts are measured and understood.

A critical limitation in past research is the conceptualization of vulnerability. Previous studies often relied on outdated vulnerability frameworks, conflating exposure with vulnerability [20,37–41,44], a conceptual issue addressed in the latest IPCC AR6 (2023) framework, which treats exposure as an external factor rather than a component of vulnerability [23]. This study addresses this inconsistency by employing the IPCC AR6 (2023) conceptualization, ensuring a more precise assessment of vulnerability. By distinguishing vulnerability from exposure, our study provides a more refined approach to disaster risk assessment and policy development, ensuring that risk reduction efforts are targeted effectively.

Another key difference between past studies and this research is the methodological approach. Prior studies in Southern Punjab have largely relied on simple index-based assessments, aggregating vulnerability scores through composite indices [37,40,42]. While informative, these methods fail to capture the heterogeneity in resilience levels across affected communities. Our study advances beyond conventional assessments by employing LCA to classify households into distinct resilience groups based on multidimensional resilience indicators and also identify key determinants of these resilience classes. This methodological approach allows for a more nuanced understanding of resilience by identifying clusters of households with varying resilience capacities, rather than assuming resilience is uniform across vulnerable populations.

Additionally, past studies have predominantly focused on economic, social, physical, and institutional components of resilience (e.g., Ref. [20,42]), and only few included psychological and natural components but in different regions of the country [42,45]. While economic resilience (e.g., income stability, livelihood diversification) and institutional resilience (governance quality, disaster response efficacy) is well-documented, aspects such as psychological resilience (mental health, stress coping strategies) have been overlooked [28,46]. This study fills this gap by incorporating a multidimensional resilience framework, which includes economic, social, institutional, natural or environmental, psychological, and physical resilience, offering a holistic understanding of flood resilience among smallholder farmers in Punjab.

Moreover, previous studies mostly predominantly employ indicator-based vulnerability and resilience assessments, often drawing from the 2010 flood data [20,41,42]. However, a notable limitation is their failure to incorporate evolving socio-economic and climatic conditions, leading to potentially outdated conclusions. This study, in contrast, is based on 2022 flood data, making it more relevant for contemporary disaster risk reduction efforts. Given the increasing intensity of climate-induced floods, findings from a more recent dataset provide updated empirical evidence that better represents current risks and adaptation strategies. Hence, the study contributes to addressing the aforementioned gaps by providing the holistic assessment and comprehensive understanding of households' vulnerability and resilience to flood risks, which is crucial for developing effective mitigation and adaptation policies.

3. Materials and methods

3.1. Study area

Abundant water resources from several rivers and fertile agricultural land have traditionally provided favourable conditions for farming activities and agricultural production in the Punjab region of Pakistan [9,47]. However, being located in high-risk, flood-prone zones and adjacent to rivers has heightened the vulnerability of the region to flood threats in recent decades [38]. Between 2010 and 2023, Punjab experienced significant losses in crops, property, lives, and infrastructure due to seven consecutive flood events [48]. The frequent occurrence of floods throughout the rainy season severely impacts the livelihoods of smallholder farming households and worsens their food security by causing crop destruction, infrastructure damage, human and livestock casualties, and loss of shelter [6,13].

Fig. 1 shows the study area, comprising three districts in Southern Punjab: Muzaffargarh, Rajanpur, and Dera Ghazi Khan (DG Khan). The first area, Muzaffargarh, lies between the Indus River to the west and the Chenab River to the east, covering a total area of 8249 km^2, with a population of around 4 million. Approximately 70 % of the population engages in agriculture, including livestock, poultry, and fish farming [49]. The second area, Rajanpur, situated along the Indus River, spans an area of 12,318 km^2, with a population of approximately 2 million [50]. Most of the population relies on agriculture and livestock for income. Rajanpur is prone to frequent floods during the summer months, primarily due to erratic rainfall and snowmelt from severe climatic fluctuations in the Chenab and Indus rivers [50]. The third area, DG Khan, is located between the Indus River and the Sulaiman Mountains, covering an area of 13,018 km^2, with a population of around 3.3 million. Two-thirds of the population depend on agriculture as their main livelihood [51]. The local community faces vulnerability to floods, particularly flash floods triggering downstream flooding, due to the area's susceptibility [43].

3.2. Sampling strategy

A multiple-sampling approach was adopted to identify the flood-affected areas within each study area. In the initial stage, the Pakistan Post-Disaster Needs Assessment report (PPDNA) [6] was utilized to pinpoint severely affected districts within the southern region of Punjab following the 2022 floods. This report was issued in the aftermath of the 2022 floods to assist the Pakistani Government in recognizing the areas most impacted by the flooding and assessing the extent of damage, losses, and the resources needed for recovery and reconstruction. Subsequently, in collaboration with local experts from academia and various Government and non-government entities, the districts of Muzaffargarh, Rajanpur, and DG Khan were identified as severely affected areas within the region. In the second step, two *tehsils* (an administrative subdivision of a district, typically consisting of multiple towns and rural areas, functioning as an intermediate level of governance) from each selected district were chosen using the PPDNA, based on the severity of their flooding impacts. In the third stage, the two most affected union councils (UCs) (smallest administrative unit in Pakistan's local government system, responsible for governance at the village or neighbourhood level) from each selected tehsil were chosen randomly, utilizing information from the District Disaster Management Plan for each district [49–51]. Finally, 22 farming households were randomly selected from each union council, resulting in a total sample size of 269 respondents. Our study targets smallholder farming households exposed to floods,[1] not the entire UC population, which includes non-farming residents and other demographics irrelevant

[1] Based on approximate coordinates, the distance from each sampled Union Council's centre to the nearest main river channel ranges roughly within 20 km.

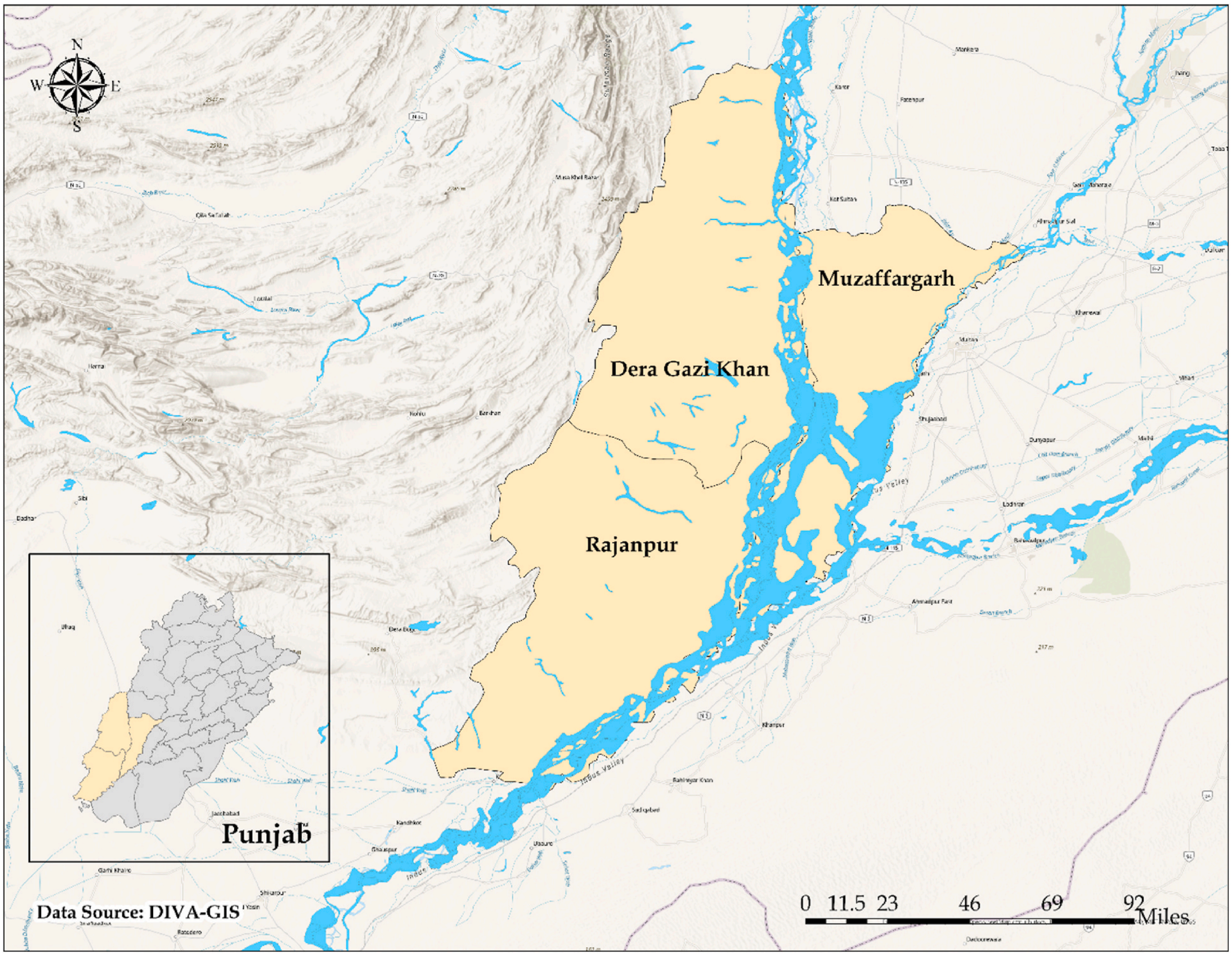

Fig. 1. Map of the study area.

to our analysis. We estimated the number of smallholder farming households in each selected Union Council (UC) based on local agricultural records and community knowledge, ensuring our focus remains on the relevant subpopulation. This approach ensures our sample of 269 households reflects the distribution of smallholder farmers, critical for assessing flood vulnerability and resilience. The detailed information about sampling procedure and UC's description is provided in Table S1 (Supplementary Material I), ensuring geographic context for our district-level analysis, as shown in Fig. 1.

3.3. *Survey design and participants*

Data were collected using questionnaire-based interviews conducted with Pakistani smallholder farming households in the study areas. It includes face-to-face interviews with household heads or their representatives (above 18 years, resident for 5+ years), ensuring responses generalize at the household level by capturing overall views on vulnerability and resilience, not individual opinions. The sample size of 269 was chosen due to practical constraints and considerations, including resource limitations, accessibility, and households' willingness to participate in the study. Previous studies with similar research objectives obtained significant results with comparable sample sizes (e.g., Ref. [16,39,43]). The design of the questionnaire was informed by an extensive literature review and consultations with local experts to ensure that the questionnaire adequately captures critical aspects related to smallholder farming households' vulnerability and resilience to floods. The questionnaire included questions capturing the sociodemographic characteristics of the respondents, as well as the impact of floods on households and the cost of flood-related damages. Vulnerability to floods was assessed by incorporating questions relating to smallholder farming households' sensitivity, and adaptive capacity. A multidimensional assessment framework was adopted to assess resilience, which consists of six components, namely: social, institutional, economic, physical, psychological, and environmental components. More details regarding the survey design can be found in Table S4 in supplementary material I.

The final questionnaire was pretested, and necessary adjustments were made based on the insights gained to ascertain the validity and reliability of the questions. Moreover, a few modifications were implemented to enhance the clarity of the statements and ensure that respondents understand and respond to the survey as intended. Interviews were carried out during the period January–February 2023. Prior to commencing the interviews, respondents were briefed on the study's objectives and data utilization, and their consent was obtained, guaranteeing the confidentiality and anonymity of all respondents. Each interview lasted between 25 and 35 min. Enumerators with social sciences background in agricultural economics and rural development conducted interviews. Before deployment to the study area, they were trained to ensure a consistent and informed approach to data collection. Furthermore, to improve the reliability of responses involving estimations (e.g., distance to the river) or subjective evaluations (e.g., infrastructure quality), a structured protocol was implemented during data collection. Respondents provided answers using predefined 5-point Likert scales (1–5), which were anchored to specific quantitative ranges (e.g., kilometers for proximity questions). Trained enumerators, drawing on their local expertise and standardized training, assisted respondents in mapping their qualitative judgments to the most accurate scale category. For example, when estimating distance to the river, respondents were guided to select a Likert value that best matched their actual proximity. This process minimized reporting bias by aligning subjective perceptions with objective ranges, ensuring greater consistency and comparability across responses.

3.4. Indicators of vulnerability assessment

To assess the smallholder farming households' vulnerability to flood risks, we used a multi-layered index that covers the two main components used in the IPCC AR6 framework: susceptibility/sensitivity, and adaptive and coping capacity (IPCC AR6, 2023). The specific indicators comprising these two components were primarily measured through the survey questionnaire, with household responses typically captured on a 5-point Likert scale (e.g., ranging from 1 representing low vulnerability aspects to 5 representing high vulnerability aspects, adjusted based on indicator phrasing). With regard to susceptibility/sensitivity, we used four indicators: the impact of floods on the ability to produce crops or raise livestock [8], the susceptibility of house construction to floods [52], farming households' location in relation to rivers [37], and the floods effects on road network and community infrastructure [31]. In relation to lack of the adaptive and coping capacity, we used seven indicators: accessibility to emergency shelters [53], knowledge of evacuation procedures [54], flood's coping mechanisms [55], preparedness to respond to floods [8], access to information and resources for flood preparation and recovery [20], support from the community and Government [7], and financial assistance from local Government or other organizations [36].

These indicators were developed through a multi-step process to ensure relevance to the study context. First, an extensive literature review informed the initial selection of indicators, aligning them with established frameworks (e.g., Ref. [8,46,56]). Second, we refined these indicators through consultations with local experts from academia, government, and non-government entities during survey design, ensuring contextual applicability to Southern Punjab. Third, the questionnaire was pretested with a small sample of respondents, and adjustments were made to enhance clarity and validity based on feedback. Table S4 in the Supplementary Material I, lists the specific literature sources supporting each indicator. These references reflect prior empirical use or theoretical grounding, complementing our validation process. Lastly, we conducted Cronbach's alpha tests to assess internal consistency, results show values of 0.70 for sensitivity and 0.71 for adaptive capacity. These are detailed in Table S5 in Supplementary Material I, with all values indicating adequate to good reliability [57].

3.5. Indicators of resilience assessment

A multidimensional community-resilience framework was adopted to assess households' flood resilience, encompassing social, economic, environmental, physical, institutional, and psychological components ([18,29]; IPCC AR6, 2023), following a protocol similar to that used for the vulnerability assessment. Social resilience was assessed using seven indicators: access to community centres [8], participation in community activities [7], community assistance during floods [54], community meetings about flood preparedness [52], and market access (for food, medicine, etc.) [31]. Economic resilience was measured using five indicators: employment status [20], multiple livelihood sources [52], insurance [7], debt to pay [20], loan access [7], and recovery periods [31]. Physical resilience was measured using six indicators: house construction material [58], quality of drinking water [56], access and quality of the internet [28], power failure rates [29], road network quality [31], and government development services [54].

Institutional resilience was assessed using six indicators: flood warnings [7], supportive guidelines and financial support from the Government [20], the effectiveness and trust in government laws [28], and institutional support for loans or credits [7]. Psychological resilience was measured using five indicators: beliefs about flood occurrence [54], perceptions of floods as regional or global realities [45], stress due to floods [45], and the ability to adapt to new situations [8]. Lastly, we measured environmental resilience using seven indicators: changes in flood frequency [55], water storage systems to mitigate flood impacts [28], the capacity of the river and drainage water systems to handle water during floods [28], protection and restoration of natural features [39], crop rotation strategies to reduce the risk [59], scheduling and cultivating less vulnerable crops to minimize flood damage risk [60]. Similarly to vulnerability indicators, resilience components were validated through literature, refined via expert input and pretesting, and tested for reliability (Cronbach's alpha: 0.664–0.763 across components; see Table S5 in Supplementary Material I). A detailed explanation and sources about the indicators of resilience and vulnerability is presented in Table S4 in Supplementary material I.

3.6. Calculating the vulnerability and resilience indices

3.6.1. Calculation of the vulnerability index

We utilized the IPCC AR6 (2023), framework to calculate an index for measuring the vulnerability of the surveyed households to flood risks. This framework represents a widely used methodology that has frequently been adopted by previous studies for calculating vulnerability indices [7,8,36,55,61]. The balanced weighted average method (BWA) was chosen for its simplicity and transparency, widely used in similar studies (e.g., Ref. [46,62–64]). This method allows for the combination of normalized indicator values, providing a single index that can be easily compared across districts and suitable for our survey-based, Likert-scale data [14,55]. Specifically, the index calculation involves indicators relating to the two components of vulnerability: sensitivity, and capacity to cope and adapt (IPCC AR6, 2023). The questionnaire included several statements that capture the likely influence of each component on households' vulnerability to flood risks, which were then combined to create the vulnerability index (VI), using a weighted average method (Equations (1)–(4)). In other words, each core component of vulnerability comprises a number of sub-components (indicators), and they are all considered to contribute to explaining households' VI [65], which can be expressed as follows:

$$VI = f\ (\ sensitivity, capacity\ to\ cope\ and\ adapt) \tag{1}$$

To normalize our survey-based Likert-scale data (1–5) to a [0,1] range for comparability, we use the min-max transformation method for its simplicity and transparency, widely used in similar studies (e.g., Ref. [8,61,64]). The sub-component index, expressed as the index for each sub-component, is shown in equation (2).

$$Index_{sc} = (X_i - X\_min)\ /\ (X\_max - X\_min\ ) \tag{2}$$

$$Index_{sc} = (Observed - minimum)/(maximum - minimum)$$

Here $Index_{sc}$ is sub-component index and X_i represents the standardized value of the sub-component. X_min, shows the minimum value of the sub-component, while X_max denotes the maximum value. After standardizing for each major component, the sub-components are averaged. The standardized values of the main components are calculated using equation (2).

$$MC_d = \frac{\sum_{i=1}^{n} Index_{sc}}{n} \tag{3}$$

MC_d represents the major component of the respective district. The number of sub-components in the major component is highlighted by n. Further, equation (4) determines the VI of the respective districts by taking the average of major indicators in a district.

$$VI_d = \frac{\sum_{i=1}^{n} w_{MCdi} MC_{di}}{\sum_{i=1}^{n} w_{MCdi}} \tag{4}$$

Here, VI_d represents VI of the district d. The wMC_{di} shows the weight of the major component based on number of minor components and each sub-component of the vulnerability index contributes equally. We applied equal weights to all indicators in the BWA method because it is a standard approach when weighting criteria are unclear, ensuring transparency and avoiding subjectivity (e.g., Ref. [56,64,65]). The VI_d scales range from 0 to 0.6, with 0 representing less vulnerability and 0.6 representing high vulnerability.

3.6.2. Calculation of the resilience index

Similar to VI calculations, we employed the BWA method to assess the levels of households' resilience to flood risks while accounting for the specificities of the local contexts in the study areas (e.g., Ref. [7,16,64]). Thirty-six sub-components (indicators) were combined with the indicators of the six core components of resilience described in sub-section 3.5 to create the resilience index (RI). Similar to what has been illustrated by equations (2)–(4) in the VI calculation method, each core component of the RI comprises a number of sub-components or indicators, and they are all considered to contribute equally to the total RI. The weighted average of major components (Equation (5)) shows the resilience index in a district denoted by RI_d. The wMC_{di} shows the major component's weight, which is calculated through the sub-components that collectively make a major component. It is necessary to emphasize that all sub-components have equal weightage to the resilience index. The resilience values are between 0 and 1; 0 means less resilient, whereas 1 means more resilient.

$$RI_d = \frac{\sum_{i=1}^{n} w_{MCdi} MC_{di}}{\sum_{i=1}^{n} w_{MCdi}} \tag{5}$$

3.7. Clustering the surveyed farming households based on their resilience index

A Latent Class Analysis (LCA) approach was used to cluster the surveyed smallholder farming households based on their RI and examine the factors influencing their membership of various household clusters. LCA is a model-based methodology that hypnotizes the presence of an unobserved categorical variable that divides a sample into distinct and non-overlapping latent classes of individuals [66]. That is, LCA identifies heterogeneities within a population by analyzing individual responses and finds common types, called classes, comprising sub-groups of individuals who share similar characteristics, making them distinct from individuals belonging to other classes [67]. A detailed mathematical representation of the LCA and its estimation is presented in Supplementary material II.

The survey comprised 36 items aimed at assessing the resilience of farming households in flood-prone regions. Participants were asked to rate their responses to each item on a 5-point Likert scale. While there is no consensus in the literature regarding the number of indicators to include in LCA [68], including all statements may have resulted in a model that was excessively complex, difficult to interpret, and potentially prone to overfitting the data [67]. Therefore, from the initial pool of statements, we decided to include 12 items in the LCA, each two of them represent one of the six components of resilience (social, physical, economic, environmental, psychological, and institutional). This selection was based on the internal consistency of the items, determined through Cronbach's alpha test (presented in Table S5 in Supplementary Material I) [57]. Additionally, the selection of items was guided by their importance within each resilience component, as indicated by the resilience index values presented in Table S7 in Supplementary material I, where higher values indicate greater significance in explaining resilience across districts. For example, within economic resilience, the indicators "multiple livelihood options are available" was chosen because it had higher values compared to other economic resilience indicators. This suggests that this factor play a more critical role in determining economic resilience across districts, making them suitable for inclusion in the LCA. Similarly, in all other resilience components, the indicators selected had higher relative importance scores across all three study districts, ensuring that the most representative variables were used. The respective resilience components addressed by each item are listed in Table 2.

The PoLCA package within R software was used to estimate the latent classes and covariates. To estimate the latent class model's parameters for categorical variables, the PoLCA uses expectation-maximization and Newton-Raphson algorithms [69,70]. We executed an expectation-maximization algorithm with the multiple clusters (classes) varying from one to five with 500 random iterations for each number of classes. The optimal number of classes was determined by minimizing the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC) [71]. According to Table S3 presented in supplementary material I, the optimal number of classes was found to be 3. In addition, the likelihood ratio Chi-square (G^2) is minimized at the three-class levels, indicating a goodness of fit at the third latent class.

In the final stage of our analysis, we estimate the determinants of class membership. This involved executing multinomial logistic regression models within the latent class framework to examine how various covariates predicted the probability of each observation being in a particular class. We specified a model for each latent class as a function of individual-level predictors while controlling for other demographic and socio-economic factors. The estimation process iteratively refined the class assignment probabilities, ensuring the most statistically significant and substantively meaningful determinants were identified. Finally, we calculated the odds ratios of the explanatory variables by taking the exponents of log-odds, which essentially represent the change in the odds of an outcome for a

Table 1
Sample characteristics (n = 269).

Characteristics	Categories	Frequency	% of the sample
Age (Years)	<26	29	10.78
	26–34	87	32.34
	35–42	72	26.77
	43–50	45	16.73
	>51	36	13.38
Household size	<5	36	13.38
	5–7	105	39.03
	8–10	72	26.77
	11–13	33	12.27
	>14	23	8.55
Level of Education	Under primary	56	20.82
	Completed primary	72	26.77
	Completed secondary	63	23.42
	Completed higher secondary	36	13.38
	University degree or above	42	15.61
Income (PKR/month)	>20,000	38	14.13
	20000–30000	49	18.22
	31000–40000	71	26.39
	41000–50000	68	25.28
	>50000	43	15.99
Type of house ownership	Owned	27	10.04
	Rented	07	2.60
	Shared	235	87.36
Farm Size (acre)	<5	46	17.10
	5–8	82	30.48
	9–12	56	20.82
	13–16	43	15.99
	>17	42	15.61
Land Ownership	Shared	30	11.10
	Rented	26	9.67
	Owned	43	15.99
	Shared and rented	170	63.20

Source: survey results. 1 USD ≈270 PKR in Jan–Feb 2023 one-unit increase in the predictor variable, while holding other predictors in the model constant. As there are three latent classes, the model contrasts each class against one another to establish a clearer understanding of which factors play significant roles in dictating class membership.

4. Results and discussion

4.1. Demographic and socio-economic characteristics

Table 1 summarizes the demographic and socio-economic characteristics of the surveyed farming households. Approximately 60 % of the respondents fell within the age range of 26–42, 30 % were 43 years or older, and around 11 % were younger farming households below 26. Nearly two-thirds of the surveyed farming households have 5 to 10 members who contribute to farming and flood response activities but may also pose substantial challenges related to resource distribution and meeting the requirements of all household members during flood events. Nearly 87 % of the respondents reside in shared housing, only 10 % own their homes, and 2 % reside in rented accommodations. Around half of the farming households surveyed reported a monthly income ranging from PKR 31 thousand to PKR 50 thousand, while 22 % earn less than PKR 31 thousand, and 16 % earn more than PKR 50 thousand. Approximately 50 % of the interviewees have below primary or completed primary education, whereas about 23 % have achieved secondary education, and the remaining 28 % have reached the higher secondary level or higher qualifications. Approximately 17 % of the surveyed smallholder farming households own less than 5 acres of land, whereas 51 % own land ranging from 5 to 12 acres, and about 32 % possess land holdings between 13 and 17 or more acres of land. Close to two-thirds of the interviewees are engaged in farming activities on owned and rented plots. In contrast, only 16 % exclusively cultivate their own land, while 10 % work on leased land, and 8 % farm on shared land.

With regard to the impact of flood hazards on the local communities, Table S2 in Supplementary Material I, highlights the extensive economic and physical damages and losses experienced by the surveyed smallholder farming households due to the 2022 flooding. In relation to economic consequences, approximately 28 % of the farming households reported crop losses on plots of less than 5 acres, while around 10 % documented substantial losses on areas exceeding 15 acres. Livestock losses represent another significant aspect of flood damage, with roughly half of the sample reporting between 1 and 6 losses and about 22 % reporting losses of 7 or more animals. These consequences, affecting both crop and livestock production, in addition to the impact of floods on other income sources, resulted in income reductions of up to 100 thousand PKR for 20 % of the surveyed farming households, between 100 and 600 thousand PKR for 30 %, and losses exceeding 600 thousand PKR for 24.5 % of them. In addition to these economic consequences, flood hazards took a considerable physical and human toll, manifested in damages to houses and casualties among family members of the surveyed farming households. In this regard, 21 % of the respondents reported significant damage to their homes, estimated costs exceeding 300 thousand PKR, and 31 % reported costs ranging from 100 to 300 thousand PKR. In terms of casualties, 22 % of the respondents reported the loss of at least one family member due to the floods.

4.2. Smallholder farming households' vulnerability index

The vulnerability index scores for the two components—sensitivity and capacity to cope and adapt—of the index, and composite vulnerability index across the study districts are illustrated in Fig. 2, detailed normalized values for all components are available in Table S6 (Supplementary Material I). The results show that Rajanpur and Muzaffargarh exhibit higher vulnerability to flood risks (0.50 & 0.47, respectively) compared to DG Khan district (0.40), indicating a greater likelihood of experiencing flooding damages in the former two districts. Regarding the sensitivity component of the vulnerability index, the results indicate that Rajanpur (0.64) scored the highest, followed by Muzaffargarh (0.62) and DG Khan (0.60). The proximity of smallholder farming households to rivers emerges as a crucial indicator of sensitivity to flood risks across all three districts. This finding aligns with the findings of Hoq et al. [55] and Ahmad & Afzal [20], underscoring that the geographical proximity of Rajanpur and Muzaffargarh districts to rivers, coupled with specific land-use patterns and infrastructure, renders them more susceptible to flooding and associated hazards. The results related to other components of the sensitivity indicator of vulnerability, such as access to emergency shelters, and house's construction material, were deemed less significant compared to the proximity to rivers in assessing sensitivity to flood risks.

Additionally, the impact of floods on the road network and infrastructure, coupled with the subsequent effects on the capacity of smallholder farming households to sustain their crop and livestock production activities, serves as a pivotal indicator for the vulnerability of smallholder farming households to flood risks in the three districts. Khan et al. [37] points out that the support provided by Pakistani institutions to smallholder farming households during flood crises is hindered by various factors, including inadequate financial resources, a shortage of machinery and hardware, administrative constraints, and a lack of professional training and expertise. In Rajanpur, the construction of houses in farming communities using less resilient materials against floodwater leads to significant damage to property, crops, livestock, and human lives [36].

In relation to lack of adaptive and coping capacity, the results generally reveal a limited ability among the surveyed smallholder farming households to adjust and respond effectively to the impacts of floods, with overall scores ranging from 0.33 in DG Khan to 0.45 in Rajanpur. In particular, the preparedness of smallholder farming households to respond to floods was a key indicator of their adaptive capacity. The readiness to respond to floods hinges on the existence and awareness of evacuation plans and determining whether households have established clear routes, assembly points, and communication methods. On the other hand, lack of the accessibility, coping mechanism, understanding of early warning systems, community engagement in preparedness programs, communication plans within households, and the level of training and education on flood risks contribute to overall lack of capacity to cope and adapt [27,42]. This finding aligns with the conclusions of Shah et al. [72], highlighting that insufficient community infrastructure and a lack of coping mechanisms contribute to reducing capacity to cope and adapt to flood hazards.

Overall, the results of the individual components of the vulnerability index, along with the district-wise values, underscore significant geographical variations in flood vulnerability, also noted in the previous studies which were based on 2010 floods [20,55]. However, a decade on, we also note that overall vulnerability levels are still alarmingly high across all surveyed areas, with limited evidence of reduction over time. This indicates that despite the lessons from 2010 to 2015 floods, structural vulnerabilities (e.g. poverty, inadequate flood defenses) persist. In contrast to some localized improvements reported in the mid-2010s, the 2022 event showed widespread vulnerability: even districts that were less severely affected in 2010 experienced devastating losses in 2022, suggesting the risk has become more pervasive. Our findings therefore underscore a continuation (or even expansion) of severe vulnerability into the present, whereas earlier post-2010 analyses might have been cautiously optimistic that vulnerability could be

Table 2
Membership probabilities in the identified latent classes.

Class	Components of RI	Conditional response probabilities				
		Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
Class I (47 %)	**Social resilience**					
	Community centres provide info about flood management	**0.3573**	**0.3516**	0.1912	0.0726	0.0273
	Government & NGOs help affected people during floods	**0.3048**	**0.3250**	0.2272	0.1102	0.0328
	Economic resilience					
	The household has a multiple livelihood option	0.0419	**0.5013**	0.2252	0.1138	0.1178
	The household has financial debts to pay	0.1916	**0.3185**	**0.3390**	0.1415	0.0093
	Physical resilience					
	Type of material used in house construction (mud, brick)	**0.4296**	**0.3357**	0.0235	0.2112	0.0000
	The village receives government development services	**0.03493**	**0.3274**	0.2835	0.0320	0.0078
	Institutional resilience					
	Govt. has procedures to compensate for flood damages	0.1037	**0.3999**	**0.3678**	0.0743	0.0543
	Trusting government disaster risk reduction programs	0.1853	**0.3116**	**0.3159**	0.1701	0.0171
	Environmental resilience					
	Cultivating less vulnerable crops to flood risks	0.0865	**0.3062**	0.2607	0.2836	0.0631
	Scheduling cultivation to minimize flood damage	**0.3058**	0.2168	0.0571	0.2067	0.2135
	Psychological resilience					
	Floods are an act of God and a reality	**0.4139**	**0.3665**	0.0857	0.1339	0.0000
	Feels stressed/depressed due to flood occurrence	0.0078	0.2189	0.2878	0.2596	0.2259
Class II (17 %)	**Social resilience**					
	Community centres provide info about flood management	0.1278	0.1577	0.0877	**0.5594**	0.0674
	Government & NGOs help affected people during floods	0.0000	0.1126	0.1862	0.1890	**0.5122**
	Economic resilience					
	The household has a multiple livelihood option	0.0000	0.0230	0.0805	**0.7866**	0.1099
	The household has financial debts to pay	0.2216	**0.4863**	0.1680	0.0610	0.0631
	Physical resilience					
	Type of material used in house construction	**0.4259**	**0.4513**	0.0000	0.1228	0.0000
	The village receives government development services	0.1061	0.2175	**0.3004**	0.2637	0.1123
	Institutional resilience					
	Gov. has procedures to compensate for flood damages	0.0748	0.1340	0.0748	**0.3153**	0.0462
	Trusting government disaster risk reduction programs	0.1206	0.2654	0.0850	**0.4384**	**0.4295**
	Environmental resilience					
	Cultivating less vulnerable crops to flood risks	0.0228	0.0888	0.1723	**0.4929**	0.2232
	Scheduling cultivation to minimize flood damage	0.2245	0.1441	**0.3141**	0.1752	0.1421
	Psychological resilience					
	Floods are an act of God and a reality	0.0232	0.0000	0.0000	**0.3846**	**0.5922**
	Feeling stressed/depressed due to flood occurrence	0.0000	**0.6723**	0.0923	0.2116	0.0238
	Social resilience					
Class III (36 %)	Community centres provide & info about flood management	0.0165	**0.3625**	**0.4728**	0.1430	0.0053
	Government & NGOs help affected people during floods	0.0000	0.2735	**0.5143**	0.2123	0.0000
	Economic resilience					
	The household has a multiple livelihood option	0.0274	0.0684	**0.5222**	0.2987	0.0832
	The household has financial debts to pay	0.0168	0.1823	**0.5816**	0.2194	0.0000
	Physical resilience					
	Type of material used in house construction	0.6844	0.1757	0.0103	0.1296	0.0000
	The village receives government development services	0.0000	**0.4292**	**0.5379**	0.0329	0.0000
	Institutional resilience					
	Gov. has procedures to compensate for flood damages	0.0892	**0.3377**	**0.4544**	0.1187	0.0000
	Feeling stressed/depressed due to flood occurrence	0.0806	**0.3969**	**0.3811**	0.1229	0.0185
	Environmental resilience					
	Cultivating less vulnerable crops to flood risks	0.0000	0.1229	**0.3830**	**0.4941**	0.0000
	Scheduling cultivation to minimize flood damage	0.0176	0.1226	0.2578	**0.5776**	0.0244
	Psychological resilience					
	Floods are an act of God and a reality	0.0000	0.2393	**0.3940**	**0.3497**	0.0170
	Feeling stressed/depressed due to flood occurrence	0.0000	**0.6979**	0.1893	0.0282	0.0847

reduced with recovery efforts. Essentially, the pattern of who is most vulnerable has remained consistent (the poorest, those in floodplains), but the scale of impact in 2022 exposed that even those measures taken after 2010 were not sufficient to significantly lower vulnerability levels.

4.3. Resilience index scores of the surveyed smallholder farming households

Fig. 3 presents the index values of the six components of the resilience and composite resilience index for the surveyed smallholder farming households across the study districts, detailed normalized values for all components are available in Table S7 (Supplementary Material I). A closer look at the results shows that the scores of the six components across the three districts are lower than 0.5, implying low resilience to flood hazards. Nevertheless, the results point out remarkable variations among the districts regarding the scores pertaining to each of the components of the resilience index.

With regard to the social component, the extent of support provided by Government and non-government organizations to smallholder farming households during flood hazards was associated with relatively higher social resilience scores, particularly in Muzaffargarh and Rajanpur. Previous research has shown that lower social resilience is linked to limited access to community centres, weaker social networks, and reduced community engagement and government support during flood events and natural disasters [73, 74]. Turning to the economic component, the results reveal sub-index values consistently around 0.4 across all three districts, indicating a generally low level of economic resilience against flood hazards. However, the diversity of livelihood sources has a more pronounced impact on smallholder farming households' economic resilience in the three districts, with values ranging from 0.57 in Rajanpur to 0.61 in Muzaffargarh. Campbell et al. [75] illustrate that engaging in various income-generating activities, such as off-farm employment, livestock rearing, or non-agricultural ventures, enables farming households to spread their economic risks. If one income source is affected by a flood hazard, other sources may remain un- or less-affected, providing a financial buffer and maintaining a certain income level. Moreover, income diversification allows farming households to capitalize on different market opportunities, reducing their dependency on a single sector vulnerable to flood-related disruptions. Poussin et al. [76] indicate that the diversity of income sources leads to higher incomes and financial security. This financial stability enables smallholder farming households to afford precautionary measures to protect their households from flood risks and invest in flood-prevention strategies [77].

Concerning the physical component of the resilience index in the three districts, the results show that the material of house construction plays a crucial role in determining the physical resilience of smallholder farming households to floods. This finding is aligned with the findings of Malgwi et al. [78] and Shah et al. [7], which indicate that the choice of construction materials influences the house's structural integrity, affecting its ability to withstand floodwaters. Houses built with materials resistant to water damage, such as elevated foundations or water-resistant materials, are more likely to endure the impact of floods without significant structural damage. This, in turn, accelerates the recovery process, allowing smallholder farming households to return to normalcy more swiftly [58].

The institutional resilience scores, ranging from 0.38 to 0.40 across surveyed districts, indicate a notable lack of preparedness and ineffective disaster management. In particular, Table S7 in supplementary material I, highlights that the lowest scores are linked to the inefficiency of government procedures in compensating farming households affected by flood damages. Farming households' mistrust

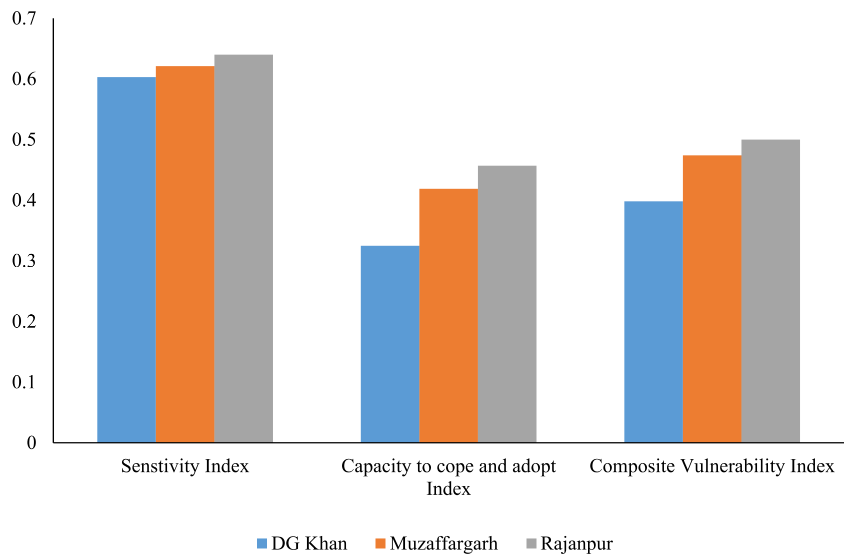

Fig. 2. Comparative analysis of VI scores for the two components of the index, and composite VI across the studied districts. The bold figures show the probabilities of the class members over 30 %. Some statements have been rephrased to shorten the text and fit it in the table. The original statements can be found in the study questionnaire in the Supplementary Material.

follows this in government disaster flood risk reduction efforts and the absence of loans and financial services to help farming households cope with the repercussions of floods on their farming activities and livelihood sources. These findings align with prior research attributing the low institutional resilience of smallholder farming households to flood risks to various factors. These include limited access to crucial resources such as financial support and information, hindering their ability to adopt resilient practices [79]. Moreover, weak support from governmental and non-governmental institutions, marked by insufficient policies, funding, and assistance programs, leaves smallholder farming households without essential flood preparation tools [80]. The capacity of institutions to manage complex challenges is compromised by insufficient legal frameworks and a lack of trained personnel, technical expertise, and coordination for effective flood management.

The environmental resilience scores are consistently low and closely aligned across the surveyed districts, suggesting that farming households in these areas possess similar capacities to restore ecosystems after flood events [43]. Corroborating Alhassan's [59] findings, the results indicate that higher environmental resilience is linked to farming households cultivating less vulnerable crops and adopting crop rotations to mitigate flood-related damage. In the same context, Broadmeadow et al. [81] explain weak environmental resilience among smallholder farming households confronting flood hazards to several other factors, including the cultivation of crops highly susceptible to floods and the limited adoption of resilient farming practices, such as crop rotation, which intensify the impact of floods on agricultural production and contribute to prolonged environmental damage.

Lastly, the results indicate that the scores for the psychological component of resilience surpassed those of all other components. The highest scores observed across the three districts were linked to farming households' beliefs about floods being an act of God and a global or regional reality, as well as their confidence in managing flood-related losses and damages. Previous research has correlated higher psychological resilience of smallholder farming households facing flood risks with the close-knit communities they inhabit, which foster a stronger sense of belonging and emotional support, contributing to overall psychological well-being and assisting farming households in coping with the stress associated with flood events [32]. For certain farming households, faith also plays a significant role, acting as an extra source of strength and comfort during challenging times and further contributing to their overall psychological resilience [82].

4.4. *Clustering smallholder farming households based on the flood resilience index scores*

Table 2 presents the estimated conditional response probabilities for the three resilience classes identified through LCA. These classes were determined based on the BIC criterion, which is widely used for model selection in LCA. The BIC criterion helps identify the optimal number of latent classes that best represent the data while balancing model complexity and interpretability. Each column in Table 2, from Pr(1) to Pr(5), represents the probability distribution of smallholder farming households within each class responding to a specific Likert scale item related to the six resilience components. The Likert scale categories are as follows: Pr(1); low probability of agreement or acceptance (strongly disagree/least resilient response); Pr(5): high probability of agreement or acceptance (strongly agree/most resilient response). The three identified latent resilience classes represent different household resilience levels based on their response patterns to resilience indicators. The bolded values in Table 2 indicate response probabilities exceeding 30 %, helping highlight the most relevant characteristics of each class.

The first class (Class I) labelled "*less resilient smallholder farming households*," constitutes 47 % of the sample. Notably, this class is characterized by a substantial proportion of responses skewed toward the lower end of the Likert scale (strongly disagree or disagree), suggesting diminished resilience to flood hazards. Specifically, households belonging to Class I tend to strongly disagree or disagree with statements regarding the information and support provided by the Government, community centres, and NGOs to enhance preparedness and response to flood impacts and damages. They acknowledge that the material used in the construction of their houses

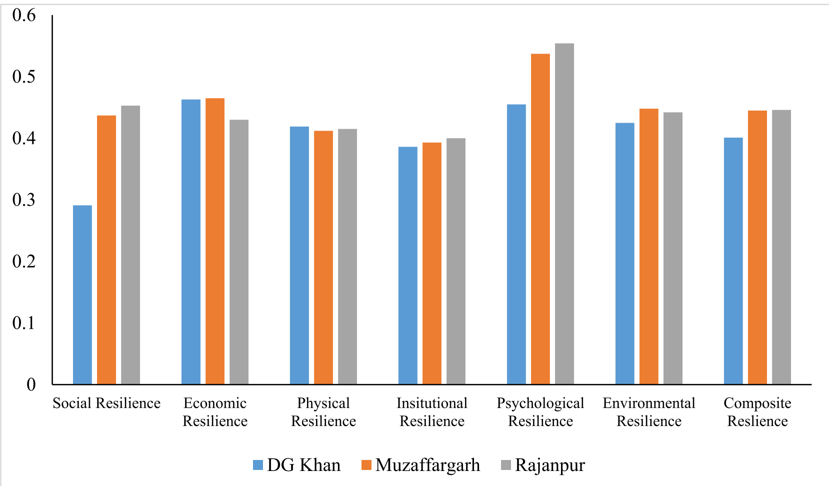

Fig. 3. Comparative analysis of RI scores for the six components of the index, and composite RI across the studied districts.

does not effectively minimize the effects of flood damage. They also disagree with the statement that their villages receive sufficient financial resources and development services from the Government to mitigate the impacts of floods. To a lesser extent, members of this class do not view floods as an act of God or a regional/global phenomenon, which further delineates their vulnerability to flood risks. Their limited agreement with the effectiveness of government support and material used in housing, indicating low resilience, aligns with findings by Ref. [80], who noted the critical role of institutional support in shaping smallholder farmers' resilience to floods. Additionally, Shah et al. [7] emphasized the need for capacity-building and awareness in reducing vulnerability, further emphasizing the challenges Class I households face.

The second class (Class II) comprises approximately 17 % of the sample and is labelled as "*highly resilient smallholder farming households*," with responses trending towards the higher end of the resilience spectrum. Members of this class are economically, psychologically, and institutionally more resilient than members of the other classes. For example, around 79 % of members of this class boast diverse sources of income, and around 49 % of them express confidence that their financial debts will not significantly impede their ability to respond and recover from the impacts of floods.

Regarding the institutional component of resilience, 31 % of smallholder farming households within Class II agree that their local governments have procedures to compensate them for flood damages, and they appear to benefit from such schemes. Impressively, nearly 86 % of Class II members demonstrate high or very high levels of trust in government disaster risk reduction and management programs. The psychological component emerges as a significant factor in their overall resilience against flood hazards, with 60 % believing that floods are an act of God and an increasingly global phenomenon. Consequently, most of them (67 %) report lower levels of stress or depression in response to the occurrence of floods. In short, Class II's higher economic and psychological resilience and trust in government programs mirror the findings from Ref. [77,79], where economic diversification and institutional trust were identified as pillars of resilience.

The third class (Class III), identified by the latent class analysis, constitutes approximately 36 % of the sample population. For most of the indicators of the resilience index displayed in Table 2, responses from smallholder farming households within this class generally cluster around the midpoint of the Likert scale. Hence, we designated them as "*moderately resilient smallholder farming households*." While members of this class exhibit moderate levels of social and economic resilience, they stand out for their high environmental resilience compared to counterparts in other classes. This stems from their agricultural practices, which involve cultivating less vulnerable crops to flood risks and scheduling their cultivation to minimize flood-induced impacts on agricultural activities aligns with the findings of [59]. Similar to members of Class II, the results highlight high psychological resilience among Class III members, attributed to their beliefs and reduced levels of stress related to flood risks. This reflects the findings of [82], who explained that for some households, religious beliefs serve as an additional pillar of support and solace amid difficult periods, thereby strengthening their overall psychological resilience.

Overall previous studies based on 2010 floods generally found low to moderate resilience in flood-affected Pakistani communities, and our results reinforce this while performing LCA. For example, Ahmad & Afzal [20] reported that households had weak resilience in terms of recovering livelihoods, with economic capacity and social support being important influences. We likewise find that nearly half of surveyed households exhibit low resilience to floods, with only a minority showing high resilience. This aligns with earlier observations that communities struggled to "bounce back" fully from the 2010 floods.

4.5. Determinants of class membership

Table 3 presents the odds ratios of explanatory variables derived by taking the exponent of the log-odds. These odd ratios reflect the likelihood of being classified into a specific resilience class relative to a reference class and illustrate covariates' significance in determining the membership of the latent resilience classes. The results reveal that income is a significant factor in categorizing farming households into Class II (*High Resilient*) and Class III (*Moderate Resilient*), with higher-income farming households more likely to fall into these classes than class I (*Low resilient*). For instance, the probability that a higher-income household would likely fall into the high-resilient class is 3 times higher than the probability of belonging to the low-resilient class. Previous studies have frequently identified income as a key determinant of resilience while it provides households with the financial buffer to absorb shocks, invest in recovery, and adopt innovations [83]. Similarly, the results show that farmers' age significantly increases the chances of being in the high resilient class (Class II) or the moderately resilient class (Class III) compared to the Low Resilient class (Class I), indicating that the probability of older individuals being more resilient is higher. Experienced farmers are usually more resilient to environmental shocks due to their accumulated knowledge, enabling them to manage climate risks and adapt to flood hazards effectively [84]. Additionally, they may have witnessed a variety of flood events, learned effective coping strategies over time, and established more robust social networks and community ties, which can provide critical support during such events.

Furthermore, a farmer's education level was found to be generally associated with greater resilience. Specifically, suppose a farmer has higher levels of education. In that case, he or she has two times more chances to fall into the higher resilience class compared to low resilience and 1.5 times as compared to moderate resilience. Education is often associated with improved access to information, better decision-making capabilities, and the adoption of innovative practices. Thus, it can increase a farming household's ability to adapt to changing conditions, thereby enhancing the farm's resilience [85]. Lastly, with regard to farm size, the results provide inconsistent evidence of its impact on households' resilience. Consistent with this finding, Alhassan [59] indicates that the relationship between farm size and resilience can be complex and non-linear: while larger farms could be severely impacted during floods, they may have more resources to invest in resilience-building measures.

5. Policy implications

The empirical findings of this study offer several valuable policy implications for formulating effective strategies and tailored interventions to strengthen resilience and mitigate vulnerability among smallholder farming households in flood-prone rural communities, not only in Pakistan but also in similar contexts within low- and middle-income countries experiencing flood hazards.

First, the results reveal that both components of vulnerability - sensitivity, and adaptive and coping capacity - are important in determining the level of household susceptibility to flood risks, but their relative importance can vary depending on the specific context. However, the results show that sensitivity is the most crucial aspect. While sensitivity contributes more to the vulnerability index than adaptive capacity, which refers to a household's ability to cope with and recover from the impacts of floods, it suggests that even households with relatively high adaptive capacity may still face significant vulnerability if they are susceptible to flood impacts. In other words, adaptive capacity may help mitigate vulnerability to some extent but might not fully offset the effects of high sensitivity. Together, these findings underscore the importance of addressing sensitivity factors to reduce vulnerability to flood hazards. Strategies to improve housing conditions, strengthen infrastructure, enhance socio-economic resilience, and address inequalities can help reduce sensitivity and thereby mitigate overall vulnerability to floods. Additionally, enhancing adaptive capacity remains crucial, but it may be more effective when coupled with efforts to reduce sensitivity factors.

Second, the results pertaining to the components of the vulnerability index reveal notable geographical disparities in flood vulnerability across the three districts. These variations, both in the individual components of the vulnerability index and in the district-wise values, underscore the significance of location-specific factors in assessing vulnerability to floods. Such findings emphasize the need for tailored approaches to disaster risk management that account for each district's unique characteristics and challenges and call for targeted interventions that address the specific vulnerabilities observed in each district. This might involve prioritizing infrastructure improvements in areas with high risk levels, implementing community-based resilience-building programs tailored to address sensitivity factors prevalent in certain demographics or housing conditions, and enhancing institutional capacity for disaster preparedness and response in districts with lower adaptive capacity scores. In addition, fostering cross-district collaboration and knowledge sharing can facilitate the exchange of best practices and lessons learned, contribute to more effective and equitable disaster risk reduction efforts across the region, and enable policymakers to work towards reducing flood vulnerability and building more resilient communities in each district.

Third, the results underscore the significance of adopting holistic approaches to measure household resilience that extend beyond conventional economic and social components. Specifically, the prominence of high scores in the psychological component of resilience highlights its often-overlooked importance in resilient indices and measurements. This is evident through higher scores related to beliefs about future flood occurrences, stress, and fears regarding the impacts on household members and assets, indicating the crucial role of psychological factors in determining resilience. Thus, to address households' resilience comprehensively, policymakers should incorporate these psychological aspects into resilience-building strategies alongside other components to enhance the effectiveness of interventions and contribute to more resilient communities in the face of flood hazards.

Fourth, the results reveal surprisingly low scores for statements related to the institutional component of resilience compared to other components. These low scores may indicate deficiencies in disaster preparedness and planning at the municipal level. This could involve inadequate risk assessment, a failure to incorporate community input into planning processes, or a lack of investment in long-term resilience-building initiatives. These scores may also highlight issues such as insufficient funding, corruption, or bureaucratic inefficiencies that impede the implementation of robust disaster management plans. Furthermore, households may perceive a lack of support from governmental or non-governmental institutions during and after flood events, which could reflect delays or inadequacies in relief efforts, limited access to financial assistance, or inadequate infrastructure for disaster response and recovery. Another interpretation could be that institutions in the study areas may struggle to effectively coordinate with each other and communicate with affected households during flood events, which can lead to confusion, misinformation, and delays in accessing vital resources and

Table 3
Relative odd ratios for the class membership determinants.

Latent classes	Covariates	Base outcome class		
		Class I	Class II	Class III
		Coefficient	Coefficient	Coefficient
Class I (Low Resilient)	Age		2.448***	1.697*
	Education		2.101***	1.007*
	Income		3.143***	2.328**
	Farm size		0.967**	0.593
Class II (High Resilient)	Age	0.258***		0.403***
	Education	0.490*		0.599***
	Income	0.511*		0.710*
	Farm size	0.565		0.902**
Class III (Moderate Resilient)	Age	0.351***	1.254**	
	Education	0.444***	1.504**	
	Income	0.342**	2.702*	
	Farm size	0.226*	0.886	

***,** and * represents significance at 1 %, 5 % and 10 % respectively.

support services. Therefore, by adopting a multi-faceted approach, local institutions can better support households in building resilience to flood hazards and reducing the impacts of future disasters. This includes strengthening governance structures, improving coordination and communication mechanisms, enhancing disaster preparedness and planning processes, and prioritizing the needs of vulnerable populations. Ultimately, addressing these institutional challenges is crucial for strengthening overall resilience and promoting sustainable disaster management practices.

Fifth, the findings from the latent class analysis revealed that nearly half of the surveyed households exhibit low resilience to flood risks, while the remaining households are classified as moderately or highly resilient. Enhanced resilience levels are primarily attributed to economic, psychological, and institutional factors, including diversified income sources, confidence in managing post-flood financial obligations, and a strong trust in government disaster management initiatives. Consequently, targeted government interventions are imperative, tailored to address the distinct needs of each resilience class. Specifically, efforts should focus on sustaining diverse income streams and fostering trust in government programs, thereby improving household resilience against flood risks.

Sixth, the analysis of the factors influencing the likelihood of classification into specific resilience classes shows that higher-income farming households exhibit a greater propensity to belong to the highly or moderately resilient groups compared to the low resilient category. Similarly, older farmers, reflecting experience, demonstrate higher odds of belonging to higher resilience classes, underscoring the value of experience in navigating environmental challenges. In addition, higher levels of education correlate with increased resilience, likely attributed to enhanced access to information and decision-making capabilities. These findings underscore the importance of establishing income-generating and financial support mechanisms to assist farming households in investing in flood-resistant infrastructure, improved agricultural practices, and alternative livelihoods. Such mechanisms may encompass subsidies, low-interest loans, and insurance schemes. Furthermore, efforts should prioritize raising awareness of flood risks among small-scale farming households and bolstering early warning systems and emergency response protocols to ensure their readiness and effective response to flood events. This could entail investments in technology, capacity-building within institutions, and enhanced coordination among stakeholders.

6. Conclusion

The frequency and severity of flood hazards in Pakistan have remarkedly increased in recent decades, posing significant socio-economic and environmental challenges to affected areas, particularly among smallholder farming communities. The present examine the vulnerability and resilience of smallholder farming households in Southern Punjab during the 2022 flood events. Specifically, it employs an updated vulnerability assessment framework based on the IPCC AR6 (2023) guidelines, distinguishing exposure from vulnerability. It also develops and operationalizes multidimensional indices to assess the vulnerability and resilience of 269 smallholder farming households across three flood-affected districts in Southern Punjab. This study advances beyond previous research by utilizing a latent class analysis (LCA) approach to cluster surveyed households based on their flood resilience index scores and examine the impact of selected sociodemographic characteristics of household heads on their cluster membership. The results reveal high vulnerability and low resilience levels across the studied districts. The results pertaining to the two components of the vulnerability index reveal notable geographical disparities in flood vulnerability across the three districts. Additionally, the findings show that resilience index scores are generally low and more or less homogenous across the studied districts, with some variations pertaining to specific components. Based on LCA analysis, the findings reveal that nearly half of the surveyed households exhibit low resilience to flood risks, while the remaining households are classified as moderately or highly resilient. Regarding the role of demographic and socio-economic characteristics in shaping the resilience of farming households, income, education, and age stand out as primary determinants of resilience.

Despite the significance of our findings, this study has some limitations that should be acknowledged. One limitation is the restricted sample size due to budgetary constraints and time limitations. In addition, it is important to note that our study focused on smallholder farming households in the areas specifically selected for their experience to flood risks in 2022. Therefore, while our findings are robust for these flood-exposed areas, they may not be directly generalizable to smallholder farming households in non-flood-exposed regions or to other parts of Pakistan with different socioeconomic and environmental conditions. However, the insights gained can be valuable for informing disaster risk reduction strategies and policies in similar flood-prone areas. In addition, another notable limitation of this study is the reliance on respondent-reported perceptions for certain spatial indicators (e.g., household distance to rivers, road network quality and accessibility). While we implemented a rigorous validation protocol through enumerator-assisted response categorization, these perceptual measures remain inherently subjective. Future research should prioritize the integration of geospatial technologies such as GIS and remote sensing to obtain objective measurements of these spatial factors. Such an approach would enable more precise quantification of exposure variables while maintaining the valuable insights from perceptual data. Furthermore, the cluster membership analysis was restricted by including only a few variables, partly due to factors beyond our control, such as incomplete responses. The analysis could have benefited from incorporating a more diverse set of variables, encompassing a broader range of socio-economic and other factors that may influence group membership. Future research could build upon these findings by examining the effectiveness of household mitigation strategies and government interventions in enhancing the flood resilience of small-scale farming households.

CRediT authorship contribution statement

Mohsin Raza: Conceptualization, Investigation, Methodology, Data curation, Software, Formal analysis, Resources, Validation, Visualization, Writing – original draft, Writing – review & editing. **Assem Abu Hatab:** Conceptualization, Investigation, Methodology, Supervision, Software, Formal analysis, Resources, Validation, Visualization, Writing – review & editing.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijdrr.2025.105600.

Data availability

Data will be made available on request.

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