**Farm Households' Perception of Weather Change and Flood Adaptations in Northern Pakistan**

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**Abstract**

This research investigates farm households' adaptations to climate change-driven monsoon floods in the rural district of Nowshera, Pakistan. Some households in these flood-affected communities have undertaken autonomous adaptations to flooding. We surveyed five hundred farm households from both flood-affected and unaffected villages to investigate the factors driving the uptake of the following autonomous flood adaptations: plinth elevation, grain storage, participation in communal flood preparations and the creation of edge-of-field tree lined shelterbelts. We used both binary and multivariate probit regressions to investigate the correlation across adaptation options. Empirical results suggest that access to agricultural extension services, off-farm work opportunities, past duration of standing floodwaters, farm to river distance, receiving post-flooding support and tribal diversity are the main drivers of flood adaptations. Moreover, we report the complementary uptake of adaptations in pairs. Given the prediction of climate change-driven flooding in the Hindu Kush, we recommend cost-effective policies that increase the resilience of vulnerable agricultural dependent rural communities. In addition, we report that respondents perceived a change in weather perception towards hotter and dryer weather over the last ten years.

*Key Words: Flooding, autonomous adaptations, climate change, resilience, agriculture*

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## 1. Introduction

South Asia has been historically susceptible to extreme monsoon driven flooding. The frequency of which has been increasing in Bangladesh, Nepal, Pakistan and India (Mirza, 2011; Dewan 2015). In the 2017 Global Climate Risk Index report, Pakistan ranks 7th among the most affected countries by natural hazards (Kreft et al., 2016). There is evidence to suggest that climate change (CC) is exacerbating floods and droughts in Pakistan (Wester et al., 2019). Several regions of Pakistan have become susceptible to increasingly frequent monsoon flooding (Gaurav et al. 2011; Ahmed, 2013; GoP, 2016). Since 1950, the past 24 major floods have affected at least 197,275 villages, caused 12,502 documented deaths and resulted in direct losses of more than US$ 38,171 billion (GoP, 2017). Poor agriculture-dependent rural populations are particularly vulnerable to flooding (Asgary et al. 2012; Rehman and Khan 2013). Pakistan's population of 207 million (GoP, 2017) is mostly rural, with a high fertility rate of 3.87, suggesting its susceptibility to CC driven natural disasters is likely to increase over time.

The Pakistani government's response to flooding has been both inadequate and inefficient for various reasons, including: poor coordination between the responsible government departments; the absence of pre-emptive provincial and federal long-term flood prevention or disaster relief planning; and, insufficient or absent disaster preparedness at the local level (Rehman and Khan 2011; Deen; 2015; GoP, 2016). Responses from both the government and NGOs have focused on providing emergency relief, monetary compensation and funding rehabilitation works (Abbas et al., 2015). However, these interventions have been disjointed, reactionary and short-term solutions, which are ultimately not self-sustaining as they lack community involvement. Also, a lack of resources and technical knowledge prevents communities and local disaster management institutions from functioning properly; further exacerbating the impact of natural hazards (Ainuddin et al., 2013) and in particular CC-induced flooding (Qasim et al., 2016).

Research suggests that only approximately 27.5% of Pakistani farmers are willing to pay for flood-related crop insurance (Arshad et al., 2016). Poor socioeconomic conditions and widespread financial illiteracy prevent rural households from seeking and obtaining flood insurance. Indeed, households' financial situation, rather than its perceived flood risk, drives the adoption of flood risk insurance (Abbas et al., 2015). The literature also suggests that household income, education, farming experience, and land ownership determine farmers' access to credit in flood-affected areas (Saqib et al., 2017). Unfortunately, the situation is exacerbated by the fact that relatively poorer households tend to be located in the most flood-prone areas (Qasim et al., 2015; Rana and Routray 2016). Concerningly, there is also very little access to, and utilisation of, gender-sensitive public health services in response to flooding (Sadia et al., 2016).

In general, Pakistani farmers are aware of climate change, and some have adapted by increasing irrigation, changing land-use and diversifying their enterprise (Arshad et al., 2017). Notwithstanding, research suggests that socioeconomic factors play a critical role in the uptake of adaptations to CC-driven natural hazards. For example, farmers in the Himalayan region of Pakistan who enjoy relatively better education, income and secured land rights tend to adapt more to drought, which consequently helps increase crop yields and thus reduces poverty (Rahut and Ali 2017). Similarly, research suggests that land ownership, income, livestock ownership, credit access, and flood support increase the likelihood of farm adaptations to droughts in Pakistan (Ashraf et al., 2014). Likewise, Pakistani rainfed-wheat farmers have identified the positive impact of climate-specific extension services in the uptake of climate change adaptations (Mahmood et al., 2020). Overall, the evidence supports the contention that economic security (farm credit services, subsidised insurance schemes) and institutional support (agricultural extension services) facilitates the implementation of autonomous[1] household flood adaptations (Hossain et al. 2019).

Generally, autonomous household adaptations, and in particular community-based adaptations involving social support networks and information exchange (Boansi et al., 2017), are cheaper than public-funded structural engineering flood prevention projects, and possibly more effective (Thorn et al., 2016). There is considerable evidence to support the effectiveness of household-level adaptation measures (Leclère et al., 2013). Farm households in Pakistan have made various adaptations such as building modifications and precautionary savings in response to floods in Khyber Pakhtunkhwa (Shah et al., 2017); tree plantation as well as changes in crop varieties, planting dates, and fertiliser use in the Punjab (Abid et al., 2015; Abid et al., 2016); and changes in crop and water management, off-farm employment, consumption smoothing, credit, and migration in response to drought in Baluchistan (Ashraf and Routray 2013). Most farmers in flood-prone areas are risk-averse and cognizant of the natural hazards affecting their farm enterprise (Ullah et al., 2015; Saqib et al., 2013). Flood-affected communities in Pakistan have attempted to mitigate their flood risk. Unfortunately, there is a difference in the perception of flood risk between flood-affected communities and the government departments tasked with mitigating their impact (Qasim et al., 2015; Rana and Routray 2016).

Studies have investigated crop management adaptations to CC, but not flooding specifically (A. Ali and Erenstein 2017); the willingness to contribute labour towards a hypothetical flood-protection scheme in rural Pakistan (Abbas et al. 2016); and, CC adaptation and risk perception in rural Khyber Pakhtunkhwa households (Ullah et al. 2018; Fahad and Wang 2018). Nonetheless, they have not quantified the drivers of flood adaptations using methodologically robust approaches. Recently, a

[1] Adaptation is an 'adjustment to actual or expected climate and its effects' (IPCC, 2014); while autonomous adaptation is spontaneous ex-post interventions in response to an undesirable climate event(s) (Fankhauser et al., 1999).

binary logit model was used to identify the factors influencing CC adaptation measures to increase crop productivity (Khan et al. 2020). However, they assume that the decision to implement a CC adaption measure is independent of the decision to implement other measures. This assumption, for obvious reasons, has low credibility. The maximum likelihood estimator is asymptotically consistent only if correctly specified. Thus, if the choices are not independent, as implied by a system of separate logit models, the estimator will be inconsistent. We contribute to the literature by estimating the drivers of flood adaptation measures using multivariate probit analysis. This approach overcomes the shortcomings of assuming independence of outcomes. Our estimation accounts for simultaneity and correlation between the uptake of flood adaptation measures.

This study, in the Nowshehra district of North-West Pakistan, investigates household level adaptations to flooding that enhance resilience and adaptive capacity as well as the factors driving their uptake. This region is subject to monsoon flooding due to its proximity to the Kabul River (Ahmed et al., 2011; Khan et al., 2013). Most households in the district are involved in agriculture with limited off-farm income opportunities, skills, and access to basic amenities (Deen, 2015). This research compares a binary probit and a multivariate probit (MVP) regression analysis to investigate the predictors of farm households' decision to invest in various adaptation measures in response to flooding. Binary probit regression in our context assumes that farmer's flood adaption decisions are independent of one another; whereas, the more realistic, MVP assumes that the binary adaptation decisions are correlated. Binary probit regression analysis has been used in various contexts including energy policy (Ziegler, 2019), land management (Liu et al., 2018), household adaptations to climate variability (Kussel, 2018), household livelihood (Haglund et al., 2011) and wildfire prediction (Albertson et al., 2009) to name the few. Although the MVP model is less prevalent than a probit model in the literature, studies have used it to investigate the joint adoption of various correlated choices, including: transport options (Becker et al., 2017); eco-innovations (Triguero et al., 2017); electricity microgeneration technologies (Baskaran et al., 2013); and, farmers' adoption of sustainable agricultural practices (Kassie et al., 2013; Cholo et al., 2018). Few studies have compared MVP with probit analysis in the context of farmers' climate adaptation decisions. Two report decision interdependence and consistent results from both approaches (Mulwa et al., 2017; Nhemachena and Hassan, 2007), while another uses MVP to correct the endogeneity in modelling pro-environment behavioural choices as a simple probit model (Martínez-Espiñeira and Lyssenko, 2011). The paper is presented as follows: Section 2 describes the material and methods of this research; section 3 discusses the results; while section 4 presents the conclusion and policy implications.

## 2. Material and methods

### 2.1 Theoretical framework

This section details a theoretical model of farm households' decision to implement flood adaptations and its welfare implications. The underlying assumption is that a typical farm households' decision to adapt, as opposed not to do so, depends on the perceived net benefits of adaptation. Rational farmers will choose to invest in adaptation measures only if the net benefits expected from such adaptation investment are perceived to exceed those expected from not adapting. In our empirical study, we use random utility theory, detailed below, to explain the binary decision to adapt.

***Random utility theory***

Random utility theory (RUT) is based on the principles of economic rationality and utility maximisation (Hall et al. 2004). Individuals are assumed to make a choice that yields the highest possible utility. We model farm households' adaptation to floods using a RUT framework (McFadden and Train 2000) which assumes that farm households make an adoption decision to maximise their utility. The standard utility function '$U_{ij}$' refers to the utility of individual '*i*' obtained from choice alternative '*j*' as follows.

$$U_{ij} = V_{ij} + \varepsilon_{ij} = \beta' x_{ij} + \varepsilon_{ij} \qquad (1)$$

'$U_{ij}$' is a function of an observable deterministic utility component, '$V_{ij}$' and an unobservable random component and '$\varepsilon_{ij}$' that captures the unobserved influences on an individual's choice. Here, '$V_{ij}$' is measured through a vector of *k*=1,…,*K* observable independent variables denoted by '$x_{ij}$' and associated with the characteristics of each individual respondent *i*; '$\beta$' is the corresponding vector of *k*=1,…,*K* utility coefficients. In our RUT probit specification the error terms '$\varepsilon_{ij}$' follow a normal distribution.

$$Y_{ij} = \begin{cases} 1 \; if \; \Delta U_{ij} = V_{i1} + \varepsilon_{i1} - V_{i0} - \varepsilon_{i0} = \Delta V_i - \Delta\varepsilon_i > 0 \\ 0 \; if \; \Delta U_{ij} = V_{i1} + \varepsilon_{i1} - V_{i0} - \varepsilon_{i0} = \Delta V_i - \Delta\varepsilon_i < 0 \end{cases} \qquad (2)$$

If the expected utility difference of alternative '*j*' for individual '*i*' then the rational choice is to adapt and the outcome variable, in this case, $Y_{ij}$= 1. Else, the individual does not make an adaptation choice and the dependent variable $Y_{ij}$= 0.

#### *2.1.1 Econometric framework*

The econometric analysis underpinning this research comprises of both a binary probit and a multivariate probit regression analysis to investigate the drivers of farm households' decision to invest in various adaptation measures in response to flooding. A bivariate probit regression is an appropriate approach to modelling a dichotomous choice dependent variable under the RUT framework. We assume that farm households adapt to reduce their risk of flood associated damages and that the adaptation decision is linked to various socioeconomic variables, which act as proxies for various constraints. Therefore, a farm households' adaptation decision is a binary variable $'Y'$ consisting of two outcomes:

$$Y = \begin{cases} 1 \ \ if\ farm\ household\ adapts \\ 0 \ \ otherwise \end{cases}$$

$$\Delta U_i = \beta' x_i + \varepsilon_i \quad (3)$$

Here the probability of adaptation is

$$Pr(y_i = 1|x) = Pr(y_i > 0|x) \quad (4)$$

While the probability of no adaptation is

$$Pr(y_i = 0|x) = 1 - Pr(y_i = 1|x) \quad (5)$$

By Substituting (3) into (4)

$$= Pr(\beta' x_i + \varepsilon_i > 0|x) \quad (6)$$

$$= Pr(\varepsilon_i > -\beta' x_i|x) \quad (7)$$

$$= 1 - F(-\beta' x_i|x) \quad (8)$$

As we assume the error term is independently a normally distributed

$$Pr(y_i = 1|x) = 1 - \Phi\left(\frac{-\beta' x_i}{\sigma}, \sigma = 1\right) \quad (9)$$

$$= \Phi(\beta' x_i) \quad (10)$$

Here keeping other things constant, for a unit change in $x$, we expect the marginal change in $\Delta V_i$ to be $\beta$. To estimate this change, we use the marginal effect that is defined by the following equation.

$$Marginal\ effect\ of\ variable\ k = \frac{\partial Pr(y_i = 1|x)}{\partial x_k} = \beta_k \varphi(\beta' x_i) \quad (11)$$

A binary probit regression, however, assumes that the decision to implement any one flood adaption measure is independent of the decision to adopt any other available adaptation measure. Such a binary response analysis ignores the information contained in the correlations between the decision to jointly invest in different adaptation measures. To overcome this limitation, we also undertook a more realistic multivariate probit analysis, premised on a multivariate normal distribution (Greene, 2003), which assumes that the binary dependent variables denoting adaptation are correlated, rather than independent.

The RUT framework (McFadden 1974) enables us to account for the unobserved heterogeneity in the uptake of flood adaptations measures. In this research, binary variables represent farm households' choice of farm adaptations in response to flooding. Nonetheless, farm households may choose to adopt a mix of measures rather than rely on any single adaptation to exploit potential complementarities among the available flood adaptation options and minimise their risk. Thus, it is prudent to use a specification that can simultaneously model the adoption of multiple adaptations and allow the error terms of each adaptation equation to be correlated. We explore the joint implementation of flood adaptations and examine complementarity in the factors the affect farm households' decision by assuming an MVP model as follows:

$$y_{im} = 1 \; if \; \beta' x_{im} + \; \varepsilon_{im} \; > 0 \qquad (12)$$

and

$$y_{im} = 0 \; if \; \beta' x_{im} + \; \varepsilon_{im} \; \leq 0 \qquad (13)$$

Where in this case, $i = 1 \dots N$ denotes individuals and $m = 1 \dots M$ denotes types of adaptation measures. $x$ is a vector of socioeconomic covariates acting as explanatory variables, $\beta$ represents parameters and $\varepsilon$ is random error with multivariate normal distribution with zero mean and a constant variance. As we probe the joint and alternative use of adaptation options, we assume the error terms are correlated. The variance-covariance matrix of the error terms is,

$$\sum = \begin{bmatrix} 1 & \cdots & \rho_{1M} \\ \vdots & \ddots & \vdots \\ \rho_{M1} & \cdots & \rho_{MM} \end{bmatrix} \qquad (14)$$

Here, $\rho$ is a measure of the correlation in off-diagonal elements of the above matrix.

***Selection of adaptation options***

To identify the most likely farm household adaptations in response to periodic flooding, we reviewed the relevant literature on developing country adaptations. Focus group discussions (FGDs) with the District Agriculture Office, Field Extension Office, and importantly, flood-affected farm households helped identify four main autonomous flood adaptation options used by farm households in the study area. The first adaptation involves elevating a farm building's base column or plinth, which reduces exposure to low-to-moderate level floods (Botzen et al., 2013; Shah et al., 2017). The second adaptation involves storing surplus wheat. Grain storage provides food security to the farmer's family and buffers against local food shortages should monsoon flooding damage standing crops. It is similar in function to the precautionary savings reported by Shah et al., (2017). Community flood preparation is the third adaptation option used by farm households in the study areas. This is a community-based approach that provides specific flood-related information, guidance and support via interactive community meetings. The fourth adaptation option involves the creation of shelter-belts in flood-affected areas by planting trees on the perimeter of agricultural fields to intercept floodwater and/or moderate peak water flow.

### *2.2 Study area*

The district of Nowshera, in the province of Khyber Pakhtunkhwa (KP), has a population of around 1.5 million. Approximately 78% of this rural dwelling population are dependent on agriculture for food, fodder, and livelihood. There are limited off-farm employment opportunities in this predominantly agricultural district. Most farms are usually small, often less than a hectare, and managed by two generations of poor farming families. The main regional crops include wheat, maise, barley, tobacco, and sugarcane, plus some commercial-scale vegetable production. There is considerable heterogeneity in farming practices, soil quality, access to irrigation and hence yield among KP farmers. The 5-year average wheat yield in KP is only 1.670t/ha (2010-15), which is below the national average of 2.779t/ha. Its value at the 2015/16 average wholesale market price in Peshawar (Rs 30,171/t), the closest representative wholesale market, was Rs50,385/ha (PBS, 2018). Also, monsoon flooding of the Kabul river regularly inundates adjacent low-lying agriculture land (Map: 1). For context, in 2015, flooding affected 4,634 villages, 1.93 million people, damaged 10,716 houses, caused 238 deaths and 232 injuries in Pakistan. Of which 11% of the villages, 19% of the persons affected, 49% of the damaged houses, 46% of the deaths and 64% of the injuries occurred in KP (GoP 2015).

**Map: 1 District Nowshehra, North-West Pakistan**


### *2.3 Data collection*

A multi-stage sampling of district Nowshera was used to select representative households for surveying both flood-affected and non-flood affected farms. Firstly, three flood-affected and two non-affected union councils were short-listed from a local agricultural office identified a pool of 27 flood-affected and 20 non-affected union councils, respectively. The second stage of sampling involved selecting homogenous villages from both subpopulations. Finally, to account for spatial heterogeneity in the population, households were sampled based on their distance to the river, farm size[2] and location in five zones along the Kabul River (Map: 1). A total sample of 500 households were surveyed in 2015, 300 of which were located in flood-affected areas and 200 in non-flood-affected areas. Several focus group discussions (FGDs), local informant interviews and a review of the relevant developing country adaptation literature informed the design of a detailed survey. The questionnaire gathered information on household socioeconomic characteristics, flooding, agricultural practices, and other pertinent information. The questionnaire was piloted twice before a team of trained enumerators conducted supervised face-to-face interviews in Pashto, the local language.

## 3. Results

This section details the descriptive and empirical results obtained from the field surveys.

### *3.1 Socioeconomic characteristics*

Table 1 presents socioeconomic statistics of the survey sample, which should be viewed in the appropriate cultural context - a fiercely tribal, patriarchal and feudal society, where the average household head typically receives a few years of primary schooling and 72% have not attended school. It should be noted that although the average household is large, the male to female ratio is suspiciously low. Household heads may have under-reported the female members in their household – a common practice in rural areas of Khyber Pakhtunkhwa.

**Table 1: Socioeconomic statistics**

| Variable | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Household head age (yr)[3] | 52.58 | 13.29 | 4 | 100 |
| Household head education (yr) | 1.80 | 1.47 | 1 | 10 |
| Male to female ratio | 1.51 | 1.20 | 0.1 | 8 |
| Household head farming exp. (yr) | 29.23 | 14.36 | 2 | 65 |
| Household monthly income (PRs ‘000) | 23.76 | 24.71 | 2 | 300 |
| Household size | 7.75 | 2.38 | 3 | 17 |

[2] Small and large farms were categorised depending on whether they were below or above 1 hectare respectively.
[3] The local cultural norm is to formally consider the eldest male as the head of the family, irrespective of their age.

### *3.2 Flood severity and damages*

Table 2 reports the severity of flooding in terms of average flood frequency, height, and land inundation. The results reveal that on average, three significant floods occurred in the past ten years in the study areas. 'Flood inundation' refers to the average number of days it took for floodwater to recede and the 'inundated agricultural area' is the average area of the flooded agricultural farm during the last main flood in 2010.

**Table 2: Flood severity**

| Indicators (Averages) | Responses |
|---|---|
| Flood frequency | 3 |
| Flood inundation (days) | 6 |
| Flood height (meters) | 2.44 |
| Inundated agriculture area (square meters) | 7082 |

Flood damage in the study areas affects agricultural output, farm housing infrastructure, livestock, and business enterprises. More than 60% of surveyed farm households suffered crop damage with the average farm losing 193,770 Pakistani rupees[4] (Rs) during the last main flood in 2010. Nearly 28% of the surveyed households incurred damages to their housing infrastructure with an average loss of approximately Rs 111,660/hh[5]. It should be noted that 'farm housing infrastructure' includes roofed and enclosed spaces for livestock, fertiliser storage and farm machinery, which are often part of or adjacent to the farmer's household abode.

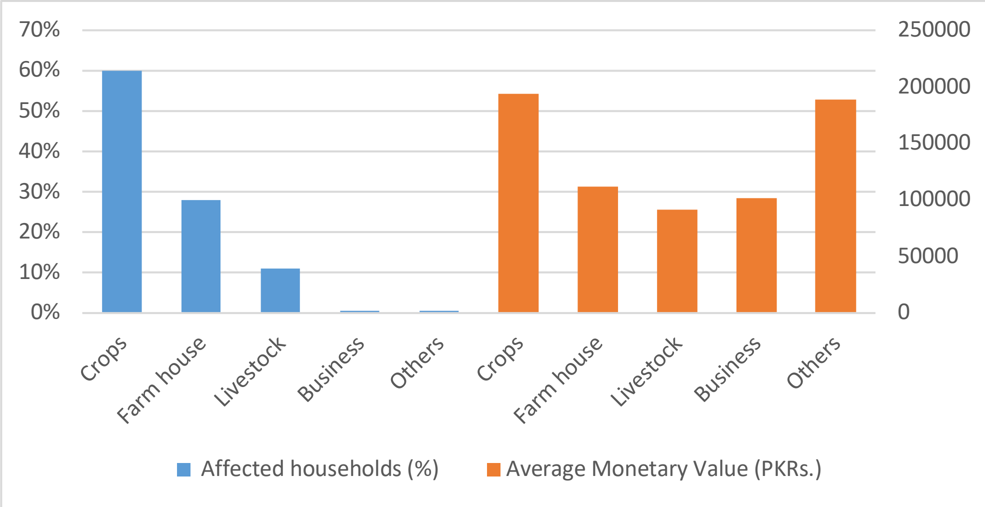
A further 11% of households experienced loss or injury to livestock, with an average monetary value of Rs 91,650[6]. Thus, the scale of the monetary losses is significant, given that these large households are heavily reliant on farming and often do not have access to savings, credit or welfare support. The business enterprise losses are predictably negligible in comparison due to the economic dominance of agriculture, which has the lion's share of the regional GDP.

[4] For context, the value of the KP 5-year average (2005-10, irrigated and unirrigated) wheat yield of 1.517t/ha at the 2010/11 average market price in Peshawar (Rs 2,5076/t), a close wholesale market, was Rs38,036/ha. Thus, Rs193,770 is 5.1 times the average per hectare value of the main wheat crop. Please note that market prices for the year before were not reported, presumably due to widespread flooding (PBS, 2011).

[5] Comparable to 2.9 times the KP 5-year average (2005-10, irrigated and unirrigated) per hectare value of the main wheat crop.

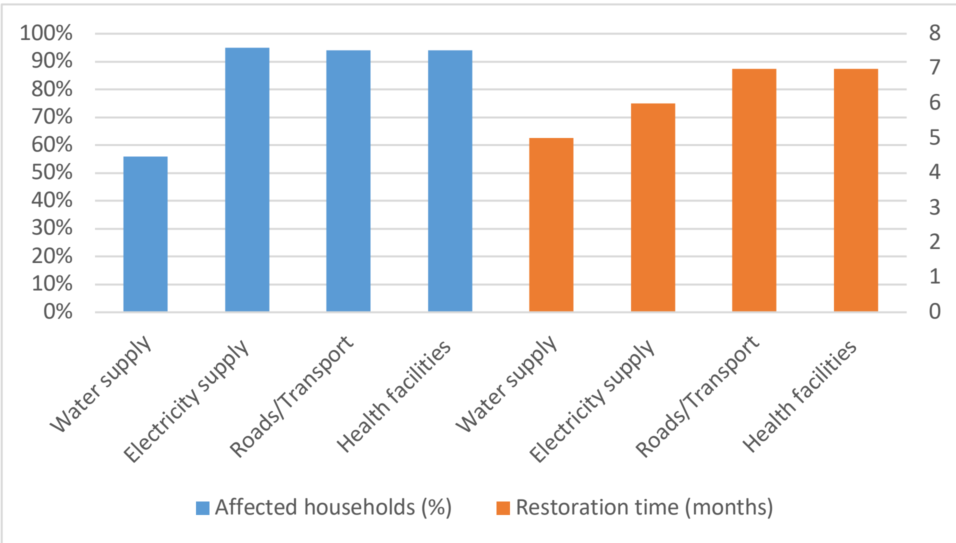
[6] This is equivalent to 2.4 times the KP 5-year average (2005-10, irrigated and unirrigated) per hectare value of the main wheat crop.

**Figure 1: Flood damages and their monetary value**




Moreover, flooding disrupted the supply of essential public services, including water, electricity, transport and health. During the floods or their immediate aftermath, approximately 56% of households lost access to domestic potable water, and more than 90% suffered disruption to their transportation network and/or the supply of health and electricity services. Figure 2 details the minimum time to restore the aforementioned disrupted services, which took anywhere between 5-7 months.

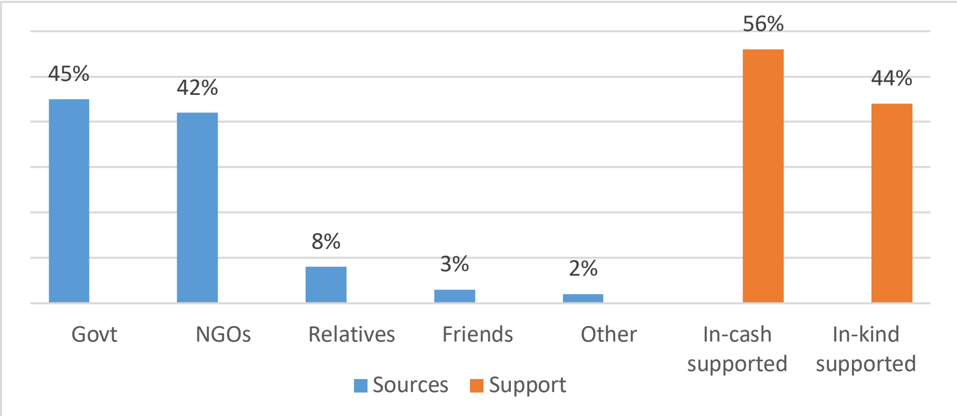
**Figure 2: Basic services disruption and restoration time**




### *3.3 Flood support*

Government and NGOs' post-flood support for flood-affected households comprises of both monetary compensations and/or in-kind support (food and shelter, etc.). The survey results suggest that 54% of the flood-affected households received flood support, of which 56% was in-cash and 44% in-kind support (Figure 3). Moreover, the government (45%), as well as local and international NGOs (42%), provided the most assistance whereas family, friends, and philanthropists contributed a further 13%.

**Figure 3: Flood support and sources**




### ***3.4 Flood warning***

The disaster management departments[7] are officially tasked with issuing flood warnings in flood-prone areas. Unfortunately, the survey suggests that 85% of households did not receive flood warnings during the last significant flood event. Thus, households were unable to take timely evasive actions to minimise the impact of flooding. The failure to communicate flood warnings promptly is a recognised problem in most flood-affected areas of Pakistan (GoP, 2016). Such failure invariably increases the vulnerability of communities in flood-prone areas (Shah et al., 2017).

### ***3.5 Barriers to flood risk management***

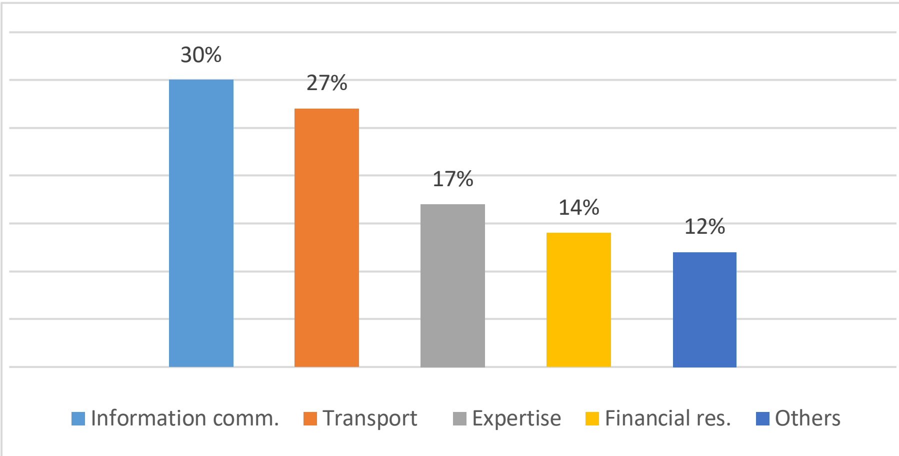
Survey respondents identified their main barriers to effective flood risk management (Figure 4). Households thought they would benefit most from technical flood-related crop management advice from agricultural extension officers, e.g. on the management of short duration crops that mature either before or early on in the monsoon season. They identified timely flood warnings and access to meteorological forecasts (flood communication) as the second main impediment. Surprisingly, farm households placed financial constraints in third place. This suggests households are willing to allocate resources to proven flood adaptation measures if they are offered timely guidance.

Around 14% of households also identified unusable road transport infrastructure as a barrier to effective flood management. Previous studies have also identified the absence of adequate flood risk training (Qasim et al., 2016) and poor flood communication (Alauddin and Sarkar, 2014; Abid et al., 2015) as barriers. It is worth noting that most flood risk management barriers involve relatively

[7] Comprising of the Pakistan Metrological Department, the National Disaster Management Authority and the Provincial Disaster Management Authorities.

inexpensive soft interventions, such as awareness, training and timely communication that increase the resilience of rural communities.

**Figure 4: Barriers to effective flood risk management**

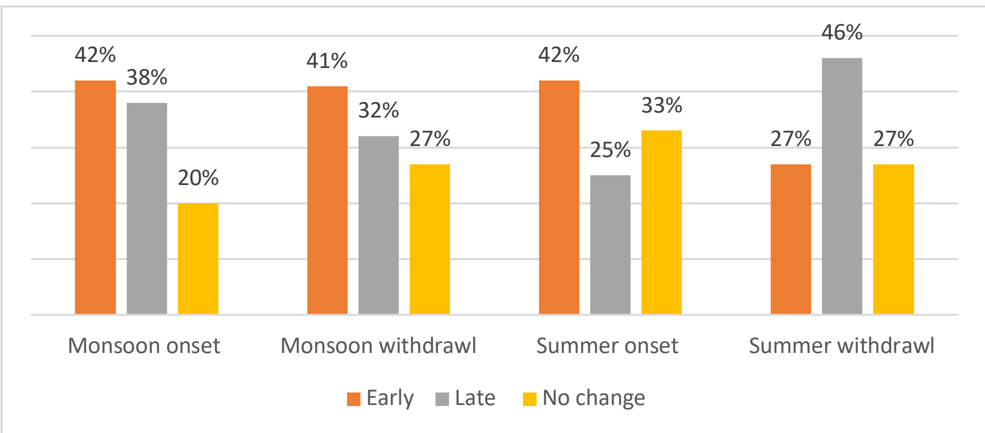



### *3.6 Weather change perceptions*

#### *3.6.1 Perception indicators*

We investigated farmers' perception of any change in the weather patterns during the last ten years (Figure 5). As much as 79% of respondents reported a noticeable *overall* change in the weather as measured by a change in either summer and monsoon season length, temperature or rainfall. The results indicate that 62% of respondents reported an increase in the average temperature; 42% believe summer starts earlier, and 46% perceive summer ending later. This suggests that a large fraction of respondents perceive summers to be longer and hotter than in the previous decade. Moreover, 47% report a perceived reduction in the frequency of rainfall. This indicates that overall farm households have perceived a shift to comparatively hotter and drier weather with longer summers in the last decade.

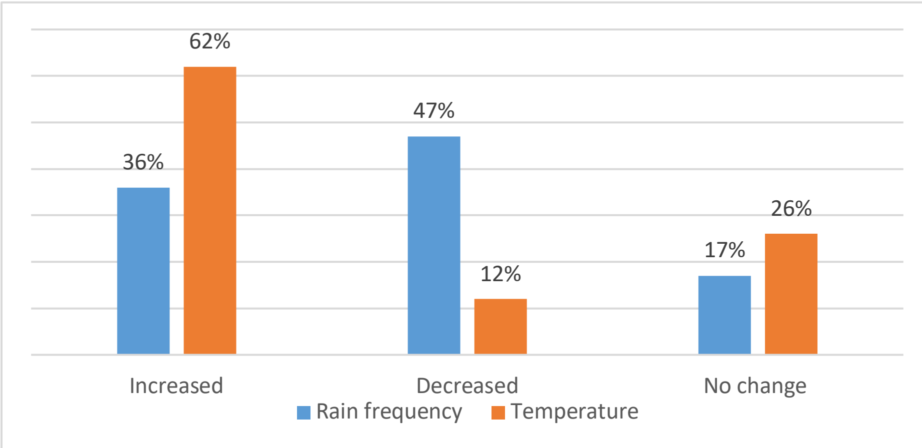
**Figure 5:** ***Weather change perceptions indicators***




A change in farm households' perception of the monsoon season's duration is less clear cut (Figure 6).

Numerous climatic studies have suggested an actual increase in temperature (Anjum et al. 2017), by about 0.24 °C per decade between 1960 and 2007 (M. A. Khan et al. 2016); and, as much as 4 °C between 1988 and 2014 (G. Ali 2018) – which is consistent with our results. However, notwithstanding spatial and temporal heterogeneity, there seems to be a general increase in precipitation (G. Ali 2018) (Sheikh et al. 2009). Although this is inconsistent with our perception, our results are consistent with weather changes as reported in the literature (Rehman and Khan, 2011; Bryan et al., 2013; Alauddin and Sarkar; 2014; Saqib et al., 2016). Interestingly, the reported changes are multifaceted involving changes in perceived temperature and volume of rainfall as well as shifts in the start, end and duration of seasons, which is arguably a manifestation of climate change.

**Figure 6: *Rainfall change perceptions***




### *3.6.2 Factors affecting weather change perceptions*

A probit regression analysis of the factors influencing farmers' perception of weather change (in any direction) was undertaken. The results suggest that farmers' wealth, off-farm work, farming experience, social interaction, and exposure to flood inundation affect their perception of weather change (Table 4). Interestingly, wealthy farmers are less likely to perceive changes in weather, possibly because they can afford electrical appliances that regulate the climate and because they can afford to stay indoors when the weather is inclement.

**Table 4: Factors affecting weather change perceptions**

| *Variables* | *Coefficients (st.err.)* | *Marginal effects* |
|---|---|---|
| Literacy | -0.045 | - |
| | (0.167) | - |
| Wealth | -0.023** | -0.006 |
| | (0.011) | (2.08)* |
| Off-farm work | 0.183** | 0.048 |

| | | |
|---|---|---|
| | (0.078) | (2.36)* |
| Farming experience | -0.010* | -0.003 |
| | (0.005) | (1.90) |
| Social interaction | 0.246** | 0.064 |
| | (0.105) | (2.38)* |
| Inundated area | -0.258* | -0.068 |
| | (0.147) | (1.77) |
| Constant | 1.095*** | - |
| | (0.226) | - |
| LR chi-square | 31.70 | - |
| Pseudo-R2 | 0.07 | - |
| log-likelihood | -202.75128 | - |
| Observations | 433 | 433 |

Standard errors in parentheses

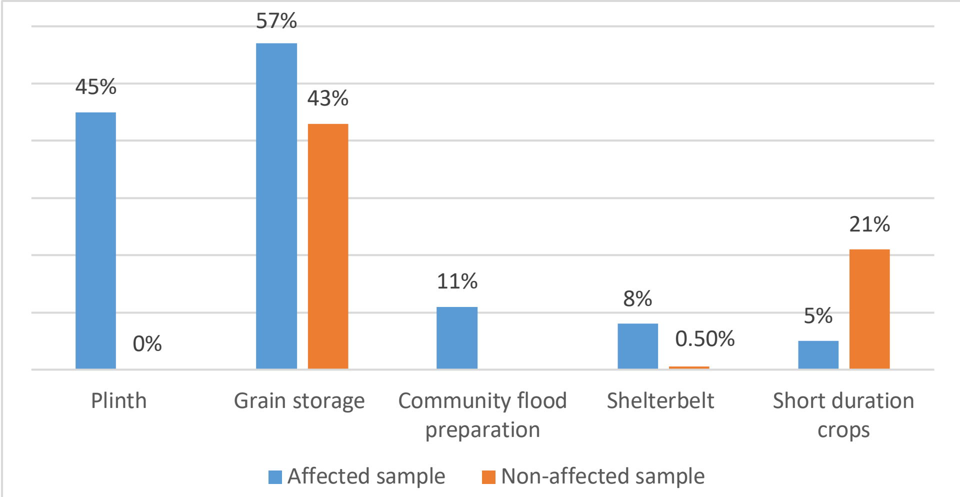
*** p<0.01, ** p<0.05, * p<0.1

Greater social interaction between farm households and their broader community increases the probability (7%) of noticing a change in the weather. Flood inundation has a negative coefficient. Localised inundation from flooding will keep the soil wet for longer; which might create the impression that the weather is getting neither hotter nor drier.  Being literate, i.e. receiving at least one year of education, does not have a statistically significant effect on the perception of weather change by farmers.

### ***3.7 Flood adaptations***

This section discusses the uptake of adaptation measures among farm households in the flood-affected areas of district Nowshehra. Figure 6 illustrates the differences in the uptake of CC adaptation options between the flood-affected and non-affected survey samples. The data indicates that about 45% of farm households in the flood-affected areas elevated their main farm building's plinth. This is indisputably a flood adaptation intervention as plinth elevation is unreported in the sample unaffected by floods. Grain storage provides multiple benefits. However, 16% more households report using it in the flood-affected areas. Grain storage enables consumption smoothing as recognised in climate adaptation literature (Baez et al., 2013; Ashraf and Routray 2013; Ashraf et al., 2014). Similarly, around 11% of flood-affected households engaged in communal flood preparation, which involves information exchange, social support and collective action in flood-prone areas.

**Figure 6: Uptake of adaptation options**




Crop diversification by creating tree-lined shelterbelts along the perimeter of agricultural fields is also a farm household flood adaptation strategy in Nowshehra. There are approximately 7.5% more farm households with shelterbelts in flood-affected areas; which is consistent with the uptake of shelterbelts in adaptation literature (Abid et al., 2015; Daigneault et al., 2016; Rahut and Ali, 2017). Nonetheless, it should be noted that shelterbelts have other uses. Not only do shelterbelts protect from the elements, but they also provide fodder, fuelwood and wood for sale. In addition, despite the reported effectiveness of short duration crops as a flood adaptation measure (Abid et al., 2015; Abid et al., 2016), their negligible uptake in our survey justifies their exclusion from our analysis. The total reported uptake of the remaining four adaptations among the surveyed flood-affected households is as follows: 23% no adaptations, 43% one adaptation, 26% two adaptations, 7% three adaptations and only 1% report using all four adaptations.

### *3.7.1 Empirical analysis*

First, we investigate the factors affecting the uptake of four adaptation options separately, by using a univariate probit model which implies independence across adaptation decisions. We then use a multivariate probit model to examine the correlation coefficients of the adaptation equations' error terms to establish dependencies between the adaptations. Table 3 provides the summary statistics of the considered variables.

### *3.7.2 Probit analysis of the flood adaptation decision*

In the probit model we used factors likely to affect the probability of farm households to invest in flood adaptations. In a probit regression, the utility coefficients (Table 5) are estimates of the marginal change in the linear utility index from a one-unit increase in the covariate. For ease of interpretation, we present the marginal effect (Table 6) of each covariate on the probability of implementing each adaptation measure in percentage terms estimated at the mean of each variable[8]. All reported models are statistically significant in terms of the likelihood ratio[9] (LR) statistic; moreover, the signs of the estimated coefficients and their statistical significance are as expected. They are discussed in detail below.

***Plinth elevation.*** Plinth elevation is an adaptation used by farm households to reduce exposure to floodwaters and associated damages. The results indicate that households with more family members working off-farm are less likely to elevate their abode's plinth in response to flooding. This primarily applies to 'pukka' (bricks and mortar) and mixed (bricks, mortar and mud) housing and not to traditional mud-only housing. Each additional off-farm worker in a household reduces the probability of adopting plinth elevation by almost 6%. This is consistent with the literature (Mulwa et al., 2017; Cholo et al., 2018) with the sole exception of Bedeke et al. (2019).

Farm households with access to agricultural extension services are nearly 11% more likely to elevate their plinths. This result is also consistent with previous research on farm adaptations (Nhemachena and Hassan, 2007; Mulwa et al., 2017; Boansi et al. 2017; Tessema et al., 2019 and Bedeke et al., 2019). Extension services encourage households to be proactive and create plinths to mitigate potential future flood damages. The coefficient estimate for the area of inundated land is highly significant with a positive sign, which suggests that households with more flooded land during the last flood are more likely to elevate their plinths. In fact, every additional hectare of inundated land increases the probability of plinth elevation uptake by nearly 24% on average. This is the highest marginal impact of a predictor on the outcome variable in our analysis.

Interestingly, the number of tribes has a positive impact on the uptake of this adaptation measure. The results suggest farm households from villages with more tribal diversity, and hence competition, are more likely to elevate their plinths. Social pressure from inter-tribal competition may explain the adoption of technologies that provide an economic safety net and/or comparative advantage.

***Communal flood preparation.*** Communal flood preparation encompasses communal flood-related interactions such as information sharing, cooperative flood planning and collective action. This is important as recent research from Pakistan suggests that flood adaptations have been hindered by the paucity of government flood-related information (Shah et al., 2017).

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[8] Appendix 1 contains the simple correlation coefficients of our considered variables.

[9] The likelihood ratio tests the null hypothesis that all the slope coefficients are simultaneously equal to zero and follows a chi-square distribution with degrees of freedom equal to the number of explanatory variables.

In keeping with previous research by Cholo et al., (2018), our results indicate that wealth level is highly significant, although its marginal impact is small: a one million increase in household assets only increases the probability of participating in communal flood preparation by 1%. Wealthier households are only marginally more likely to engage in communal flood activities. This may be explained by the importance of social networks in feudal tribal societies. Well-off households are more likely to engage in social interactions to reinforce their social standing. Again, farm households from villages with more tribes are more likely to be involved in communal flood preparation. Tribal diversity encourages engagement in communal flood preparation in the study areas, and its marginal impact is nearly 2%.

Also, farm households that have benefited from previous adaptive actions are almost 9% more likely to adopt communal flood preparation. This suggests that previous realisation of adaptation benefits provides an incentive to participate in future communal flood preparation measures. As expected, farm households that are furthest from local markets and the river are less likely to engage in communal flood preparation as an adaptation strategy. These results are comparable with those of Mulwa et al., (2017), Boansi et al. (2017) and Tessema et al., (2019) but not with those reported by Nhemachena and Hassan, (2007) and Bedeke et al., (2019). Similarly, flood support has a positive influence on communal flood preparation and encourages its adoption by almost 12% (Mulwa et al., 2017).

***Table 5: Probit estimates of the factors affecting the adaptation decision***

| ***Variables*** | ***Adaptation decision*** | ***Plinth elevation*** | ***Communal flood prep.*** | ***Shelterbelt*** | ***Grain storage (flood affected)*** | **Grain storage (non-flood affected)** |
|---|---|---|---|---|---|---|
| Literacy | 0.062<br>(0.224) | 0.110<br>(0.188) | -0.044<br>(0.289) | -0.333<br>(0.378) | -0.224<br>(0.201) | 0.244<br>(0.258) |
| Wealth | -0.032<br>(0.033) | -0.019<br>(0.026) | 0.103***<br>(0.038) | 0.055<br>(0.052) | -0.008<br>(0.028) | 0.009<br>(0.013) |
| Off-farm work | -0.391***<br>(0.110) | -0.165*<br>(0.095) | -0.308<br>(0.196) | -0.368<br>(0.244) | -0.415***<br>(0.105) | 0.122<br>(0.114) |
| Market distance | 0.012<br>(0.047) | -0.024<br>(0.037) | -0.218**<br>(0.100) | 0.036<br>(0.068) | 0.056<br>(0.042) | 0.356*<br>(0.200) |
| No. of tribes | 0.096**<br>(0.038) | 0.065**<br>(0.031) | 0.138**<br>(0.054) | -0.012<br>(0.062) | 0.007<br>(0.033) | 0.012<br>(0.058) |
| Agriculture extension | 0.868***<br>(0.224) | 0.309*<br>(0.171) | 0.146<br>(0.261) | 0.775**<br>(0.332) | 0.756***<br>(0.190) | -0.572**<br>(0.270) |
| Farming experience | 0.012*<br>(0.007) | -0.001<br>(0.006) | -0.009<br>(0.010) | -0.032***<br>(0.012) | 0.011*<br>(0.006) | 0.003<br>(0.011) |
| Farm size | 0.683**<br>(0.307) | 0.061<br>(0.202) | -0.149<br>(0.324) | 0.114<br>(0.310) | 0.411<br>(0.305) | -0.110<br>(0.189) |
| Farm to river distance | -0.205** | -0.086 | -0.489** | -0.407* | -0.137 | 0.472*** |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (0.102) | (0.086) | (0.203) | (0.231) | (0.098) | (0.076) |
| Flood duration | 0.052**<br>(0.023) | 0.018<br>(0.019) | 0.032<br>(0.031) | -0.086**<br>(0.043) | 0.059***<br>(0.021) | -0.091<br>(0.065) |
| Inundated area | -0.011<br>(0.172) | 0.663**<br>(0.282) | 0.067<br>(0.197) | -0.449<br>(0.511) | -0.393<br>(0.360) | -<br>- |
| Past adaptat. benefits | 0.207<br>(0.325) | 0.086<br>(0.250) | 0.649**<br>(0.315) | 0.920**<br>(0.406) | 0.473*<br>(0.284) | -<br>- |
| Flood support | 0.132<br>(0.202) | 0.255<br>(0.175) | 0.909***<br>(0.320) | 1.220***<br>(0.423) | 0.427**<br>(0.181) | -<br>- |
| Constant | -0.842**<br>(0.406) | -1.083***<br>(0.361) | -2.454***<br>(0.674) | -0.899<br>(0.648) | -0.872**<br>(0.375) | -5.136***<br>(1.051) |
| LR chi-square | 74.67 | 34.72 | 49.43 | 39.83 | 78.37 | 92.93 |
| Pseudo-R2 | 0.26 | 0.09 | 0.29 | 0.32 | 0.22 | 0.36 |
| Log-likelihood | -108.872 | -161.349 | -61.985 | -42.885 | -138.532 | -81.042 |
| Observations | 260 | 260 | 260 | 260 | 260 | 191 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

***Shelterbelt.*** Shelterbelts typically comprise of fast-growing poplar trees at the edge of field boundaries. Shelterbelts also help diversify farm income by generating saleable timber and fuelwood for domestic use. However, it is the only adaptation we considered that potentially increases soil drainage and thus decreases flood height as well as duration. Research has shown that shelterbelts can significantly increase the infiltration of water into soils, and storage thereafter, which consequently moderates overland flow and flood peaks (Carroll, et al., 2006). All the other considered adaptations' aim to reduce the impact of flooding on households, without affecting flood waters.

Farm to river distance negatively affects shelterbelt creation. As expected, farm households furthest from the river, and thus relatively less flood affected, are less likely to create shelterbelts. The probability of shelterbelt creation reduces by almost 4% with every 1km increase in distance to the river. Notwithstanding flood intensity, in general, trees are more likely to survive standing floodwaters than crops. The flood duration coefficient is significant but only marginally negative. Suggesting that households that have experienced longer standing floodwaters during the last main flood are less likely to create shelterbelts. Clearly, the effectiveness of shelterbelts to mitigate flooding depends on the severity of the flooding; they are more effective at attenuating less severe low-level flooding. It is plausible that the historical precedents of long-standing floodwaters discourage shelterbelt creation.

As expected, farm households with access to agriculture extension advice are more likely to grow shelterbelts by almost 7%. Again, this is consistent with previous research on farmer adaptation (Nhemachena and Hassan, 2007; Mulwa et al., 2017; Boansi et al. 2017; Tessema et al., 2019 and Bedeke et al., 2019). Farming experience is significant and inversely related to creating shelterbelts, although its impact is negligible. This is consistent with Cholo et al. (2018) but not Nhemachena and Hassan, 2007. This indicates that relatively experienced farmers are less likely to use this adaptation. It is plausible that inexperienced farmers are less confident of their ability to solely rely on conventional crops and are inclined to minimise risk by diversifying their income. Moreover, the use of shelterbelts is not a traditional farming practice, and maybe something relatively less experienced farmers partake in. Similarly, farm households that have benefited from past adaptations are more likely to create shelterbelts. In keeping with Mulwa et al., (2017), the results also suggest that households in receipt of previous flood support are nearly 11% more likely to create shelterbelts relative to households that have not received support previously.

***Grain storage.*** Farm households create grain storage facilities to counter the possibility of crop failure from heavy flooding. The stored amount, typically between 5-10 maunds (200-400 kg), is sufficient to sustain the average household, comprising of 7-8 individuals if crops fail. Like plinth elevation, off-farm work is significant and predictably negative for grain storage as households with more family members employed in off farm activities are less likely to adapt by creating grain storage. Again, this result is similar to Mulwa et al., (2017) and Cholo et al., (2018) but not Bedeke et al., (2019). Each additional off-farm worker reduces a farm household's likelihood of creating grain storage by almost 13%. Flood duration is significant and positive for grain storage. This indicates that households whose crops were submerged for longer, and hence more damaged during the last flood, are more likely to create grain storage facilities. Each additional day of standing water increases crop damage and encourages grain storage by nearly 2% on average.

***Table 6: Marginal effects of factors affecting adaptation decision***

| ***Variables*** | ***Adaptation decision*** | ***Plinth elevation*** | ***Communal flood prep.*** | ***Shelterbelt*** | ***Grain storage (flood affected)*** | **Grain storage (non-flood affected)** |
|---|---|---|---|---|---|---|
| Literacy | - | - | - | - | - | - |
| Wealth | -<br>- | -<br>- | 0.013<br>(2.85)** | -<br>- | -<br>- | -<br>- |
| Off-farm work | -0.093<br>(3.80)** | -0.058<br>(1.77) | -<br>- | -<br>- | -0.125<br>(4.33)** | -<br>- |
| Market distance | - | - | -0.028 | - | - | 0.086 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | -<br>- | -<br>- | (2.21)* | -<br>- | -<br>- | (1.82) |
| No. of tribes | 0.023<br>(2.62)** | 0.023<br>(2.16)* | 0.018<br>(2.64)** | -<br>- | -<br>- | -<br>- |
| Agriculture extension | 0.207<br>(4.16)** | 0.109<br>(1.84) | -<br>- | 0.068<br>(2.37)* | 0.228<br>(4.39)** | -0.139<br>(2.20)* |
| Farming experience | 0.003<br>(1.76) | -<br>- | -<br>- | -0.003<br>(2.58)** | 0.003<br>(1.81) | -<br>- |
| Farm size | 0.163<br>(2.28)* | -<br>- | -<br>- | -<br>- | -<br>- | -<br>- |
| Farm to river distance | -0.049<br>(2.04)* | -<br>- | -0.064<br>(2.46)* | -0.036<br>(1.79) | -<br>- | 0.114<br>(8.75)** |
| Flood duration | 0.012<br>(2.27)* | -<br>- | -<br>- | -0.008<br>(2.06)* | 0.018<br>(2.90)** | -<br>- |
| Inundated area | -<br>- | 0.235<br>(2.43)* | -<br>- | -<br>- | -<br>- | -<br>- |
| Past adaptat. benefits | -<br>- | -<br>- | 0.085<br>(2.09)* | 0.081<br>(2.34)* | 0.142<br>(1.69) | -<br>- |
| Flood support | -<br>- | -<br>- | 0.118<br>(2.94)** | 0.107<br>(2.91)** | 0.129<br>(2.44)* | -<br>- |
| Observations | 260 | 260 | 260 | 260 | 260 | 191 |

Households in receipt of flood support payments and/or in-kind support (food and shelter, etc.) from either government or NGO are around 13% more likely to adopt plinth elevation than those without. Households may be allocating a portion of their support payments to enhance their future adaptive capacity by investing in flood adaptations, or they might learn of flood adaptations in the process of receiving this support. Nonetheless, this suggests that flood support, if properly designed and targeted, can facilitate poor rural households to subsequently undertake further adaptation measures. Similarly, as expected, farm households that have benefited from past adaptations are 14% more likely to create shelterbelts. Lastly, farming experience is statistically significant with a positive coefficient; however, its marginal impact is minimal. This is similar to the findings of Nhemachena and Hassan, 2007 but opposite that of Cholo et al., (2018). It is reasonable to assume that experienced farmers are more inclined to buffer their food supply by investing in grain storage.

Grain storage also provides consumption smoothing and buffer against other agricultural production shocks such as disease outbreaks, i.e. it is not solely used to mitigate the adverse impact of flooding. Thus, we undertook an analogous analysis of the factors driving the uptake of grain storage in comparable non-flood affected districts of Nowshera. Among the non-flood affected farm households, access to agricultural extension services is highly significant but negative; in fact, extension services make households nearly 14% less likely to create grain storage facilities in non-flood affected regions.

Conversely, farm households with access to agricultural extension services are almost 23% more likely to adopt. This is consistent with previous research on farmer adaptation (Nhemachena and Hassan, 2007; Mulwa et al., 2017; Boansi et al. 2017; Tessema et al., 2019 and Bedeke et al., 2019).

As expected, the distance from the local market is positive, and every additional kilometre between the farm and market increases the probability of grain storage by nearly 9% on average. These results make intuitive sense. Local markets are the only source of amenities in remote rural communities. The further the distance separating a household from the market, the more risk minimising measures are likely to be adopted. Likewise, farm to river distance increases the likelihood of creating grain storage by 11%. This makes intuitive sense as increasing distance from the river implies increasing distance from the main road in the non-flood affected areas.

***Adaptation decision.*** We also modelled flood affected farm households' decision to implement any one of the considered flood adaptations. This helps understand the general drivers behind the overall decision to adapt, regardless of the specific form of adaptation. Off-farm work is significant and negative, implying that farm households with off-farm employment opportunities are less likely to adapt, probably because such employment reduces the household's vulnerability to flood damage. In percentage terms, each additional off-farm household worker reduces the decision to adapt by at least 9%. It is plausible that farm households with additional sources of income are more resilient and less vulnerable to flood damages. Farming experience is also significant and positive, implying households with more farming experience are more likely to adapt. However, the marginal contribution of farming experience is negligible.

Farm distance from the river is negatively related to the decision to adapt but relatively less significant. It makes intuitive sense since the further a farm household is from the river, the lower the risk of flooding and incentive to adapt. Flood duration is significant and positively related to the decision to adapt. This is expected as households that have experienced longer-lasting floods are more likely to adapt. Every additional day of standing floodwaters during the last main flood increases the probability that a farm household will adapt. Again, tribal diversity, as measured by the number of tribes, has a small but significant positive relationship with adaptation. This implies that farm households from villages that are home to a greater number of tribal clans are more likely to adapt in response to flooding. This can be attributed to increased competition between patriarchal tribes in a feudal society where agricultural production is the principal reliable source of income.

As expected, access to agricultural extension is positive, highly significant and increases the probability of adapting by almost 21% - which is substantial. This chimes with the respondent's plea for more agronomic/technical guidance on flood adaptations. Similarly, farms that are larger than the sample's average are 16% more likely to adapt. Larger farms have more farm earnings and are thus able to invest in flood adaptations. Unfortunately, we were unable to collect data on farm income directly as respondents were not willing to disclose it. Greater farming experience, on the other hand, is positive but only significant at the 10% level of significance and exhibits a diminutive marginal impact.

### *3.7.2 Multivariate probit analysis of the joint flood adaptation decision*

A multivariate probit (MVP) model was used to investigate the joint uptake of farm household flood adaptations to investigate their interdependencies using 1000 pseudo-random draws in STATA 15 (Table 7). The MVP analysis has two components.

Firstly, in terms of the socioeconomic factors, the MVP estimates are essentially identical to those from the probit analysis. The coefficients' signs and significance are the same across both model specifications, except for farm distance from the river in shelterbelt and past adaptation benefits in grain storage. However, these two variables were already at the margin in the probit results. Thus, both model specifications support the same relationship between the predictors and dependent variables. The MVP estimates confirm that the probit results are robust, enabling us to confidently identify the drivers of farm households' choice of flood adaptations in our study area, e.g., both model specifications suggest that access to agriculture extension and past flood support substantially impact the decision to adapt.

Secondly, we used MVP to probe the joint and alternative use of farm household flood adaptations, which is not possible with univariate probit analysis. Table 7 details the statistically significant positive correlation between the uptake of three pairs of adaptations: plinth elevation and shelterbelt; grain storage and communal flood preparation; as well as grain storage and participation in communal flood preparation. This suggests that, even after controlling for the observable attributes of farm households, there is/are some unobservable factor(s) that increase the probability of using one adaptation measure while also increasing the probability of using the other in the pair.

**Table 7:** ***Multivariate probit estimates of the joint flood adaptation decision***

| *Variables* | *Plinth elevation* | *Communal flood prep.* | *Shelterbelt* | *Grain storage* |
|---|---|---|---|---|
| Literacy | 0.119<br>(0.188) | -0.076<br>(0.291) | -0.433<br>(0.389) | -0.217<br>(0.202) |
| Wealth | -0.020<br>(0.026) | 0.099***<br>(0.038) | 0.056<br>(0.053) | -0.007<br>(0.028) |
| Off-farm work | -0.166*<br>(0.095) | -0.293<br>(0.194) | -0.346<br>(0.241) | -0.411***<br>(0.105) |

| | | | | |
|---|---|---|---|---|
| Market distance | -0.023<br>(0.038) | -0.222**<br>(0.098) | 0.038<br>(0.070) | 0.054<br>(0.042) |
| No. of tribes | 0.065**<br>(0.031) | 0.136**<br>(0.053) | -0.005<br>(0.062) | 0.006<br>(0.033) |
| Agriculture extension | 0.309*<br>(0.171) | 0.138<br>(0.260) | 0.792**<br>(0.326) | 0.745***<br>(0.189) |
| Farming experience | -0.001<br>(0.006) | -0.009<br>(0.010) | -0.030**<br>(0.012) | 0.011*<br>(0.006) |
| Farm size | 0.059<br>(0.205) | -0.112<br>(0.326) | 0.176<br>(0.311) | 0.370<br>(0.292) |
| Farm to river distance | -0.087<br>(0.087) | -0.477**<br>(0.204) | -0.379<br>(0.236) | -0.140<br>(0.097) |
| Flood duration | 0.017<br>(0.019) | 0.040<br>(0.032) | -0.076*<br>(0.041) | 0.061***<br>(0.021) |
| Inundated area | 0.656**<br>(0.283) | 0.056<br>(0.215) | -0.601<br>(0.521) | -0.355<br>(0.350) |
| Past adaptat. benefits | 0.090<br>(0.250) | 0.623**<br>(0.317) | 0.790**<br>(0.389) | 0.422<br>(0.279) |
| Flood support | 0.260<br>(0.175) | 0.941***<br>(0.322) | 1.102***<br>(0.404) | 0.439**<br>(0.181) |
| Constant | -1.083***<br>(0.360) | -2.550***<br>(0.679) | -0.925<br>(0.615) | -0.868**<br>(0.377) |
| Correlation coefficients | | | | |
| $\rho_{31}$ | 0.504**<br>(0.233) | | | |
| $\rho_{42}$ | 0.323*<br>(0.194) | | | |
| $\rho_{43}$ | 0.467*<br>(0.285) | | | |
| Wald chi-square: 132.40 | Log-likelihood: -398.21 | | Observations: 260 | |
| Likelihood ratio test:<br>rho21 = rho31 = rho41 = rho32 = rho42 = rho43 = 0: chi2(6) = 13.0715 Prob > chi2 = 0.0419 | | | | |

The likelihood ratio test suggests that we are 96% confident that the error terms of the four models are correlated. Therefore, the hypothesis that the error terms of the four adaptation equations are independent, implicit in the separate binary probit approach, is firmly rejected. This confirms the hypothesis that farm households make joint decisions in choosing to adopt a mix of adaptation measures - therefore justifying the MVP specification. The results are consistent with previous research on the joint use of farmer adaptations to climate change, e.g. Nhemachena and Hassan (2007), Kassie et al., (2013), Mulwa et al., (2017), Boansi et al., (2017) and Cholo et al., (2018). The other possible correlations, not reported in Table 7, are insignificant at any reasonable level of significance.

## 5. Discussion and Policy implications

Unfortunately, flood-affected farming communities have received minimal short-term post-disaster government support in Pakistan. Moreover, pre-emptive long-term strategic flood prevention and adaptive planning are non-existent. Much to the frustration of households, government departments have taken far too long to resolve disruptions to essential services after past floods. Flood affected communities will become more resilient if relevant institutions can ensure timely restoration of essential services. Interestingly, households believe that such delays are the result of inefficiencies and not any resource constraints. However, households identified a lack of technical flood adaptation strategies, and in particular agronomic adaptation expertise, as the main barrier to effective flood risk management - even more than a lack of resources. Not surprisingly, our results suggest that respondents in receipt of past government support have taken the initiative and independently undertaken climate change adaptations. Those in receipt of government support were worst affected, which seems to have prompted further adaptations. Therefore, government agencies should prioritise the development of cost-effective systems for early flood warning, flood prevention strategies, and programmes to educate rural communities on how to adapt to flooding, which includes technical agronomic advice on flood resilient crop management. Rural communities that are heavily reliant on farming and lack diversified sources of income would benefit most from targeted resilience-building measures.

Our results suggest that communities have registered weather-related changes and are cognizant of future unexpected and unprecedented flooding events. They are alarmed and willing to take-up measures to avoid the potential adverse effects of climate change. The empirical results show that both the number of family members employed in off-farm work and social interaction are positively related with perceiving a change in the weather. Evidently, farm households' adoption of autonomous adaptations suggests they implicitly understand flood risks and are willing to invest and/or participate in resilience-building measures. This important result evidence the farm households' willingness to engage with policy interventions.

Both probit and MVP regression analysis identified the same statistically significant factors that affect the uptake of autonomous flood adaptations. As expected, access to agriculture extension plays a crucial decisive role in the uptake of farm-level adaptations; it is significant in all of the models, except for communal flood preparation, and also displays considerably high marginal impact. This is a significant result as it implies that a well-thought-out and resourced agricultural extension service has the potential to increase farmers' resilience to flooding. Similarly, the number of family members working off-farm discourages the probability of farm households' implementation of flood adaptations. This suggests that diversification of household livelihoods reduces households' willingness to invest in agricultural resilience-building measures. Likewise, the duration of standing water during the last main flood, which approximates potential crop damage from flooding, also drives the decision to adapt. Interestingly, the data suggests a social dimension to investing/participating in adaptation. The results imply farm households from villages with higher tribal diversity, and arguably more competition, are more likely to adapt, to elevate their plinths and to engage in communal flood preparation. Probably, social pressure from inter-tribal competition in a traditionally feudal and male-dominated society may explain the adoption of technologies that provide an economic safety net or comparative advantage.

Encouragingly, MVP analysis confirms that the uptake of flood adaptation measures is not mutually exclusive, i.e. farm households that adopt one adaptation may also implement another. Also, farm households in receipt of past adaptation benefits are more likely to subsequently adopt further adaptations in the form of communal flood preparation, shelterbelt creation and grain storage facilities in flood-affected areas. This insight enables policymakers to differentiate between households and target adaptation incentives and/or outreach education activities based on households' prior experience of implementing flood adaptations. Likewise, from a policy perspective, our results are encouraging as receiving previous flooding support subsequently facilitates both grain storage, shelterbelt creation and participation in communal flood preparation. The adaptation results make intuitive sense with farm to river distance showing a negative effect; while, flood duration, farm experience and the number of tribes being positively associated (except for shelterbelts) with the decision to implement flood adaptations. Interestingly, market distance is negatively correlated with communal flood preparation: farm households furthest from the local market are less likely to engage in communal flood preparation as an adaptation strategy.

We find that effective and timely flood communication, which is relatively inexpensive, has the potential to significantly improve the resilience of vulnerable rural communities in the study area. Unfortunately, farmers in flood-prone areas have not exploited the full potential of autonomous adaptations. While some have confirmed limited uptake of adaptations, others have not implemented any measure. For instance, hardly any households in the study areas grow short duration crops that are suited to flooding. The findings highlight the need to facilitate and encourage flood adaptations though a programme of agriculture extension services and other soft interventions.

In addition, it is imperative to conduct agricultural research and development into 'waterproofing' food crops (Bailey-Serres, Lee, and Brinton 2012) as it has produced tangible benefits (Sarangi et al. 2016). Governments should support research into the creation of flood-resistant crops, cost-effective soil drainage networks and purpose-built flood water accumulation ponds in the landscape that attenuate floods, etc., as a priority.

## 6. Conclusions

This research investigates the perception of climate change, the impact of flooding and the drivers of autonomous farm household adaptations in the flood-affected agricultural districts of North-West Pakistan. The survey data suggests that most farmers have perceived a trend towards hotter, drier and longer summers. The findings confirm frequent flooding in the monsoon season and associated damages to crops, livestock and farm infrastructure. In undertaking both binary and multivariate probit regressions, we were able to investigate the correlation across adaptation options. Empirical results suggest that access to agricultural extension services, off-farm work opportunities, past duration of standing floodwaters, farm to river distance, receiving post-flooding support and tribal diversity are the main drivers of flood adaptations. Importantly, we report the complementary uptake of adaptations in pairs which has implications for budget-constrained policymakers attempting to cost-effectively incentivise flood adaptations in poor rural household with limited knowledge and resources.

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