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Flood Risk Management in Agriculture: A Case Study of Flood Prone Area in South Punjab, Pakistan

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ABSTRACT

The most dangerous natural risks to human societies are floods. Flood frequency and severity have increased in frequency and intensity due to climate change over the past few decades. The most significant adverse impacts of floods are observed in the agriculture sector, where the floods cause damage to standing crops, livestock, tube wells, storage and other infrastructures and disrupt the mechanisms of inputs and output markets. The present study is designed to investigate the impacts of the 2022 floods in South Punjab and how the farming communities are responding to flood risks by adopting various flood risk management strategies. The study used a structured questionnaire to collect data from 150 sampled respondents from two districts, namely Rahim Yar Khan and Rajanpur of South Punjab. Two separate binary logistic models were employed to analyze the collected data. The findings revealed that perceptions of flood risks and pest and disease risks significantly discourage the use of on-farm diversification as a flood risk management strategy, while farm size and livestock losses are reported to significantly encourage the adoption of on-farm diversification to manage flood risks. For off-farm diversification, the significant variables are monthly income, perceptions of flood risk, and livestock losses due to floods. The study recommended that relevant information on flood risks be provided to the farming community. This will enable farmers to anticipate the climatic events and to adopt sophisticated risk management strategies accordingly.

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INTRODUCTION

Climate change poses one of the most critical challenges of our time. The vulnerability of the global agricultural sector is of great concern, as climate fluctuations threaten to undermine food production and supplies permanently. This presents a significant obstacle to food systems worldwide, especially in countries heavily reliant on agriculture for their economy and productivity (Abbass et al., 2022). The impacts of climate change have further exacerbated the frequency and intensity of floods and other climate-related events worldwide. While completely preventing such natural disasters is often impractical and costly due to inherent vulnerabilities, the concept of risk management has gained prominence as a more feasible solution, garnering increasing attention in flood research (Schanze, 2006).

Flood risk management has been extensively discussed (Schanze, 2006), but it often overlooks the key actors involved. Flood risk management has typically evolved using a heuristic technique characterized by extremely sluggish and sporadic advancements that have not always considered significant or unexpected shifts in policies and practices over time (Sayers et al., 2018). Unlike conventional methods, modern flood risk management necessitates a diverse portfolio of strategies and actions to address current and anticipated hazards (Vitale, 2023). Despite substantial investments in flood prevention, forecasting, and preparation resulting from past inundations, the destruction and casualties caused by flood-related incidents in some of the wealthiest and most technologically advanced nations in central Europe in July 2021 have once again highlighted the vulnerability and exposure to floods (Pathfinder and Cornwall Council, 2021). The adoption of a risk-based strategy underscores the importance of collaboration between spatial designers and water managers in the context of flood risk management (Howe and White, 2004; Hartmann and Juepner, 2017).

In long-term efforts to prevent and minimize floods, technical solutions have proven to be insufficiently successful (Ellis et al., 2023) and have resulted in some negative environmental effects (Huang et al., 2022). The term "safe development paradox" describes the possibility that the implementation of technical safeguards could increase the accessibility of social resources (Haer et al., 2020) or negatively impact the connectivity of floodplains and their ecological roles (Khosravi et al., 2020). As a result, FRM techniques have shifted towards methods that leverage natural features, processes, and management decisions to enhance water retention in catchments and floodplains. Natural processes inspire and facilitate These actions and procedures, although they may also require technical inputs for adoption and maintenance. These strategies are expected to have various effects, including desynchronizing the spatiotemporal distribution of peak flows during severe floods and reducing Drainage and instream flow by storing water. In situations lacking space to store water, such as urban landscapes, nature-based solutions (NBS) are combined with built infrastructure to form mixed approaches (Alves et al., 2020). However, regardless of the setting, a catchment-wide perspective is required to mobilize co-benefits of various NBS and support water-responsive geographic growth (Albrecht and Hartmann, 2021). Considering the above discussion, the present study has been designed to investigate the risk-coping tools adopted by the sampled farmers and to assess the impacts of various socio-economic attributes and farm characteristics on adopting these tools in the flood-prone districts of South Punjab.

METHODOLOGY

The multistage sampling technique is used to select the sample households required for the data collection. As Punjab province was significantly impacted by the massive flood that devastated Pakistan in June 2022, Punjab province was carefully selected for the study in the initial stage. Two districts from the Punjab province—Rahim Yar Khan and Rajanpur—are purposefully chosen for the second stage. A questionnaire was developed to gather primary data from 150 participants. The primary data was collected through face-to-face interviews, utilizing a well-structured questionnaire tailored specifically for this study. The data were collected on farmers' age, education, family size, experience in fieldwork, family members involved in farming, and whether they own or rent the land.

An appropriate, complete sample was necessary if limited research was to produce reliable results. For this, the tehsil, villages and respondents were selected in District Faisalabad and a multistage purposive sampling technique (to make the sampling process more practical, dividing the large populations into small stages) was used. Poate and Daplyn (1993) gives the formula for sample selection as

$$n=\frac{Z^2\,(100-p)}{x^2} \tag{1}$$

Where 'n' is the sample size, the confidence level is represented as '.'p being proportion constant and "x in the denominator represents the level of precision.

A binary logistic model, also known as a binary logistic regression model, is a statistical method used to predict the probability of a binary (categorical) outcome based on one or more predictor variables. The dependent variable in a binary logistic model can only have two possible outcomes, typically represented as 0 and 1 (or sometimes as "failure" and "success"). The binary logistic model is an extension of simple logistic regression, which is used when the dependent variable is binary and there is only one predictor variable. In binary logistic regression, the relationship between the predictor variable(s) and the binary outcome is modeled using the logistic function, which transforms the linear combination of predictors into a probability value bounded between 0 and 1.

The formula for binary logistic regression is as follows:

$$p = 1 / (1 + \exp(-z)) \tag{2}$$

Where p is the probability of the binary outcome being 1, exp is the exponential function and z is the linear combination of the predictor variables. The linear combination z is calculated as:

$$z = \beta 0 + \beta 1*x1 + \beta 2*x2 + ... + \beta n*xn \tag{3}$$

Where β0, β1, β2,... βn are the coefficients of the predictor variables (also known as model parameters) while x1, x2, ..., xn are the values of the predictor variables. The goal of binary logistic regression is to estimate the coefficients (β0, β1, β2, ..., βn) that best fit the data and maximize the likelihood of the observed outcomes. This estimation process is often done using maximum likelihood estimation (MLE). Once the coefficients are estimated, the binary logistic model can be used to predict the probability of the binary outcome for new observations based on their predictor values. If the predicted probability is greater than or equal to 0.5, the predicted outcome is usually assigned as 1; otherwise, it is assigned as 0.

In our case, the dependent variable is dichotomous and represents the adoption of two risk-coping tools: on-farm and off-farm diversification by the sampled farmer. The independent variables comprised socio-economic characteristics, farm attributes, climate change perceptions, and losses due to floods of the sampled respondents, which influenced the adoption of flood risk management tools.

RESULTS AND DISCUSSION

This section provides the main findings of the study in light of the main objective set for the study. The first sub-section comprised the summary statistics of the independent variables, while the second sub-section provided the findings of binary logistic regression used to assess the impacts of various independent variables on the adoption of flood risk management tools.

Floods

Overflowing of water onto normally dry land, often caused by heavy rainfall, dam failures, or coastal storms. Table 1, for both districts, shows the distribution of sampled respondents' perceptions of the risk of flooding. The flood incidence and severity are categorized into a) Very High, b) High, c) Normal, d) Very Low, and e) Low, according to the sample respondents.

Table 1: Incidence/severity of floods

Districts		Low	Normal	High	Very High	Total
Rahim Yar Khan	Incidence	0	0	21(28)	54(72)	75
	Severity	0	0	19(25.33)	56(74.66)	75
Total		2(1.33)	11(7.33)	40(26.66)	110(73.33)	150
Rajan Pur	Incidence	2(2.66)	11(14.66)	31(41.33)	31(41.33)	75
	Severity	0	0	32(42.66)	43(57.33)	75
Total		2(1.33)	11(7.33)	63(42)	74(49.33)	150

Droughts

Extended periods of abnormally low precipitation result in water scarcity, crop failure, and ecological damage. Table 2 for both districts shows the distribution of sampled respondents' perceptions of the risk of droughts. The drought incidence and severity are categorized into a) Very High, b) High, c) Normal, d) Very Low, and e) Low, according to the sample respondents.

Table 2: Incidence and severity of Droughts

Districts		Very Low	Low	Normal	High	Very High
Rahim Yar Khan	Incidence	0	0	0	38(50.66)	37(49.33)
	Severity	0	0	0	38(50.66)	37(49.33)
Total		0	0	0	76(50.66)	74(49.33)
Rajan Pur	Incidence	0	0	14(18.66)	16(21.33)	45(60)
	Severity	0	0	9(12)	28(37.33)	38(50.66)
Total		0	0	23(15.33)	44(29.33)	83(55.33)

Impact of flood at farm level

Floods can significantly impact farms at various levels, affecting crops, livestock, infrastructure, and overall farm productivity. Here are some of the common impacts of floods at the farm level.

Loss of livestock

Floods can endanger livestock by drowning them or limiting their access to food and clean water. Livestock may also be susceptible to diseases and infections in flood-affected areas, leading to illness or death. Floods can disrupt the entire livestock supply chain, including feed availability and transportation. The impact of the flood on the livestock sector in both districts is shown in Table 3.

Table 3: Loss of livestock

Districts	Name of Livestock	Total Owned Avg.	Avg. Died	Avg. Lost	Avg. Injured	Avg. Value of Lost Animals
Rahim Yar Khan	Own Information					
	Buffalo	5.40	1.25	0	2.05	69134.62
	Cow/Bullocks	5.82	1.88	1	2	208555.6
	Sheep/Goat	10.08	3.66	0	3.25	182000
Rajan Pur	Buffalo	5.6	0	0	2.06	7903.226
	Cow/Bullocks	5.21	0.5	0	1.96	72133.33
	Sheep/Goat	9.63	2.5	0	2.86	56803.13

Crops damages

Floods can significantly impact crops, causing both short-term and long-term consequences. Overall, the impact of floods on crops can be devastating, affecting food production, agricultural economies, and food security in the affected regions. Implementing effective flood mitigation strategies, such as improved drainage systems and flood-resistant crop varieties, can help minimize these impacts and enhance resilience in agricultural systems. When floodwaters inundate agricultural areas, the consequences are far-reaching and multifaceted. The immediate effects include soil erosion, waterlogging, nutrient loss, and physical damage to crops. These factors directly contribute to reduced crop yields, compromised quality, and financial losses for farmers. Moreover, floods can initiate a chain reaction with long-term implications, including soil degradation, disease outbreaks, pest infestations, and crop contamination. The flood severely affected several crops in both districts, as shown in Table 4.

Table 4: Crop damages

District	Crop Name	Avg. Cultivated area	Avg. Flood Affected Area	Avg. Estimated Loss due to the onset of floods
Rahim Yar Khan	Cotton	18.1	15.98	450000
	Rice	14.67	8.6	250000
	Sugarcane	15.43	10	150000
Rajanpur	Cotton	14.04	13.81	356000
	Rice	7.42	7.42	300000
	Sugarcane	5.22	4.44	120000

Strategies adopted after the flood

After a flood event, farmers often employ various strategies at the farm level to recover from the damage and resume agricultural activities. Here are some common strategies adopted after a flood: a) On-Diversification, b) Off-Farm Diversification, c) Precautionary Savings, d) Credit, e) Crop Insurance, f) Government Support, g) Forward Contract, h) Improve Drainage, I) Reduced Investment. These strategies are categorized as Adopted or not adopted out of the total sample respondents, as shown in Table 5.

Table 5: Strategies adopted after the flood.

Strategies	Adopted	Not Adopted	Total
On-Diversification	40(26.66)	110(73.33)	150
Off-farm diversification	55(36.66)	95(63.33)	150
Precautionary Savings	83(55.33)	67(44.66)	150
Credit	105(70)	45(30)	150
Crop Insurance	0	0	150
Government support	35(23.33)	115(76.66)	150
Forward contract	42(28)	108(72)	150
Improve Drainage	25(16.66)	125(83.33)	150
Reduced Investment in farm	0	0	150

In both districts, the majority of the respondents, 73.33 percent, had not adopted the on-farm diversification, and only 26.66 percent of respondents were adopted out of the total sample respondents. Similarly, the majority of both districts, with 63.33 percent of respondents, have not adopted the off-farm diversification, and only 36.66 percent have adopted it. In both districts, more than half of the respondents, 55.33 percent of the respondents have adopted the strategy of precautionary saving. At the same time, 44.66 respondents were not adopted out of the total sample respondents. In Rahim Yar Khan and Rajanpur district, most respondents adopted credit, with a percentage of 70 out of the total sample respondents. Only 30 percent have not adopted this strategy. The government support in both districts was 76.66 percent, not adopted, and only 23.33 percent adopted out of the total sample respondents. In both districts, less than half of the respondents, 28 percent of the respondents have adopted the strategy of forward contract. At the same time, 72 respondents were not adopted out of the total sample respondents. In both districts, more than half of the respondent's 83.33 percent of the respondents did not adopt the strategy of improving Drainage. Meanwhile, 16.66 respondents were adopted out of the total sample respondents.

Risk Management Tools Combinations

Two risk management tools (on-farm and off-farm diversification) were considered for this study, and four combinations were formed. The percentage of respondents (in the two districts) who use various combinations of the risk management methods considered in this study is shown in Table 6. The risk management tools are categorized into 0 and 1, respectively. The term 0 means farmers are responding yes and 1 referred to no. In on-farm diversification, the majority of the respondents, with a percentage of 47.33, showed interest, while 14 percent in Rahim Yar Khan and 15.33 percent in Rajanpur showed no interest in on-farm diversification. On the other hand, the off-farm diversification majority of the respondents from Rahim Yar Khan, with a percentage of 54 and Rajanpur, with a percentage of 10 showed interest. In contrast, 15.33 and 23.33 percent of respondents show no interest in off-farm diversification.

Table 6: Risk Management Tools

Risk Management tools	Rahim Yar Khan	Rajanpur	Total
On Farm Diversification (0, 1)	71(47.33)	15(10)	
	21(14)	23(15.33)	150
Off-farm diversification (0, 1)	81(54)	11(7.33)	150
	23(15.33)	35(23.33)	

Parameter Estimates of the Binary logit model

Parameter estimates from the binary logit model are presented in Table 7 in two combinations: on-farm and off-farm combinations. Independent variables are age, education, experience, farm size, monthly income, family size, temperature perception, rainfall perception, flood perception, drought perception, Disease perception, livestock perception, and livestock losses and dependent variables are on farm diversification and off-farm diversification. As shown in combination 1, the variable age is positively and insignificant associated with on-farm diversification. An increase in age discourages the on-farm diversification. Education is also positively and insignificant associated with on-farm diversification, as an increase in the level of education discourages on-farm diversification. While the variable experience is negatively and insignificantly associated with on-farm diversification. The variable farm size is positively and significantly associated with on-farm diversification. If the farm size is increased, on-farm diversification will be encouraged. Monthly income is positively and insignificantly associated with on-farm diversification. As the increase in the monthly income decreases, so does the on-farm diversification. Family size is negatively and insignificantly associated with on-farm diversification; an increase in the family size discourages on-farm diversification. Temperature perception is positively and insignificantly associated with on-farm diversification. If the temperature increases, discourage on-farm diversification. Rainfall perception is negatively and insignificantly associated with on-farm diversification, an increase in the rainy season decreases on-farm diversification. The independent variable, flood perception, is positively and significantly associated with on-farm diversification. Most respondents' livelihood depends only on farming, which is why flood perception is positively associated with on-farm diversification. Drought perception is negatively and insignificantly associated with on-farm diversification. Pest disease perception is negatively and insignificantly associated with on-farm diversification. While livestock diseases are negatively and insignificantly associated with on-farm diversification. The variable livestock losses are positively and significantly associated with on-farm diversification if the increase in livestock losses encourages on-farm diversification.

Table 7: On-farm diversification

Independent Variables	B	S.E.	Wald	df	Sig.	Exp(B)
Age	.000	.038	.000	1	.994	1.000
Education	.045	.041	1.240	1	.265	1.046
Experience	-.011	.036	.099	1	.753	.989
Farm size	.145	.041	12.862	1	.000	1.156
Monthly income	.011	.018	.348	1	.555	1.011
Family size	-.030	.036	.719	1	.396	.970
Temp-perceptions	.243	.289	.707	1	.400	1.275
Rainfall perceptions	-.147	.279	.277	1	.598	.863
Flood perceptions	-1.876	.635	8.721	1	.003	.153
Drought perceptions	-.981	.625	2.468	1	.116	.375
Pest Diseases Perceptions	-1.020	.518	3.882	1	.049	.361
Livestock Diseases	.120	.345	.120	1	.729	1.127
Livestock losses	.004	.001	6.574	1	.010	1.004
Constant	7.736	3.296	5.507	1	.019	2288.163

As shown in Table 8, the variable age is negatively and significantly associated with off-farm diversification. An increase in age encourages off-farm diversification. Education is also positively and insignificant associated with off-farm diversification, as an increase in the level of education discourages off-farm diversification. While the variable experience is positively and significantly associated with off-farm diversification. If the experience is increased, it encourages off-farm diversification. The variable farm size is negatively and significantly associated with off-farm diversification. If the farm size is increased, off-farm diversification will be encouraged. Monthly income is positively and significantly associated with off-farm diversification. An increase in the monthly income increases the off-farm diversification. Family size is positively and insignificantly associated with off-farm diversification, but an increase in family size discourages it. Temperature perception is negatively and insignificantly associated with off-farm diversification. If the temperature increases, discourage off-farm diversification. Rainfall perception is positively and insignificantly associated with off-farm diversification. An increase in the rainy season decreases off-farm diversification. The independent variable, flood perception, is positively and insignificantly associated with on-farm diversification. If the flood perception increases, it discourages off-farm diversification. Drought perception is positively and insignificantly associated with off-farm diversification. Pest disease perception is positively and insignificantly associated with off-farm diversification. While livestock diseases are negatively and insignificantly associated with off-farm diversification. The variable livestock losses are positively and insignificantly associated with off-farm diversification if the increase in livestock losses discourages off-farm diversification.

Table 8: Off-farm diversification

Independent variable	B	S.E.	Wald	df	Sig.	Exp(B)
Age	-.160	.049	10.551	1	.001	.852
Education	.098	.043	5.278	1	.022	1.103
Experience	.094	.045	4.366	1	.037	1.098
Farm size	-.056	.039	2.035	1	.154	.945
Monthly income	.046	.020	5.495	1	.019	1.047
Family size	-.019	.037	.268	1	.605	.981
Temp-perceptions	.312	.303	1.060	1	.303	1.367
Rainfall perceptions	.014	.288	.002	1	.962	1.014
Flood perceptions	1.200	.589	4.155	1	.041	3.321
Drought perceptions	.402	.649	.384	1	.535	1.495
Pest Diseases Perceptions	-.768	.544	1.996	1	.158	.464
Livestock Diseases	-.040	.336	.014	1	.905	.961
Livestock losses	.004	.002	6.522	1	.011	1.004
Constant	-1.870	3.064	.372	1	.542	.154

CONCLUSION

The main conclusion drawn from the study is the fact that most of the farmers in the study area were affected by the 2022 flood and suffered heavy losses in terms of damage to standing crops, diseases of livestock, disruption of input-output markets, damage to infrastructure including roads and storages, etc. Due to the lack of access to formal risk management strategies, i.e., the Crop Loan Insurance Scheme, the farmers tend to adopt informal tools to manage flood risk at the farm level. The most common of the informal tools in the study area were on-farm and off-farm diversification. The decision to adopt on-farm and off-farm diversification was affected by several factors, including their socio-economic attributes, perceptions of major risks, and losses from last year's flood. Understanding the significant effect of these variables on the adoption of diversification will provide significant insights into how the farm-level decisions on the adoption of risk management tools are made and how these policy interventions can be made to facilitate the process.

REFERENCES

Abbass, K., Qasim, M. Z., Song, H., Murshed, M., Mahmood, H., & Younis, I. (2022). A review of the global climate change impacts, adaptation, and sustainable mitigation measures. *Environ. Sci. and Pollu. Resear. 29*:42539-42559.

Albrecht, J., & Hartmann, T. (2021). Land for flood risk management—Instruments and strategies of land management for polders and dike relocations in Germany. *Environ. Sci. & Poli.118*:36-44.

Alves, A., Vojinovic, Z., Kapelan, Z., Sanchez, A., & Gersonius, B. (2020). Exploring trade-offs among the multiple benefits of green-blue-grey infrastructure for urban flood mitigation. *Science of the Total Environ. 703*:134-180.

Ellis, K. N., First, J. M., Strader, S. M., Grondin, N. S., Burow, D., & Medley, Z. (2023). The climatology, vulnerability, and public perceptions associated with overlapping tornado and flash flood warnings in a portion of the southeast United States. *Weath.clim, and socie.15*: 943-961.

Haer, T., Husby, T. G., Botzen, W. W., & Aerts, J. C. (2020). The safe development paradox: An agent-based model for flood risk under climate change in the European Union. *Global Environ. Chan.60*:102-109.

Hartmann, T., & Juepner, R. (2017). The flood risk management plan between spatial planning and water engineering. *Journal of Flood Risk Management*, *10*(2), 143-144.

Howe, J., & White, I. (2004). Like a fish out of water: The relationship between planning and flood risk management in the UK. *Planning Prac. And Resear. 19*: 415-425.

Huang, X., Xu, B., Zhong, P. A., Yao, H., Yue, H., Zhu, F., ... & Liu, W. (2022). Robust multiobjective reservoir operation and risk decision-making model for real-time flood control coping with forecast uncertainty. *Jour. of Hydrol.605*: 127-134.

Khosravi, K., Panahi, M., Golkarian, A., Keesstra, S. D., Saco, P. M., Bui, D. T., & Lee, S. (2020). Convolutional neural network approach for spatial prediction of flood hazard at national scale of Iran. *Jour. of Hydro. 591*:125-152.

Pathfinder, D. P. F. R. S. and D. C. Cornwall Council. 2021. Property Flood Resilience Climate Champions 2021. Online available at https://climatevision.co.uk/wp-content/uploads/2022/01/CV-PFR-Climate-Champions771low.pdf. https://doi.org/10.1016/j.envsci.2018.10.003

Poate, C. D., & Daplyn, P. F. (1993). *Data for agrarian development*. Cambridge University Press.

Sayers, P., Penning-Rowsell, E. C., & Horritt, M. (2018). Flood vulnerability, risk, and social disadvantage: current and future patterns in the UK. *Regi. Environ. Chan.18*: 339-352.

Schanze, J. (2006). Flood risk management–a basic framework. In *Flood risk management: Hazards, vulnerability and mitigation measures* Sprin. Netherl.20:1-20

Vitale, C. (2023). Understanding the shift toward a risk-based approach in flood risk management, a comparative case study of three Italian rivers. *Environ. Sci. & Poli. 146*:13-23.