**POLICY INSIGHT ARTICLE****Economic Losses, Recovery and Institutional Support among Farm Households after the 2025 Floods: Evidence from Depalpur Tehsil, Okara District, Pakistan**Zobia Abid¹, Azhar Abbas^{1*} & Muhammad Amjed Iqbal¹¹Institute of Agricultural and Resource Economics, University of Agriculture, Faisalabad, Pakistan* Corresponding author: azhar.abbas@uaf.edu.pk**ARTICLE INFO****Keywords**

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The 2025 floods on the Ravi, Sutlej and Chenab rivers affected 4.77 million people in Punjab, Pakistan, yet household-level evidence on losses and recovery remains scarce. This study quantifies economic losses, recovery and institutional support among flood-affected farm households in Depalpur Tehsil, Okara District. A structured questionnaire was administered to collect data from 120 households randomly selected within five purposively chosen flood-affected villages, and data were analyzed using descriptive statistics, chi-square, and multiple regression. The average economic loss was Rs 52,937 per household, more than the average monthly household income (Rs 46,972), with crops (51.6% of total loss), housing (23.7%) and livestock (21.0%) the largest components. No household reported full recovery: 48.3% were partially recovered, 31.7% not yet recovered and 20.0% worse off than before the flood. Sixty percent received no government or NGO support, and only 3.3% named government compensation as their main source of recovery funds; households relied mainly on savings (43.3%) and informal loans (36.7%). Larger farm size, family size and income raised losses, whereas greater distance from the river and the household head's education reduced them ($R^2 = .64$). The results indicate a recovery gap rooted in thin, in-kind and unevenly distributed support. We discuss policy implications for consideration: pre-arranged cash transfers, accessible crop insurance, flood-contingent credit, riverine early warning and coordinated district-level response.

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1. INTRODUCTION

Floods are among the most damaging and recurrent hazards in Pakistan, which has recorded 29 major floods since 1947 (Waseem & Rana, 2023). Their burden falls disproportionately on poor, agriculture-dependent households, whose assets are concentrated in exposed land, livestock and mud-brick housing and who have few formal means of absorbing shocks (Cutter et al., 2003; Hallegatte et al., 2017). The 2022 floods alone affected about 33 million people (Government of Pakistan, 2022), and uninsured shocks of this kind can have lasting effects on household welfare because families deplete productive assets to cope (Dercon, 2004).

The 2025 floods were exceptional on the eastern rivers. Heavy monsoon rainfall and upstream releases placed the Ravi, Sutlej and Chenab in flood together, at levels not seen since 1988 (UN OCHA, 2025). The Provincial Disaster Management Authority (PDMA) Punjab recorded 4.77 million people affected in 4,754 villages across 27 districts, 1.46 million acres of farmland affected and 162,542 houses damaged, of which 69% were mud houses (Ilyas, 2025). Okara District, which lies between the Sutlej and Ravi, has been flooded repeatedly (1988, 1998, 2010, 2014 and 2022). District-level estimates indicate that more than 12,000 people from 618 families were evacuated and about 50,000 acres of agricultural land were affected in 2025, with Depalpur Tehsil the worst hit.

Household studies in Pakistan have examined flood risk perception, mitigation and coping, mostly after earlier events. Ahmad and Afzal (2020) analyzed the factors shaping household perception and mitigation of flood hazards, while Abbas et al. (2018) found that distance from the river and elevated housing reduced riverine flood damage and that coping ranged from borrowing and reduced food consumption to savings use and asset disposal. Quantitative evidence on the economic losses, recovery and institutional support after the 2025 floods at household level in Okara has not been documented. Such evidence is needed because decisions on compensation, insurance and relief depend on local data rather than provincial averages.

This study therefore (i) quantifies the economic losses of flood-affected farm households in Depalpur Tehsil, (ii) documents recovery, coping and the support received from communities and institutions, and (iii) identifies the determinants of loss in order to derive policy options (Figure 1).

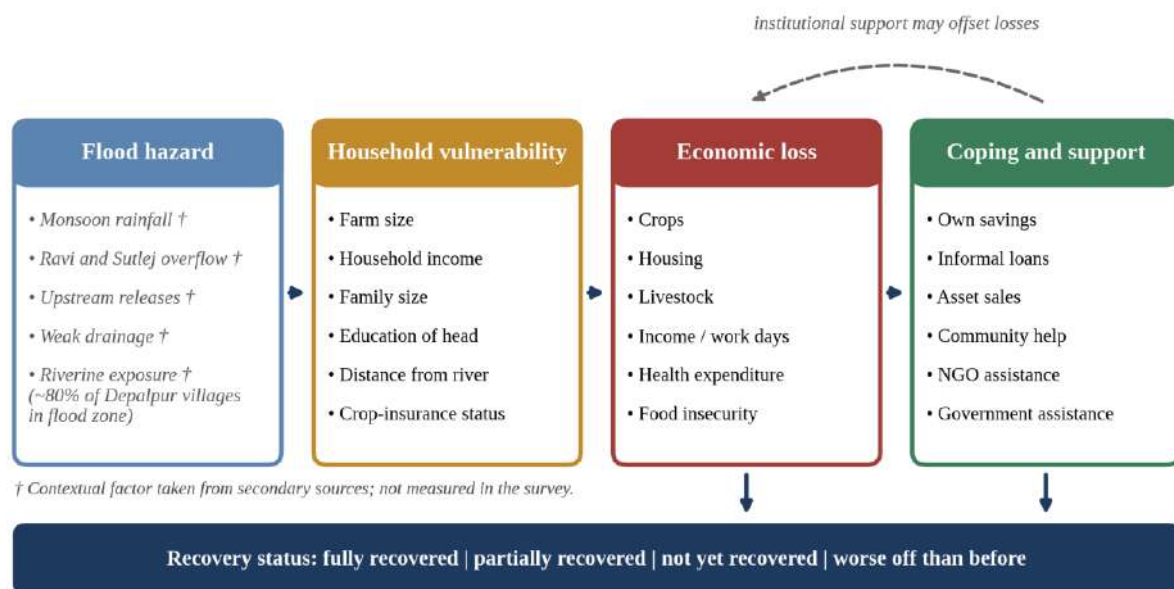


Figure 1. Conceptual Framework Linking Flood Hazard, Household Vulnerability, Economic Loss, Coping and Support, and Recovery Status

To our knowledge, none of these earlier studies has documented household-level losses after the 2025 floods, when the Ravi, Sutlej and Chenab flooded together. This study adds (i) household-level loss estimates for five villages of Depalpur Tehsil; (ii) self-reported recovery status, analyzed alongside financing and coping; and (iii) the reach and form of government and NGO support, linked to losses and recovery. Table 1 maps each construct in Figure 1 to the survey variables.

Table 1. Measurement of the Constructs in the Conceptual Framework (Figure 1)

Construct	Survey variables	Unit or coding	Measurement status
Flood hazard and exposure	Distance from the river	km	Partly measured: exposure captured only as distance from the river; flood depth and duration not collected
Flood hazard (rainfall, river overflow, upstream releases, drainage)	Not collected in the survey	—	Contextual factors taken from secondary sources
Household vulnerability	Household income; farm size; family size; education of the household head; age group; gender; land tenure; number of earners; dependence on agriculture	Rs per month; acres; persons; years; categories; %	Measured
Preparedness	Crop-insurance status	Yes/no	Partly measured: availability, affordability and demand not recorded; receipt of early warning not collected
Economic loss	Losses by category (crop, housing, livestock, income, health expenditure) and in total; share of crop and housing damaged; weeks of work disrupted; food insecurity	Rs; %; weeks; yes/no	Measured
Coping	Primary source of recovery funds; informal borrowing; asset sales; constraints faced	Categories; % of households	Measured
Institutional support	Government and NGO assistance received, and type of assistance	Yes/no; type	Measured
Recovery status	Fully recovered, partially recovered, not yet recovered, worse off than before	Four categories	Measured

2. MATERIALS AND METHODS

2.1 Study Area

Okara District of Punjab is bordered by Sahiwal, Pakpattan, Faisalabad, Nankana Sahib and Kasur. About 75% of its population depends on agriculture, and the main crops are cotton, maize, rice, sugarcane, sesame and wheat. Depalpur Tehsil was selected purposively because it is the most exposed to Sutlej flooding, with approximately 80% of its villages lying in the riverine flood zone.

2.2 Sampling and Data Collection

A two-stage design was used. In stage one, five flood-affected villages of Depalpur Tehsil were selected purposively (Sulemanki, Basti Lal Shah, 52/4R, 55/4R and 60/4R). In stage two, households were drawn by simple random sampling from each village's list of flood-affected households. With 618 affected households and a 5% margin of error, the Yamane (1967) formula, $n = N/(1 + Ne^2)$, gives a required sample of 243. We interviewed 120 households (19.4% of the eligible households) because of time and funding constraints. With 120 households, the maximum margin of error for a proportion (95% confidence, $p = .5$, finite-population correction) is about ± 8 percentage points rather than ± 5 , before allowing for clustering within villages, and estimates for subgroups are less precise. The results are therefore treated as indicative of the five surveyed villages only; the allocation of the sample across villages is shown in Table 2. Data were collected face to face by trained enumerators using a structured, pre-tested questionnaire with six sections, in February 2026, about five months after the floods.

Table 2. Sampling Frame and Sample Allocation across the Five Villages

Village	Eligible households	Households sampled	Sampling fraction (%)
Sulemanki	135	32	5.2
Basti Lal Shah	130	28	4.5
52/4R	122	22	3.6
55/4R	118	20	3.2
60/4R	113	18	2.9
Total	618	120	19.4

Note: Eligible households are the flood-affected households listed in each village. The order of the sample sizes follows the order in which the villages are listed in the submitted manuscript.

2.3 Variables and Analysis

Households reported losses in rupees by category (crop, housing, livestock, income and health expenditure) and in total, their recovery status (fully recovered, partially recovered, not yet recovered, worse off than before), the primary source of recovery funds, coping strategies, constraints, and any government or NGO support received. Data were analyzed in IBM SPSS 26 and Excel. Descriptive statistics were followed by a chi-square test of the association between government support and recovery status, and one-way ANOVA with Tukey's post-hoc test across recovery groups. Determinants of total loss were estimated by multiple linear regression on household income, farm size (acres), education of the household head (years), distance from the river (km) and family size. Significance was assessed at $\alpha = 0.05$, with normality and homogeneity of variance checked beforehand.

3. RESULTS

3.1 Respondent Profile

Respondents were mostly male (80.8%), middle-aged and poorly educated (Table 3). No respondent was younger than 31 years. Nearly three-quarters of households (71.7%) depended on agriculture, farms averaged 9.47 acres, most households (61.7%) had five to seven members and two-thirds (68.3%) had a single earner. Average monthly household income was Rs 46,972. This profile combines low income, high dependency and strong exposure, which are characteristics associated with high flood vulnerability.

The household was the unit of analysis. One respondent was interviewed per household: the household head, or, if the head was absent, the adult responsible for farm and household finances. Respondent characteristics in Table 3 are therefore those of the household head, and "education of household head" in the regression refers to the same person. No respondent was younger than 31 years because heads of farm households in these villages are rarely under 31. The 19.2% female respondents ($n = 23$) were female household heads or the main decision-makers in their households.

Table 3. Profile of the Surveyed Households ($N = 120$)

Characteristic	Value
Gender of respondent	Male 80.8%; female 19.2%
Age group	31–45 years 33.3%; 46–60 years 41.7%; over 60 years 25.0%
Education	None 36.7%; primary 39.2%; middle 24.2%
Land tenure	Owners 24%; owner-cum-tenants 57%; tenants 19%
Average farm size	9.47 acres
Agriculture-dependent households	71.7%
Family size of five to seven members	61.7%
Households with a single earner	68.3%

Note: Characteristics are those of the household head or the adult responsible for farm and household finances (Section 3.1).

3.2 Economic Losses, Health, and Food Security

The average economic loss was Rs 52,937 per household, compared with an average monthly household income of Rs 46,972; total loss across the 120 households was Rs 6,352,445. Mean losses were highest for crops (Rs 88,250), followed by housing (Rs 79,033), livestock (Rs 44,333), income (Rs 17,045) and health expenditure (Rs 8,973) (Table 4 and Figure 2a). Crops accounted for the largest share of total loss (51.6%), then housing (23.7%) and livestock (21.0%).

Table 4. Average Loss per Household by Category and Share of Total Sample Loss ($N = 120$)

Loss category	Mean loss per household (Rs)	Share of total loss (%)
Crop	88,250	51.6
House	79,033	23.7
Livestock	44,333	21.0
Income	17,045	2.5
Health expenditure	8,973	1.2

Damage was severe but graded. For crops, 74.2% of households lost 25–50% of their crop and 25.8% lost 50–75%. For housing, damage was 20–34% for 35.0% of households, 35–50% for 41.7% and 50–75% for 23.3%. All 120 households incurred health expenditure (average Rs 8,973), work was disrupted for 3.72 weeks on average, and 57.5% (69 of 120) reported going without food or reducing food groups.

3.3 Recovery, Coping, and Support

No household reported full recovery (Figure 2). Recovery was partial for 48.3% of households, 31.7% had not yet recovered and 20.0% were worse off than before the flood. Mean total loss rose across these groups – from Rs 17,649 for partially recovered households to Rs 25,406 for those not yet recovered and Rs 33,013 for those worse off (Figure 2b), and the differences were significant ($F(2, 117) = 302.97, p < .001$; all Tukey pairwise comparisons $p < .001$).

Recovery was financed mainly privately: own savings (43.3%) and loans from friends and relatives (36.7%) were the primary sources, against bank loans (10.0%), NGO support (5.0%), government compensation (3.3%) and asset sales (1.7%). Overall, 80% of households borrowed informally and 53.3% sold assets to cope. The most common constraints were lack of money (93.3%), no help from government or NGOs (81.7%), high material costs (71.7%), lack of access to credit (61.7%), poor road access (56.7%) and no crop insurance (53.3%).

Institutional support was limited. Government assistance reached 16.7% of households and NGO assistance 32.5%; 9.2% received both and 60.0% received neither. Among households receiving government help, 90% received medicines and 70% animal feed, while only 10% received cash.

Receipt of government support (20 households, 16.7%) was associated with better recovery status ($\chi^2(2) = 25.66, p < .001$; Cramér's $V = .46$; Table 5). This association should not be read as an effect of aid, because support may have reached less-affected households.

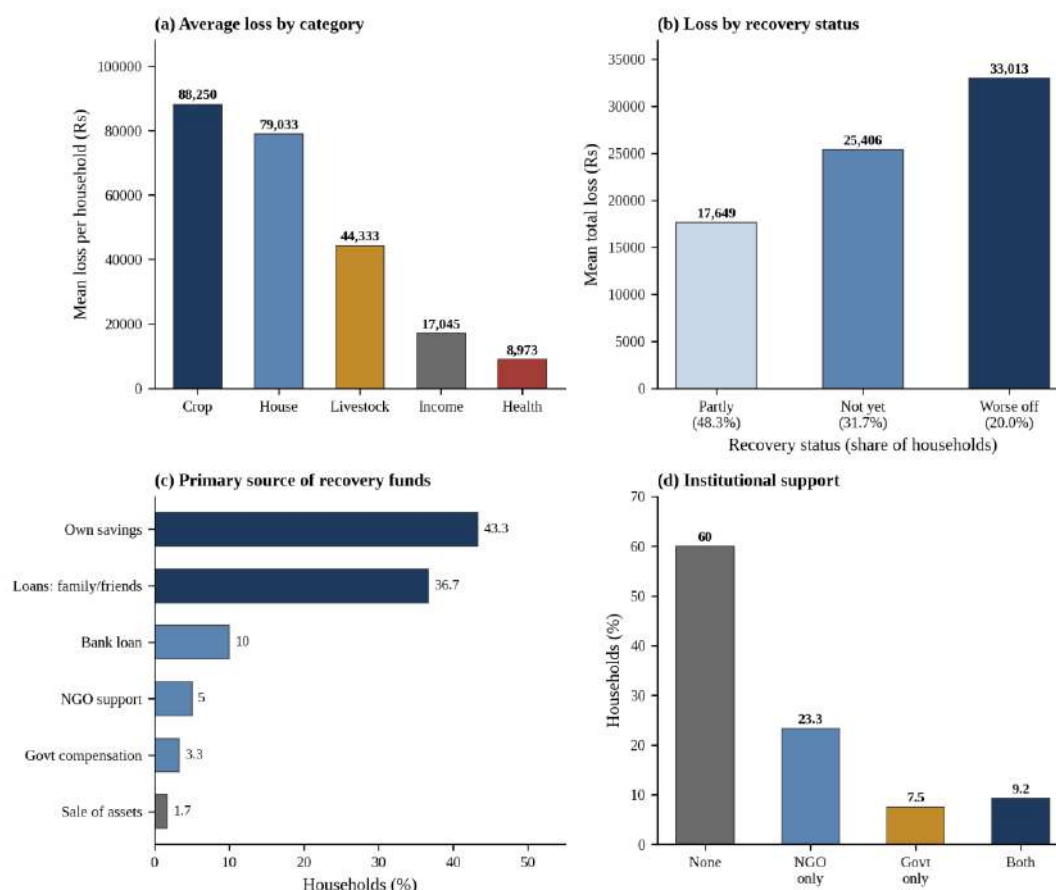


Figure 2. Losses, Recovery, and Support after the 2025 Floods (N = 120): (a) Average Loss per Household by Category; (b) Mean Total Loss by Recovery Status; (c) Primary Source of Recovery Funds; (d) Government and NGO Support Received

Table 5. Tests of Recovery Status, Government Support and Total Loss

Test	Comparison	Statistic	df	p	Effect size or note
Chi-square	Government support $\times$ recovery status	$\chi^2 = 25.66$	2	< .001	Cramér's $V = .46$
One-way ANOVA	Total loss by recovery status	$F = 302.97$	2, 117	< .001	Tukey pairwise comparisons all $p < .001$

Note: Government support reached 20 households (16.7%); the association should not be read as an effect of aid.

3.4 Determinants of Flood Loss

The regression explained 64.2% of the variation in total loss (adjusted $R^2 = .626$; $F = 40.86$, $p < .001$; Table 6). Farm size was the strongest positive determinant: each additional acre was associated with about Rs 86 of additional loss ($0.086 \times 1,000$), holding other variables constant. Household income and family size also increased losses, whereas education of the household head and distance from the river reduced them. To be precise, each additional year of education of the household head was associated with about Rs 41 less flood loss, and each additional kilometer of distance from the river with about Rs 118 less.

Table 6. Multiple Regression of Total Flood Loss on Household Characteristics ($N = 120$)

Variable	B	SE	t	p
Constant	0.842	0.286	2.944	0.004
Household income	0.012	0.004	3.000	0.003
Farm size (acres)	0.086	0.018	4.778	< .001
Education of head (years)	-0.041	0.018	-2.278	0.024
Distance from river (km)	-0.118	0.035	-3.371	0.001
Family size (persons)	0.073	0.028	2.607	0.010

Note: $R^2 = .642$; adjusted $R^2 = .626$; $F = 40.86$ ($p < .001$). Dependent variable: total flood loss, stated by the authors as Rs '0000 per household. Explanatory variables: household income (Rs '0000); farm size in acres; education of the household head in years; distance from the river in km; family size in persons. B = unstandardized coefficient.

4. DISCUSSION AND POLICY IMPLICATIONS

4.1 Interpretation

The central result is that an average loss of Rs 52,937 exceeded a month of household income (Rs 46,972), and that it was concentrated in crops and housing, the assets on which farm families depend for both consumption and future earnings. Crops alone accounted for more than half of total loss, and housing for more than a quarter. Most houses were substantially damaged (65% lost at least 35% of the structure), consistent with the predominance of mud-brick construction reported for Punjab (Ilyas, 2025). Recovery tracked losses closely: households that were worse off had mean losses almost twice those of partly recovered households. Households closer to the river lost more, consistent with Abbas et al. (2018), while the negative education coefficient suggests that awareness and preparedness matter, though schooling may also proxy for non-farm income and housing quality.

The financing pattern is the main policy concern. Four in five households financed recovery from savings or informal kin loans, and more than half sold assets. For single-earner households with low incomes, losses of this size cannot be absorbed from savings without cutting consumption or investment. Such strategies replace one loss with another and, as Dercon (2004) shows for rural households more generally, can leave welfare lower for years. Abbas et al. (2018) observed savings use mainly among high-damage households, whereas informal borrowing dominated in this sample, which may reflect the thinness of formal credit; only 10% of households used a bank loan.

4.2 Policy Implications for Consideration

The evidence is consistent with six implications for consideration, summarized in Table 7. Their sequencing matters. Cash transfers address the immediate gap and prevent distress sales, since cash was received by only one in ten of the households that obtained government help and in-kind aid cannot replace lost income or crops. Pre-arranged delivery is the key design feature: evidence on shock-responsive social protection stresses advance financing, targeting data and delivery systems (O'Brien et al., 2018), and existing registries such as Pakistan's social-protection database could be used for rapid payments, supplemented by verified damage assessment for timely recovery. Crop insurance and flood-contingent credit act before the next season, because crops were the largest loss and only 10% of households used bank credit. Early warning and riverine targeting reduce exposure, but they require investment

and district capacity. Finally, extended support and a single district coordination body address the fragmentation implied by the 60% of households reached by neither government nor NGOs.

Table 7. Policy Implications for Consideration, Linked to the Study's Evidence

Option	Supporting evidence	Main constraint	Support from this study's data
1. Pre-arranged cash transfers	Cash reached 10% of government-assisted households; 80% borrowed informally	Fiscal cost; targeting errors	Direct
2. Simple, subsidized crop insurance	Crops were the largest loss; 53.3% cited no insurance	Premium affordability; claims trust	Not tested (availability, affordability and demand not measured)
3. Flood-contingent credit and reconstruction support	61.7% lacked credit; 71.7% cited high material costs	Lender capacity; price control	Indirect
4. Riverine early warning and targeting	Loss rose closer to the river; ~80% of villages in flood zone	Investment; local capacity	Indirect (distance-to-river result)
5. Gender-responsive and long-term support	19.2% of respondents female; recovery incomplete in all households	Not tested by gender in this study	Not tested (policy principle; no gender analysis)
6. District coordination of government and NGOs	60% reached by neither	Institutional will	Indirect

Note: Wider coverage and targeting of relief, which Section 4.2 also describes as supported directly by the descriptive evidence, is not a separate row in this table.

The results suggest several implications, which differ in how directly the data support them (Table 7). Two are supported directly by the descriptive evidence: faster and more flexible liquidity after floods (80% of households borrowed informally, 53.3% sold assets, 93.3% cited lack of money, and only 10% of households receiving government help received cash), and wider coverage and targeting of relief (60% received no government or NGO assistance, and losses were higher on larger farms and closer to the river). The remaining items are hypotheses for further research. For crop insurance, 53.3% of households reported having no cover, but the survey did not measure whether insurance was available, affordable or wanted, so demand and willingness to pay should be assessed first. Early warning, credit and coordination are suggested only indirectly, by the distance-to-river result, reported credit constraints (61.7%) and the small overlap between government and NGO assistance (9.2%); warning receipt, repayment capacity and coordination processes were not measured. Gender-responsive support is a policy principle rather than a result: the sample included 23 female respondents, too few for a reliable comparison, and outcomes were not analyzed by gender.

4.3 Limitations

The sample covers five purposively selected villages in one tehsil and is below the Yamane target of 243 households, so results are indicative rather than representative of Okara. Losses are self-reported and subject to recall error, the data are cross-sectional and in current rupees, and the association between support and recovery cannot be interpreted causally. Exposure was captured only through distance from the river and preparedness only through crop-insurance status; flood depth and duration, and receipt of early warning, were not collected. Differences by gender of household head were not analyzed, so Option 5 rests on the vulnerability profile rather than on a tested gender gap.

5. CONCLUSIONS

The 2025 floods imposed an average loss of Rs 52,937 on the surveyed households in five villages of Depalpur Tehsil, more than a month of average household income and concentrated in crops and housing, and none had fully recovered. Sixty percent received no government or NGO assistance, and recovery relied on savings, informal borrowing and asset sales. Losses were greater for larger farms, larger families and households closer to the river. The results point to implications for consideration: pre-arranged cash transfers, accessible crop insurance and credit, riverine early warning and district-level coordination could shift recovery from household self-financing towards institutional support, although most of these items rest on indirect evidence (Section 4.2). Larger, multi-district studies, including follow-up surveys, would show whether these findings hold across the Ravi–Sutlej belt and how long recovery takes.

References

- Abbas, A., Amjath-Babu, T. S., Kächele, H., Usman, M., Iqbal, M. A., Arshad, M., Shahid, S., & Müller, K. (2018). Sustainable survival under climatic extremes: Linking flood risk mitigation and coping with flood damages in rural Pakistan. *Environmental Science and Pollution Research*, 25(32), 32491–32505. <https://doi.org/10.1007/s11356-018-3203-8>
- Ahmad, D., & Afzal, M. (2020). Flood hazards and factors influencing household flood perception and mitigation strategies in Pakistan. *Environmental Science and Pollution Research*, 27(13), 15375–15387. <https://doi.org/10.1007/s11356-020-08057-z>

- Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social vulnerability to environmental hazards. *Social Science Quarterly*, 84(2), 242–261. <https://doi.org/10.1111/1540-6237.8402002>
- Dercon, S. (2004). Growth and shocks: Evidence from rural Ethiopia. *Journal of Development Economics*, 74(2), 309–329. <https://doi.org/10.1016/j.jdeveco.2004.01.001>
- Government of Pakistan. (2022). Pakistan floods 2022: Post-disaster needs assessment. Ministry of Planning, Development and Special Initiatives.
- Hallegatte, S., Vogt-Schilb, A., Bangalore, M., & Rozenberg, J. (2017). Unbreakable: Building the resilience of the poor in the face of natural disasters. World Bank. <https://doi.org/10.1596/978-1-4648-1003-9>
- Ilyas, M. (2025, December 27). The year the rivers reclaimed their routes. *The Express Tribune*. <https://tribune.com.pk/story/2584220/the-year-the-rivers-reclaimed-their-routes>
- O'Brien, C., Holmes, R., Scott, Z., & Barca, V. (2018). Shock-responsive social protection systems research: Synthesis report. Oxford Policy Management.
- UN OCHA. (2025, August 30). Pakistan: Monsoon floods 2025, flash update #4. <https://www.unocha.org/publications/report/pakistan/pakistan-monsoon-floods-2025-flash-update-4-30-august-2025>
- Waseem, H. B., & Rana, I. A. (2023). Floods in Pakistan: A state-of-the-art review. *Natural Hazards Research*, 3(3), 359–373. <https://doi.org/10.1016/j.nhres.2023.06.005>
- Yamane, T. (1967). *Statistics: An introductory analysis* (2nd ed.). Harper & Row.

Declarations

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Ethics Compliance: Written consent was obtained before the interviews.

Author Contributions: Zobia Abid conceptualized, investigated, conducted formal analysis, and writing (original draft); Azhar Abbas supervised and writing (original draft); and Muhammad Amjed Iqbal supervised and writing (review and editing).

Use of AI: AI-assisted tools (LLMs) were used to improve the language, grammar and formatting the figure(s). The author reviewed and approved all content and assume full responsibility for its accuracy.