Farmers' perceptions of and adaptation strategies to climate change and their determinants: the case of Punjab province, Pakistan

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Abstract

Climate change is a global environmental threat to all economic sectors, particularly the agricultural sector. Pakistan is one of the negatively affected countries from climate change due to its high exposure to extreme events and low adaptive capacity. In Pakistan, farmers are the primary stakeholders in agriculture and are more at risk due to climate vulnerability. Based on farm household data from 450 households collected from three districts in three agro-ecological zones in Punjab province of Pakistan, this study examined how farmers perceive climate change and how they adapt their farming in response to perceived changes in climate. The results demonstrate that awareness to climate change persists in the area, and farm households make adjustments to adapt their agriculture in response to climatic change. Overall 58 % of the farm household adapted their farming to climate change. Changing crop varieties, changing planting dates, plantation of trees and changing fertilizers were the main adaptation methods implemented by farm households in the study area. Results from the binary logistic model revealed that education, farm experience, household size, land area, tenancy status, ownership of tube well, access to market information, information on weather forecasting and extension all influence the farmers' choice of adaptation measures. Results also indicate that adaptation to climate change is constrained by several factors such as lack of

information; lack of money; resource constraint and shortage of irrigation water in the study area. Findings of the study suggest the need for greater investment in farmer education and improved institutional set-up for climate change adaptation to improve farmers' wellbeing.

1. Introduction

Climate change is a global environmental threat and development concerns. Developing countries are most adversely affected by the negative effects of climate-induced events because of their low level of adaptation (IFAD, 2010) . It is projected that climate change is likely to affect the food security in the world by the middle of the 21st century. The largest number of food-insecure people will be located in South Asia (Hijioka, 2014). It is projected that from 2001 to 2059, in South Asia per hectare cereal yield will decline up to 30 % along with up to 37 % loss in gross per capita water (Parry, 2007).

According to various studies and reports (IUCN, 2009, Kreft and Eckstein 2014, LP 2008), Pakistan is one of the highly affected countries by climate change. Pakistan has been indexed at the 12th place in the Global Climate Risk Index in term of exposure to various extreme climate events over the period of 1993 to 2012 (Kreft and Eckstein, 2014). The World Bank included Pakistan in the list of 12 highly exposed countries to variability in climate (Noman and Schmitz, 2011). Pakistan is an agro-based economy where agriculture contributes about 21.4 % to GDP, employs around 45 % of the total labor force and feeds 62 % of the rural population (Abid et al., 2011a; Farooq, 2013). Despite its significant share of the overall economy, this sector is facing serious challenges of climate change induced impacts, i.e. rising temperatures, floods, droughts and yield losses (Noman and Schmitz, 2011).

Agriculture is the main source of support for the majority of the rural households and attached urban populations in developing countries as well as in Pakistan. Hence, adapting the agricultural sector to the negative effects of climate variability is necessary to assure food security for the country and to protect the livelihood of rural households. Adaptation to climate change is an effective measure at farm level, which can reduce climate vulnerability by taking in rural households and communities better able to set themselves and their farming to changes and variability in climate, avoiding projected damages and supporting them to deal with adverse events (IPCC, 2001).

The current level of support for the agriculture sector in terms of climate change adaptation in

Pakistan is very limited due to an ineffective climate policy and a very low technological and financial capacity of the country in adapting to climate change (Ullah, 2011). At the national level, an integrated policy for adapting the agriculture sector to changes in climate is required (Farooqi et al., 2005). Research shows that farmers' awareness, investment in new heat-tolerant varieties, crop insurance, social awareness and protection programs may be the some important aspects of the adaptation policy to climate change (Schlenker and Lobell, 2011).

Perceiving climate variability is the first step in the process of adapting agriculture to climate change (Deressa et al., 2011). A better understanding of farmers' concerns and the manner they perceive climate change is crucial to design effective policies for supporting successful adaptation of the agricultural sector. Further, it is also important to have precise knowledge about the degree and extent of adaptation methods being taken up by farmers and need for further advances in existing adaptation setups. Hence, understanding how farmers perceive changes in climate and what factors shape their adaptive behavior is desirable for adaptation research (Mertz et al., 2009; Weber, 2010). The choice of adaptation methods by farmers depends on various social, economic and environmental factors (Deressa, 2007; Brayan et al., 2013). This knowledge will ultimately enhance the credibility of policies and their strength to tackle the challenges being imposed by climate change on farmers (Deressa et al., 2009). Adaptation will require the participation of multiple players from different profiles such as research, policy, extension, private welfare organizations, local communities and farmers (Bryan et al., 2013).

A great number of studies have been done on farm level adaptation to climate change across different disciplines in various countries which explored farmers' adaptive behavior and its determinants (Bryan et al. 2009; Deressa et al., 2009; Hassan and Nhemachena 2008; Thomas et al., 2007). Despite internationally extensive research on adaptation in the agriculture sector to climate change, little work is done so far in South Asia. Similarly in Pakistan, the scope of research linking climate change to agriculture is very restricted (TFCC, 2010). To date, studies on climate change and agriculture in Pakistan have been entirely limited to impacts of climate change on particular crops or sectors (Nomman and Schmitz, 2011; Hussain and Mudasser, 2007; Hanif et al., 2010; Ashfaq et al., 2011). None of the studies considered farmers' perspective of climate change adaptation. Hence, this study was designed to fill the existing research gap in Pakistan with respect to climate change adaptation in the agriculture sector.

This study mainly seeks to answer two research questions. First we will look, how do farmers perceive long-term changes in local climate? Second we will analyze, how do farmers adapt their farming in response to perceived changes in climate? Further, this study also considers the factors affecting farm level adaptation methods adopted by farm households in the study area. Most of the factors affecting the farm household’s choice of adaptation measures to climate change are already known, but the actual impact of these factors varies across regions. Hence, this study attempts to quantify the actual impacts of various explanatory factors on the probability of adopting different farm-level adaptation measures by farmers. The present study employs a logistic binary model to examine determinants of adaptation measures.

This paper is divided into four sections. Section 2 of the study presents a conceptual framework and empirical specification of explanatory variables. Section 3 describes the materials and method. Section 4 describes the results and discussion of the study and in section 5 we conclude our results and present some policy implications of the study.

2. Conceptual framework and methodology

2.1. Description of the study area

This study was done in the Punjab province, which is geographically located approximately between 30°00'N latitudes and 70°00'E longitudes in the semiarid lowlands zone (Wikipedia 2014). Punjab is the most populous and second largest province of Pakistan. It is a fertile agricultural region based on an extensive irrigation network and playing a leading role in the development of the economy (Abid et al., 2011b). The province accounts for 56.2 % of the total cultivated area, a 53 % share of the total agricultural gross domestic product and 74 % share towards the total cereal production in the country (PBS, 2011; Badar et. al., 2007). Figure 1 shows the map of study areas located in Punjab province.

The mean annual minimum temperature in Punjab ranges from 16.3^{o} C to 18.2^{o} C over the period 1970-2001. Mean annual maximum temperature in Punjab ranges from 29.3^{o} C to 31.9^{o} C. The distribution of rainfall in Punjab is wide-ranging, mostly linked with the monsoon winds. Punjab receives 50-75 % of rainfall during the monsoon season. The rain-fed zone receives the highest quantity of rainfall followed by the rice zone, mixed zone and cotton zone respectively (Mohammad, 2005).

Based on Pakistan agricultural research council maps (PARC, 2014), the Punjab province can be divided into four major and eleven sub agro-ecological zones based on climate, agricultural production, and aridity. Study districts come from three of the main agro-ecological zones. Study sites in the district Rahim Yar Khan are located in cotton and Cholistan sub-zones where average rainfall ranges from 72.8 to 462.5 millimeters annually. The second study district, Toba Tek Singh is located in the central mixed zone, which receives average rainfall ranging between 219.5 and 718 millimeters annually. The third district Gujrat is partially located in both rain-fed and rice zones which receive average rainfall between 697 and 1401 mm annually (Mohammad, 2005). The average household's characteristics which play an important role in shaping the decision-making process in climate change adaptation vary to some extent in all three regions. For example, according to our study, the average land holding size varies between the districts Rahim Yar Khan (18), Toba Tek Singh (14), and Gujrat (16). Little variation is found for average household size (9-10) and years of schooling (8-9) in all three districts. In terms of agricultural income shares, relatively high values are found for the districts of Rahim Yar Khan (85 %) and Toba Tek Singh (79 %) but a substantially lower value for Gujrat (26 %).

2.2. Sampling and data collection

To investigate the farm level perceptions of climate change and associated choices of adaptation methods in Punjab, the selection of study districts took into account different agro-ecological zones (AEZs), cropping patterns, irrigation source networks, and climate. Particularly, study sites in the district Rahim Yar Khan are located mainly in irrigated plains (Zone A) and partially in marginal lands (Zone D). The study district Toba Tek Singh is located in irrigated plains (Zone A). The study district Gujrat is located in a rain-fed zone (Zone B) (PARC, 2014).

A multi-stage sampling technique was used to select the study sites and sample farm households in the study area. In the first stage, the Pakistan province of Punjab was selected as overall study area. In the second stage, three districts were selected from three agro-ecological zones based on the agriculture share to the total national economy, weather and climatic conditions, cropping patterns and irrigation networks in the area. In the third stage, two cities were selected from each district. In the fourth stage, we choose 10-13 union councils from each district depending on number of union councils located in each district. We excluded the urban union councils. In the fifth stage, two to three villages were randomly selected from each union council using Pakistan Village Statistics (Government of Pakistan, 1998) and in the sixth and last stage, 6 farmers were randomly selected from each village. Table 1 depicts the numbers of farmers interviewed from the study areas.

The survey was conducted between March and April in 2014. For the data collection, about 450 farmers were interviewed irrespective of gender, farm size or tenancy status through a farm household survey. Interviews were conducted for the cropping year 2012-13 which includes the *Rabi* (winter) season 2012-13 and the *Kharif* (summer) season of 2013. A fully structured questionnaire was used to gather information on socioeconomic characteristics, crop and domestic livestock management, land tenure, detail of farm inputs and outputs, access to various institutional services, current and past knowledge of climate change, current adaptation measures undertaken, and limitations to adaptation. Prior to the study, a pretesting of the questionnaire was performed to avoid missing of any important information. The enumerators received field training about the study objectives and farm household survey.

2.3. Dependent and independent variables

Several agricultural adaptation measures can reduce losses due to increasing temperature and decreasing precipitation (Hassan and Nhemachena, 2008). In this study, a binary logistic model was used to examine the factors influencing the choice of different adaptation measures applied by the farm households in the study area. The decision to adapt requires that farm households recognize local changes in long-term climate such as temperature and rainfall patterns (Bryan et al., 2013).

Following previous studies by Kato et al. (2011) and Bryan et al. (2013), we assume that farm households will adapt only if they perceive a reduction in the risk to crop production or an increase in expected net farm benefits. Consider a latent variable (Y_{ij}*) which is equal to expected benefits from the adoption of certain adaptation measures:

$$Y_{ij}* = \alpha + \sum \beta_k X_k + \varepsilon_{Y_{ij}*} \quad (1)$$

In this equation, Y_{ij}* is a latent binary variable with subscript i depicting the household who adapted to climate variability and j depicting eight different adaptation measures. X_k represents the vector of exogenous explanatory variables that influence the farmers' choice of adopting particular adaptation measures and k in the subscript shows the specific explanatory variable (varies from zero to 14). The symbol α denotes the model intercept, β_k the vector of binary regression coefficients and $\varepsilon_{Y_i*} \cong N(0, \sigma^2)$ is the error term which is normally distributed and homoscedastic (zero mean and constant variance) (Schmidheiny, 2013). We do not observe the latent variable (Y_{ij}*) directly. All we observe is:

$$Y_{ij} = \begin{cases} 1 & if \quad Y_{ij}* > 0 \\ 0 & if \quad Y_{ij}* \leq 0 \end{cases} \tag{2}$$

Where Y_{ij} is an observed variable which indicates that household i will choose to opt for certain measures j (Figure 4) to adapt to perceived changes in climate ($Y_{ij} = 1$) if his or her anticipated benefits are greater than zero ($Y_{ij}* > 0$), and otherwise household i will not choose adaptation measure j if the expected benefits are equal to or less than zero ($Y_{ij} \leq 0$).

Hence, we can interpret equation (2) in terms of the observed binary variable (Y_{ij}) as:

$$\Pr(Y_{ij} = 1) = Y_{ij} = G(X_k \beta_k) \tag{3}$$

Where G (.) takes the specific binomial distribution (Fernihough 2011).

2.4. Marginal effects and partial elasticities

The estimated parameters (β_k) of the binary logistic model only give the direction of the effect of the regressors (independent variables) on the binary dependent variable (regressand) and statistical significance associated with the effect of increasing an independent variable just like ordinary least square (OLS) coefficients (Peng et al., 2002). Thus, a positive coefficient β_k tells that an independent variable X_k increases the likelihood that Y_{ij}= 1 (which is adoption of particular adaptation measure in our case). But this coefficient cannot explain how much the probability of household i to adopt particular adaptation measure (Y_{ij}=1) will change when we change X_k, i.e. the coefficient (β_k) does not show the magnitude of the effect of a change in explanatory variable X_k on Pr (Y_{ij}=1). Thus, to interpret and quantify the results, we need to calculate either marginal effects or partial-elasticity. Marginal effects (y_{ij}') describe the effect of a unit change in the explanatory variable on the probability of dependent variable, i.e. Pr (Y_{ij}=1). Derivation of marginal effects is discussed in detail in appendix A. The final equation of the marginal effect (y_{ij}') after derivation becomes:

$$y_{ij}' = \Pr(Y_{ij} = 1) \cdot (1 - \Pr(Y_{ij} = 1))\beta_k \tag{4}$$

Another alternative to interpret the results of a logistic regression is to use partial elasticities which measure the percentage change in probability of the dependent variable (adoption of certain adaptation measure to climate variability) due to a 1 percent increase in the explanatory variable X_k (see appendix A for further detail). We may interpret the partial elasticity of the logit model calculated at mean as:

$$\eta_Y(\overline{X_k}) = \beta_k \overline{X_k} \Pr(Y_{ij}=1)\cdot(1-\Pr(Y_{ij}=1)) \qquad (5)$$

2.5. Description of explanatory variables

The choice of explanatory (independent) variables used in this study is based on data availability and review of the literature. The independent variables include household characteristics (e.g. farming experience of household head, household head's education, size of household, tube well ownership, land holding and tenancy status of farm households), institutional factors (e.g. access to credit, market information, weather forecasting information, information on water deliveries, agricultural extension services), and dummies for agro-ecological zones. Instead of using agro-ecological factors (e.g. temperature and rainfall) and cultural traits in different regions directly, we used dummy variables for agro-ecological and cultural given the absence of variability in temperature and rainfall for households in the same district.

Prior to the survey, a multinomial logit (MNL) modeling approach was proposed for this study. Because most of the previous studies of farmers' adaptation to climate change employed the MNL approach (Deressa et al., 2009; Hassan and Nhemachena, 2008; Hisali et al., 2011), where respondents are restricted to select only one adaptation measure. However, in the course of this study, we frequently found that farm households adopted more than one adaptation measure simultaneously. This behavior made the use of the MNL approach inappropriate. A possible remedy would be to combine similar measures into single categories (Bryan et al., 2013). However, such grouping into self-defined categories may lead to misinterpretation (Bryan et al., 2013). Furthermore, the set of explanatory variables influencing the farmers' decision was also expected to be different for different adaptation measures. Therefore, we employed the logistic regression technique to examine the factors that affect the choice of adaptation measures. Table 2 shows the description and expected signs of explanatory variables used in this study.

2.6. Hypothesis testing for model significance

We tested all of our models for significance and accuracy of predictions. There are different ways to measure goodness of fit for logistic models. In the first step, we used the classification table method to measure the extent to which our models accurately predict the dependent variable (in our case adoption of the particular adaptation measure by the farm household). The classification table is calculated by comparing the predicted scores of observations on the basis of independent variables in our model, with their actual responses given in the data (Hosmer and Lameshow, 2004). Higher percentages indicate a better fit of the model. The results of the classification table test (Table 3) show that the overall percentage correctness for all models is above 71 % which confirms the better fit of all of the models used in this study.

In the second step, to test the overall significance of models, we used a global null hypothesis approach. For this analysis, we established a null hypothesis by assuming and setting all the regression coefficients of logistic models equal to zero versus the alternative that at least one of the regression coefficients (β_k) is not zero (Peng et al., 2002):

$H_0 : \beta_k = 0$

H_1 : at least one $\beta_k \neq 0$

This approach is the same as the F-test for model testing in OLS regression. This test checks, whether the model with predictors, i.e. equation (1), fits significantly better than the model with just an intercept (i.e. an intercept-only model):

$$Y_{ij}^{*} = \alpha \quad (6)$$

The test statistic is calculated by taking the difference of the residual deviance for the model with predictors or independent variables from the null deviance of intercept-only model. The test statistic is distributed chi-squared with degree of freedom that is equal to the differences between the number of variables in the model with predictors and intercept-only model (Stephenson et al., 2008).

From Table 3, it can be examined that chi-square values for all adaptation models are positive and vary between 28 and 65. The associated p-values are less than 0.001 except in the model for crop diversification that is significant at p -value 0.01 from which it can be concluded that our models with predictors fit significantly better than the intercept-only model. Hence, on the basis of test statistics, we can reject the null hypothesis (H_0) and accept the other alternative hypothesis (H_1) that at least one of the regression coefficients (β_k) is not zero.

Further, we calculated the Pseudo-R^2 measure to determine the goodness of fit of our adaptation models. The values of Pseudo-R^2 for all models ranged from 0.15 to 0.28 which indicate a better fit of our models in explaining adaptation to climate variability.

Based on the results from the classification table, global null hypothesis and Pseudo-R^2, it can be assumed that all the models selected for this study are fit and can accurately estimate the factors affecting the adoption of different adaptation methods.

3. Results and discussion

3.1. Farm level perceptions of climate change

As discussed above, farmers' perception of long term or short term changes in climate is a crucial pre-indicator in the adaptation process (Adger et al., 2009). Hence, respondents were asked how they perceive long-term changes in climate indicators in their area.

The study results (Figure 2a) indicate that large number of farmers perceived a slight increase in temperature for both summer (56.9 %) and winter seasons (39.3 %). In perceiving the precipitation patterns, the percentage of farmers who reported a slight decrease in precipitation in both summer (44 %) and winter (48.9 %) seasons are more than the farmers who perceived significant or no change in both summer and winter seasons (Figure 2b). The majority of the surveyed farmers (52.2 %) perceived an increase in growing season length for the *Rabi* (winter) season, while 57.1 % of the farmers observed no change in growing season length for the *Kharif* (summer) season (Figure 2c).

Farm level perceptions of majority of farmers about climate indicators in both summer and winter seasons are in accordance with actual trends presented in Figure 3 (a-b). According to Figure 3a, the mean temperature in winter and summer season shows a significant slight increase over the period of 1990-2010, while Figure 3b depicts a slight decrease in winter and summer precipitation over the same period.

3.2. Farm-level adaptation process

In our study, we also analyzed the whole adaptation process across all three study districts (Figure 4). Results show that overall and across districts, there is a substantial reduction in the number of responses of farmers, from perceptions of changes in climate to the final adaptation to climate change. In the first stage (perception stage) overall 81 % of the respondents indicated climate change, with maximum perception in district Gujrat (86 %) and lowest perception in Rahim Yar Khan (73 %). In the second stage (intention stage), overall 75 % of the farmers show their intentions to adapt to climate change with highest intentions in district

Gujrat (85 %) and lowest intentions in Rahim Yar Khan (66 %). In the third and last stage (adaptation process), overall only 58 % of the respondents adapted to climate variability with greatest adaptation in Gujrat district (70 %) and lowest adaptation in Rahim Yar Khan (49 %). In Toba Tek Singh district, about 55 % of the farm households adapted their farming in response to climate variability. As can be observed from the results, from perception stage to intention stage on average a drop from 81 % to 75 % was observed in responses while from intention stage to adaptation stage, responses of farm households were dropped from 75 % to 58% on average. In the same way, moving from perception stage to adaptation stage, farmers' responses were dropped from 81 % to 58 %. .From the results, it can be determined that the number of farmers who adapted to climate change is substantially less than the farmers who perceived some form of climatic risk or planned to adapt in earlier stages of the adaptation process. This reduction in numbers may be associated with various constraints, and internal or external factors explained in the next section.

3.3. Farm-level adaptation strategies and constraints

Farmers who observed variability in the climate over the period of 10 to 20 year were further asked to describe the farm level adaptation measures undertaken in response to climate change. The results of the study demonstrated that farm households applied a wide range of adaptation measures in response to the changes in climate. As shown in Figure 5, the most common adaptation measures were: changing crop varieties (32.20 %), changing planting dates (28.40 %), planting trees (25.30 %) and changing fertilizers (18.70 %) followed by changing crop types (10.20 %), increasing irrigation (9.80 %), soil conservation (9 %), crop diversification (7.56%), migration to urban areas and renting out land (2.20 %). Greater use of changing crop varieties and changing planting dates as adaptation measures could be associated with ease of access and low cost of adaptation method by farmers. The lesser use of renting out of land and migration to urban areas may be attributed to the fewer opportunities in urban areas or other sectors for unskilled farmers.

Implementation of adaptation measures by farm households varied across the three study districts (Figure 5). In the Gujrat district, major adaptation measures adopted by farmers were: use of different crop varieties (39 %), changing planting dates (36.70 %), planting shade trees (31.30 %) and changing fertilizers (24 %). The main reason for changing crop variety, planting dates and plantation of shaded trees may be due to more dependence of farming on rain and groundwater for cultivation of crops in the Gujrat district. That's why farmers need to modify their farming behaviors according to the variability in climate. In Toba Tek Singh district, changing crop variety (36 %), changing planting dates (17.30 %) and planting shade trees (17.30 %) were the primary adaptation measures. In Rahim Yar Khan, farmers mainly used changing planting dates (31.30 %), planting shaded trees (27.30 %), changing crop variety (22 %), changing fertilizer (20 %) and changing crop types (18 %) as the adaptation measures in a changing climate (Figure 5).

Moreover, we identified a number of constraints faced by the farmers who perceived long-term changes in climate and intended to adapt their farming in the second stage of the adaptation process, but did not adapt their farming in the third stage of the adaptation process. The major constraints identified by the majority of the respondents (Figure 6) were lack of information (44 %) and lack of money (22 %) followed by resource constraint (17 %), shortage of irrigation water (14 %) and other constraints (2 %). Lack of information deals with less information access by the farmers either from private or public sources about how to modify their agriculture in case of extreme weather events, including high rainfall, water stress at sowing stage, extreme high temperature or extreme low temperature which are frequently mentioned as indicators of climate change. Farmers showed their intention to adopt particular adaptation measure in case of extreme weather events but did not manage to adapt due to improper information either about the adaptation method or usefulness of certain adaptation for their crops.

Lack of money is identified by responding farmers as another key constraint for adaptation, even if they plan to adapt to climate variability. Use of farm credit in the study sites is limited, despite access to micro-credit facilities available at the town level. High interest rates on credits are one of the reasons for little attraction of credit institutions to farmers. Less access to or availability of resources at farm level constrains the capability of adapting to climate change. Physical resources may include farm inputs (improved seed, fertilizers); farm implements (tools for soil conservation, cultivators, harvesters etc.) and institutional resources (water and soil testing laboratories).

Further, we asked farmers to identify best measures to enhance effective adaptation to climate variability. Respondent farmers identified provision of subsidies on farm inputs, updated farm information services and sufficient irrigation water supply as necessary means to enhance the adaptation of agriculture to climate variability in the study area.

3.4. Adaptation to climate variability across regions and different farm characteristics

From the results of the adaptation process explained above in section 3.2 and Figure 9, we can observe that farm level adaptation processes (perceptions, intentions and adaptation) are influenced by various factors. These adaptation measures can be further explored based on different characteristics of farm households or their location. Hence, we assume that perceptions, intentions and final decisions of adapting to climate change all differ in term of extent to choose different adaptation measures. To analyze this variation, we categorize the farm households on the basis of education and farming experience. On the basis of education, we divided farmers into three categories: illiterate farmers having no formal education; farmers having 1 to 10 years of schooling; and farmers having more than 10 years of schooling (Figure 7). In terms of farming experience, we again divided farmers into three categories, i.e. farmers having less than 10 years of experience in farming; farmers having 10-20 years of farming experience, and farmers having more than 20 years of experience.

From the results shown in Figure 7, it can be observed that moving from a low education level to higher education level leads to an increase in the perception, intentions to adapt and final adaptation to climate change in all study districts. Overall, farmers with more than 10 years of schooling were more likely (44.2 %) to perceive changes in climate over the past 10-20 years than farmers with less than 10 years of schooling (25.8 %) or no education (11.3 %). In the case of intentions to adapt, farmers with less than 10 years of schooling (23.6 %) or no education (10.9 %) were less willing to adapt compared to farmers with more than 10 years of schooling (40.2 %). The same was found true in the case of adaptation to climate change where more than 31 % of the farmers who adapted to climate change had more than 10 years of schooling, and 18.2 % of the farmers had education between 1 and 10 years. Adaptation was lowest in case of illiterate farmers who were the only 8.4 % of the total sampled farmers who adapted to climate change. The same trend can be observed for all three study districts Rahim Yar Khan, Toba Tek Singh and Gujrat at district level with little variation (Figure 7).

Analysis of adaptation measures across different categories of farmers based on farming experience is explained in Figure 8. Farmers with more than 20 years of experience were more likely (40.9 %) to perceive variability in climate than farmers having experience between 10-20 years (28.2 %) or farmers having less than 10 years of experience (12.2 %). Similar results were obtained for both intentions to adapt and final adaptation to climate change. Overall, farmers with more than 20 years of farming experience (38.4 %) have higher intentions to adapt compared to the farmers in the other two groups, i.e. farmers with experience between 10-20 years (26.2 %) and farmers with less than 10 years of experience (10 %). Farmers with more than 20 years of farming experience were the 30 % of the total farmers who adapted to climate change while farmers with experience between 10-20 years (20 %) and farmers with less than 10 years of experience (7.8 %) adapted less. Figure 8 shows the same pattern for all districts. In summary, the higher the level or education and farming experience for a given household, the higher its probability of adaptation to climate change.

3.5. Factors affecting adaptation measures

To quantify the impact of various explanatory factors affecting farmers' choice of adaptation methods, we used logistic regression models for all adaptation measures. The coefficients of logistic regression that tell us about the direction of effect of independent variables are presented in Table 4 and the marginal effects that explain the effect of a unit change in explanatory variables on the dependent variable are shown in Table 5. Finally partial-elasticity calculations to elaborate the percentage impact of various factors on the probability of different adaptation measures are described in Table 6. In the following sub-sections, we describe the impact of various explanatory variables on the probabilities of adopting different adaptation measures in response to variability in climate.

3.5.1. Years of experience in farming

The coefficient of years of experience in farming has a positive sign for most of the adaptation measures indicating a positive relation between farming experience and possibility of adapting to climate change. According to results in Table 4, years of farming experience significantly increase the probability of choosing changing crop varieties, changing plantation dates and changing fertilizer as adaptation measures. Elasticity calculations in Table 6 show that 1 % increase in the years of experience increases the probability of adopting changing crop variety (0.14 %), changing planting dates (0.15 %) and changing fertilizer (0.11 %) as adaptation measures respectively. The results of the study are in accordance with those from Maddison (2007) and Nhemachena and Hassan (2007) which also found a positive relationship between farming experience and adaptation to climate change. Hence, it can be concluded that farmers with higher farming experience are likely to be more aware of past climate events and may judge better to adapt their farming to extreme weather events.

3.5.2. Education

Education is assumed to be an important factor in accessing advanced information on new improved agricultural technologies and increased agricultural productivity (Norris and Batie, 1987; Elahi et al., 2015). In our study, the highly significant coefficient of education of the household head shows that the probability of adapting to changes in climate increases with an increase in the years of schooling of the household head (Table 4). Results of elasticities in Table 6 show that 1 % increase in the years of schooling of household head would lead to an increase in the probability of changing crop type (0.08 %), changing crop variety (0.09 %), changing planting dates (0.17 %), plantation of shaded trees (0.08 %), soil conservation (0.08 %), changing fertilizer (0.15 %) and irrigation (0.09 %) as adaptation measures to climate variability. Various studies (Bryan et al., 2013; Deressa et al., 2009 and Maddison, 2007) also found a significant positive relationship between education of household head and adaptation to climate change that supports the finding of this study. Hence, it can be concluded that farmers with more years of schooling are more likely to adapt to changes in climate compared to the farmers with little or no education.

3.5.3. Household size

A positive coefficient of household size indicates a positive relationship between household size and probability of adaptation. For instance, an increase in one member of the average household would lead to a 0.20 % increase in the likelihood of plantation of shaded trees and 0.47 % increase in choice of soil conservation as adaptation measure. Findings of the studies of Croppenstedt et al. (2003) and Deressa et al. (2009) also support our findings of a positive relationship between household size and adoption of agricultural technology or adaptation to climate change.

3.5.4. Land area

Land area represents the total land area held by a farm household and may be taken as a proxy for farm household wealth. Results in Table 4 indicate that the land area has positive and significant impacts on changing crop varieties and crop types. A 1 % increase in the land area increases these probabilities of changing crop type and changing crop varieties by 0.01 % and 0.06 % respectively (Table 6).

3.5.5. Tenancy status

Tenancy status indicates farmers’ land tenure status as owner or tenant. In this study, tenancy status has a negative sign for most of the adaptation measures which indicate that tenants are more likely to adapt their farming to perceived climate change compared to the self-operating farmers (owners). This can be observed from marginal effects presented in Table 5 that if the farmer is the owner, it reduces the probability of changing crop type (9.29 %), changing planting dates (7.64 %) and changing fertilizers (9.77 %). Increased likelihood of adaptation for tenants may be due to the reason that tenants are more conscious about their farm income compared to owners as former also has to pay the rent of land hence they will adapt more to climate change to keep their gross revenue above total cost as compared to owners.

3.5.6. Tube well ownership

Tube well ownership indicates adequate supply of ground water for crops in time of need. The ownership of tube well is positively associated with the majority of the adaptation measures, even though the coefficients are insignificant. Moreover, ownership of tube well leads to 7.16 % increase in the likelihood of adopting changing crop type and 9.69 % increase in the probability of changing fertilizer (Table 5). Hence, it can be concluded that farmers having a tube well are more likely to adapt their agriculture to climate change as they have the assurance of sufficient water supply to make any adjustment at farm level in response to variability in climate.

3.5.7. Distance from the local market

Proximity to market may serve as a means of sharing and exchanging information with farmers and other service providers (Maddison, 2007). In this study for most of the adaptation measures, the coefficient of distance from the local market is negative which indicates that farmers located near to the local market have more chances to adapt to climate change compared to farmers who are far away from the market. A 1 % increase in the distance of the farm from nearest local market would result in a decrease of 0.05 % in the probability of the changing crop type (Table 6).

3.5.8. Access to farm credit

Access to farm credit has an insignificant effect on the adaptation to climate change. Access to farm credit is positively related to changing crop variety and increased irrigation and negatively related to the changing crop type, changing planting dates, plantation of shaded trees, soil conservation, changing fertilizer and crop diversification, although not significantly.

3.5.9. Access to information on water deliveries

Access to information on water deliveries has positive but insignificant impact on most of the adaptation measures except changing planting dates (Table 4). The access to information on water deliveries increases the likelihood of changing planting dates by 11.73 % (Table 5). We can conclude that farmers who have more access to information on water deliveries are more likely to adjust the planting dates according to water availability.

3.5.10. Information on weather forecasting

Information on seasonal and daily weather forecasting (i.e. temperature and rainfall) has a positive and significant effect on the probability of changing crop types, changing planting dates, plantation of shaded trees, soil conservation, changing fertilizer, irrigation and crop diversification as adaptation methods. Results in Table 5 show that access to information on seasonal and daily weather increases the probability of plantation of shaded trees (41.33 %), increased irrigation (17.50 %), changing fertilizers (16.95 %), soil conservation (16.33 %), changing planting dates (15.15 %), changing crop type (11.33 %), and crop diversification (8.17 %). In summary, the information on weather forecasting increases the likelihood of adaptation to climate change.

3.5.11. Extension of crop and livestock production

Agricultural extension is an ongoing process and can be defined as a systematic tool of dissemination of useful and practical information related to agriculture, including improved farm inputs, farming techniques and skills to farmers or rural communities with the objective of improving their farm production and income (Syngenta, 2014, Swanson and Claar, 1984).

Results in Table 4 indicate that the extension of crop production is significantly and positively related to changing crop variety. On the other hand, it is significantly and negatively related to the probability of changing crop type which may be due to the reason that farmers get poor information from crop production and adaptation to climate change, or the quality of extension is outdated. The results of the marginal effect in Table 5 show that access to extension services leads to 13.07 % increase in the likelihood of changing crop variety and decrease of 6.36 % in the likelihood of changing crop type as an adaptation method. For all other adaptation measures, no significant relationship is found between extension and adaptation measures. These results support the farmers' complaint about lack of updated information on adaptation to climate change by the extension department.

3.5.12. Access to market information

Results of logistic regression show a positive association between access to market information and the adaptation to climate change though most of the coefficients are insignificant. The probability of changing crop type increases by 8.56 % if farmers have access to market information (Table 5).

3.5.13. Irrigated plains mixed cropping zone (base rain-fed zone)

Farmers living in different agro-ecological zones used different adaptation measures. For example, the farming in mixed cropping zones leads to an increase in the likelihood of changing crop variety (11.21 %), changing planting dates (24.47 %), planting trees (12.45 %) and changing fertilizers (13.35 %) compared to the farming in the cotton zone or rain-fed zone (Table 5). From the results, we can conclude that farmers in different cropping zones adapt differently based on cropping patterns and needs.

3.5.14. Irrigated plains cotton zone (base rain-fed zone)

Likelihood of changing crop type (7.82 %), soil conservation (7.10 %), irrigation (7.15 %) and crop diversification (6.89 %) increases in case of farming in the cotton zone (Rahim Yar Khan) compared to the farming in other zones. Moreover, farming in the cotton zone reduces the probability of changing crop varieties and changing plantation dates as adaptation methods by 28.85 % and 9.69 % respectively compared to the farming in other zones.

3.6. Schematic framework of farmers' adaptation process

A schematic framework of the farmers' adaptation process was developed based on field data analysis to summarize the adaptation process at farm level (Figure 9). In this framework, we described the farmers' adaptation process as a three-step procedure. In the first step, farm households perceive climate change and its adverse impacts on their agricultural production. These perceptions can be defined through various internal (socio-economic) and external (e.g. environmental or institutional) factors. In the second stage, farmers show their intentions to adopt certain measures to adapt to climate change that again can be described or influenced by internal and external factors mentioned in section 2.1. In the last and third stage, farmers decide either to adapt or not to perceived changes in climate. Farmers' adoption of particular adaptation measures again may be subject to various internal and external factors (Table 4). While the farmers' decisions of not adapting to climate variability may be explained by various constraints elaborated by farmers, who do not adapted even having intentions (Figure 2). In this framework, the width of connection lines shows the significance or insignificance of individual variables on the perceptions, intentions or adaptations. Green and blue lines represent positive and negative relations between interdependent variables (perceptions, intentions or adaptations), respectively, while dotted lines represent a weak link, and full lines show a significant relationship.

3.7. Partial-elasticity comparisons across regions

We further analyzed and compared the partial elasticities of explanatory variables for all adaptation methods across three study districts (Figure 10). From the results, it can be observed that elasticity scores range from -0.01 to 0.20 except for elasticity scores (0.30-0.40) of weather information variable in the planting trees model. Elasticity of farming experiences is higher for farmers in the district Rahim Yar Khan for most of the adaptation methods followed by farmers in district Toba Tek Singh and Gujrat respectively. The highest elasticity of farming experience was observed in case of adaptation measures changing crop varieties (0.15) and changing planting dates (0.16) in Rahim Yar Khan which indicates that farming experience increases the chances of adaptation to climate change in Rahim Yar Khan more compared to the districts of Toba Tek Singh and Gujrat. The same trend was found for elasticity of education where highest score (0.18) was obtained for changing planting dates in Rahim Yar Khan and a lowest elasticity score was found for crop diversification (0.02) in Gujrat. It can be concluded that education has more significant effects on adaptation to climate change in the district Rahim Yar Khan.

Elasticity calculations for household size show the highest elasticity in the case of planting trees in Rahim Yar Khan (0.19) while the lowest elasticity of household size ((but insignificant) was observed for changing crop variety (-0.07) for the Rahim Yar Khan district. Elasticities of household size were close to zero for the irrigation and crop diversification method of adaptation. In case of the variable of total land holding, the highest coefficient was observed for changing crop variety in district Rahim Yar Khan (0.07) while for adaptation methods soil conservation, changing fertilizer, irrigation and crop diversification, the coefficient was close to zero which indicates little or no effect of land holding on adoption of these measures. Elasticity coefficients for tenancy status variable were higher for district Rahim Yar Khan followed by district Toba Tek Singh and Gujrat.

4. Conclusions and policy suggestions

Climate change is a reality which is expected to have significant impacts on Pakistan's economy with an increase in the frequency of extreme events including floods and droughts and changing rainfall patterns (Asif 2013). Being severely dependent on natural water resources, agriculture in Pakistan is particularly vulnerable to further climate change. Hence, suitable adaptation measures to climate change are important. This study uses novel farm-level data from three distinct agro-ecological zones in Pakistan to analyze farmers' awareness and their adaptive capacities and measures to changes in climate.

This study reveals real and perceived constraints for farm-level adaptation to climate change. Most constraints are institutional in nature and can be covered with improving the institutional services in term of access, use and viability for climate adaptation. Furthermore, this study shows the importance of different types of institutional services such as easy access to information on weather forecasting and improved agricultural technologies; easy access to resources and financial services for the enhancement of farm level adaptation. However, the services currently provided at farm level are not sufficient to support an effective adaptation process. Hence there is dare need for collaborations at different levels of the adaptation process. These collaborations may include public-private partnerships or integration at horizontal and vertical levels of public and private organizations. This study also shows that farmers in different agro-ecological zones prefer different adaptation measures. This diversity confirms the need for research at local levels, i.e. in different agro-ecological zones, to develop efficient and effective adaptation strategies for the agriculture sector.

The study also shows that historical adaptation measures at farm level do generally not include advanced management technologies but are limited to simple measures, particularly changing crops or crop varieties. Very few farmers adopted advanced adaptation measures. As we already mentioned, the reason behind not using advanced measures lies in lack of knowledge and support from local institutions. Hence, future policies need to address barriers for the adoption of advanced adaptation measures at farm-level such as providing information and support, introducing climate smart varieties, promoting soil conservation and new adaptation measures based on different agro-ecological zones. Despite the need for locally specific adaptation of agriculture to climate change, investment and research are also needed at macro-level. Particularly, commodity prices, resource endowments, and environmental impacts depend on regional and international developments but interact with local adaptation measures.

Appendix A: Marginal effect and elasticity calculations

Let us have a logit function (in term of observed variable Y_{ij}) already explained in equation (3) in section 2:

$$\Pr(Y_{ij}=1)=Y_{ij}=G(X_k\beta) \tag{A1}$$

where G(.) takes the specific binomial distribution (Fernihough 2011).

If we take the partial derivative of equation (3) with respect to explanatory variable X_k, by applying chain rule (Dawkins, 2005), it will give us the marginal effect:

$$\frac{\partial Y_{ij}}{\partial X_k}=\frac{\partial G(X_k\beta)}{\partial X_k}=\frac{\partial G(X_k\beta)}{\partial X_k\beta}.\frac{\partial X_k\beta}{\partial X_k}=G'(X_k\beta).\beta_k=g(X_k\beta)\beta_k \tag{A2}$$

As we know that

$$G(X_k\beta)=\frac{e^{X_k\beta}}{1+e^{X_k\beta}}$$

So the derivative of G(Xkβ) with respect to Xkβ by applying quotient rule (Dawkins, 2005), will be followed as:

$$g(X_k\beta)=\frac{\left(1+e^{X_k\beta}\right)\cdot e^{X_k\beta}-e^{X_k\beta}\cdot e^{X_k\beta}}{\left(1+e^{(X_k\beta)}\right)^2}$$
$$=\frac{e^{(X_k\beta)}}{\left(1+e^{X_k\beta}\right)^2} \tag{A3}$$

If we put the value of g(Xkβ) from equation (A3) into equation (A2) then it becomes:

$$\frac{\partial Y_{ij}}{\partial X_k}=\frac{e^{(X_k\beta)}}{\left(1+e^{X_k\beta}\right)^2}\cdot\beta_k \tag{A4}$$

Usually marginal effects are calculated at mean of explanatory variables ($\overline{X_k}$) so we may replace X_k with mean value of $\overline{X_k}$ (Schmidheiny, 2013):

$$= \frac{e^{(\overline{X_k}\beta)}}{1+e^{(\overline{X_k}\beta)}} \cdot \frac{1}{1+e^{(\overline{X_k}\beta)}} \cdot \beta_k$$

$$= \Pr(Y_{ij}=1) \cdot \left(1 - \frac{e^{(\overline{X_k}\beta)}}{1+e^{(\overline{X_k}\beta)}}\right) \cdot \beta_k$$

$$= \Pr(Y_{ij}=1) \cdot \left(1 - \Pr(Y_{ij}=1)\right) \cdot \beta_k$$

Partial-elasticity can be easily calculated from marginal effects. As we already know, elasticity is responsiveness of the dependent variable in percentage for a percentage change in the independent variable. But the elasticity measure for logistic regression is different from other normal elasticity measures because in case of logistic regression the dependent variable is a unit less number and takes the values between 0 and 1 (Curran 2010). Hence partial-elasticity (η_Y) for logistic regression may be defined as:

$$\eta_Y(X_k) = X_k \cdot \frac{\partial G(X_k\beta)}{\partial X_k} \qquad \text{(A5)}$$

As $\frac{\partial G(X_k\beta)}{\partial X_k}$ is simply the marginal effect of logistic regression (see equation 4) so we may write equation A5 as:

$$\eta_Y(X_k) = X_k \cdot \Pr(Y_{ij}=1) \cdot \left(1 - \Pr(Y_{ij}=1)\right) \beta_k \qquad \text{(A6)}$$

Moreover we can conclude partial-elasticity X_k times the marginal effect (y_{ij}') (Rahji and Fakayode, 2009).

In a similar way of calculating marginal effects, partial elasticities are also calculated at mean of explanatory variables ($\overline{X_k}$) so we may write equation (7) as:

$$\eta_Y(\overline{X_k}) = \beta_k \overline{X_k} \Pr(Y_{ij}=1)\left(1 - \Pr(Y_{ij}=1)\right) \qquad \text{(A7)}$$

Where $\Pr(Y_{ij}=1) = \frac{e^{(\overline{X_k}\beta)}}{1+e^{(\overline{X_k}\beta)}}$

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Table 1. The Study Districts

Districts	City (*Tehsil*)	Union councils selected	No of farmers interviewed
Rahim Yar Khan	Khanpur	4	75
	Liaqatpur	6	75
Toba Tek Singh	Toba Tek Singh	6	75
	Gojra	6	75
Gujrat	Gujrat	7	75
	Kharian	6	75
Total		35	450

Table 2. Description of Explanatory Variables Used in the Model

Explanatory variable	Mean	Std. Deviation	Description	Expected signs
Years of experience in farming	24.37	11.97	Continuous	(+)
Years of education	8.510	4.256	Continuous	(+)
Household size (numbers)	9.664	5.133	Continuous	(+)
Land holding (acres)	16.06	28.53[1]	Continuous	(+)
Livestock ownership	0.607	0.489	Dummy takes the value 1 if owned and 0 otherwise	(+)
Tube well ownership	0.630	0.482	Dummy takes the value 1 if owned and 0 otherwise	(-)
Distance from local market (km)	9.089	7.610	Continuous	(-)
Access to credit	0.096	0.294	Dummy takes the value 1 if have access and 0 otherwise	(+/ -)
Extension on crop and livestock production	0.260	0.439	Dummy takes the value 1 if have access and 0 otherwise	(+)
Information on weather forecasting	0.836	0.371	Dummy takes the value 1 if have access and 0 otherwise	(+)
Access to marketing information	0.762	0.426	Dummy takes the value 1 if have access and 0 otherwise	(+)
Access to information on water deliveries	0.784	0.412	Dummy takes the value 1 if have access and 0 otherwise	(+/ -)
Irrigated plains cotton zone (base rain-fed zone)	0.330	0.472	Dummy takes value 1 if district "Rahim Yar Khan" and 0 otherwise	(+/ -)
Irrigated plains mixed cropping zone (base rain-fed zone)	0.330	0.472	Dummy takes value 1 if district "Toba Tek Singh" and 0 otherwise	(+/ -)

[1]This large standard deviation is due to presence of large land holders in district Rahim Yar Khan

Table 3. Hypothesis Testing for Model Significance and Predictive Power

Models	Chi-square (χ2)	df	P-level	-2*log likelihood	AIC	Model [1] correctness (%)	Nagelkerke pseudo R2
Changing crop type	65.18	14	0.00	-115.89	261.77	89.90	0.28
Changing crop variety	64.91	14	0.00	-250.38	530.77	71.30	0.19
Changing planting dates	66.99	14	0.00	-235.20	500.40	76.40	0.20
Planting trees	68.55	14	0.00	-220.41	470.82	76.40	0.21
Soil conservation	56.71	14	0.00	-188.25	258.07	91.10	0.22
Changing fertilizer	46.52	14	0.00	-114.04	406.51	83.60	0.19
Irrigation	42.51	14	0.00	-122.82	275.65	90.40	0.19
Crop diversification	28.19	14	0.01	-106.40	242.81	92.40	0.15

[1] based on the classification table
P-level shows the statistical significance to reject the null hypothesis (Ho)
AIC (Akaike information criterion) measures the relative quality of the statistical mode

Table 4. Parameter Estimates of the Logistic Regression Models of Farm Level Adaptation Measures

Explanatory variables	Changing crop type	Changing crop variety	Changing planting dates	Planting trees	Soil conservation	Changing fertilizer	Irrigation	Crop diversification
Intercept	-5.0048***	-1.2789**	-3.1395***	-4.9009***	-6.9262***	-4.845***	-5.587***	-3.826***
Farm experience (years)	0.0065	0.0316***	0.0350***	-0.0029	0.0217	3.314***	0.018	0.002
Years of Education	0.1336***	0.0618**	0.1229***	0.0641**	0.1395***	1.397***	0.142***	0.038
Household size	0.0316	-0.0365	0.0141	0.1102***	0.0644**	2.469	-0.002	-0.007
Land area (acres)	0.0093**	0.0200***	0.0026	-0.0048	-0.0020	-1.679	0.003	0.006
Tenancy status owner (base tenant)	-1.2338***	-0.4066	-0.6840***	-0.0057	-0.5095	-7.371**	-0.565	-0.322
Tube well ownership	0.9512**	-0.1819	0.0511	0.2835	0.4408	7.316**	0.405	0.213
Distance from the local market	-0.0773**	-0.0156	-0.0104	0.0163	-0.0378	-6.844	-0.051	-0.063
Access to farm credit	-0.1793	0.0876	-0.0924	-0.4597	-0.0478	-1.736	0.247	-0.192
Access to information on water deliveries	-0.7165	0.5820	0.6729**	-0.1998	0.2123	5.549	-0.210	0.158
Information on weather forecasting	1.5052**	-0.2564	0.8692**	2.5448***	2.2544**	1.279**	2.207**	1.255**
Extension on crop and livestock production	-0.8448**	0.6958**	0.2537	0.2829	-0.3809	-1.976	-0.536	-0.642
Access to market information	1.1377**	0.1153	-0.0616	0.0088	0.1759	9.942	0.161	0.165
Mixed cropping zone (base rain-fed zone)	-0.7351	-0.5965**	-1.4044***	-0.7664**	-0.6644	-1.008**	-0.696	-0.954
Cotton zone (base rain-fed zone)	1.0392**	-1.5353***	-0.5562**	-0.1057	0.9810**	-3.330	0.901**	1.058**
N	450	450	450	450	450	450	450	450

***, ** Significant at 1 % and 5 % probability level, respectively

Table 5. Marginal Effects from the Binary Logistic Models of Farm Level Adaptation Measures

Explanatory variables	Changing crop type	Changing crop variety	Changing planting dates	Planting shaded trees	Soil conservation	Changing fertilizer	Irrigation	Crop diversification
Farm experience (years)	0.0005	0.0059	0.0061	-0.0005	0.0016	0.0044	0.0014	0.0001
Years of Education	0.0101	0.0116	0.0214	0.0104	0.0101	0.0185	0.0112	0.0025
Household size (numbers)	0.0024	-0.0069	0.0025	0.0179	0.0047	0.0033	-0.0001	-0.0004
Land area (acres)	0.0007	0.0038	0.0005	-0.0008	0.0001	0.0000	0.0002	0.0004
Tenancy status owner (base tenant)	-0.0929	-0.0764	-0.1192	-0.0009	-0.0369	-0.0977	-0.0448	-0.0210
Tube well ownership	0.0716	-0.0342	0.0089	0.0460	0.0319	0.0969	0.0321	0.0139
Distance from the local market	-0.0058	-0.0029	-0.0018	0.0026	-0.0027	-0.0009	-0.0041	-0.0041
Access to farm credit	-0.0135	0.0165	-0.0161	-0.0747	-0.0035	-0.0230	0.0196	-0.0125
Access to information on water deliveries	-0.0539	0.1093	0.1173	-0.0324	0.0154	0.0735	-0.0166	0.0103
Information on weather forecasting	0.1133	-0.0482	0.1515	0.4133	0.1633	0.1695	0.1750	0.0817
Extension on crop and livestock production	-0.0636	0.1307	0.0442	0.0459	-0.0276	-0.0262	-0.0425	-0.0418
Access to market information	0.0856	0.0217	-0.0107	0.0014	0.0127	0.0132	0.0128	0.0108
Irrigated plains mixed cropping zone (base rain-fed zone)	-0.0553	-0.1121	-0.2447	-0.1245	-0.0481	-0.1335	-0.0552	-0.0621
Irrigated plains cotton zone (base rain-fed zone)	0.0782	-0.2885	-0.0969	-0.0172	0.0710	-0.0441	0.0715	0.0689
N	450	450	450	450	450	450	450	450

Table 6. Elasticity Calculations of the Binary Logistic Models of Farm Level Adaptation Measures

Explanatory variables	Changing crop type	Changing crop variety	changing planting dates	planting shaded trees	Soil conservation	Changing fertilizer	Irrigation	Crop diversification
Farm experience (years)	0.0119	0.1445	0.1487	-0.0114	0.0383	0.1070	0.0348	0.0026
Years of Education	0.0817	0.0942	0.1739	0.0845	0.0821	0.1503	0.0911	0.0203
Household size (numbers)	0.0230	-0.0662	0.0238	0.1729	0.0450	0.0316	-0.0014	-0.0041
Land area (acres)	0.0113	0.0604	0.0074	-0.0124	0.0023	0.0000	0.0032	0.0062
Tenancy status owner (base tenant)	-0.0752	-0.0619	-0.0965	-0.0008	-0.0299	-0.0791	-0.0363	-0.0170
Tube well ownership	0.0451	-0.0215	0.0056	0.0290	0.0201	0.0611	0.0202	0.0088
Distance from local market	-0.0529	-0.0267	-0.0164	0.0241	-0.0249	-0.0082	-0.0371	-0.0374
Access to farm credit	-0.0043	0.0053	-0.0052	-0.0239	-0.0011	-0.0074	0.0063	-0.0040
Access to information on water deliveries	-0.0421	0.0853	0.0915	-0.0253	0.0120	0.0574	-0.0130	0.0080
Information on weather forecasting	0.0952	-0.0405	0.1272	0.3472	0.1371	0.1424	0.1470	0.0687
Extension on crop and livestock production	-0.0273	0.0562	0.0190	0.0198	-0.0119	-0.0113	-0.0183	-0.0180
Access to market information	0.0651	0.0165	-0.0082	0.0011	0.0097	0.0100	0.0097	0.0082
Irrigated plains mixed cropping zone (base rain-fed zone)	-0.0183	-0.0370	-0.0808	-0.0411	-0.0159	-0.0441	-0.0182	-0.0205
Irrigated plains cotton zone (base rain-fed zone)	0.0258	-0.0952	-0.0320	-0.0057	0.0234	-0.0146	0.0236	0.0227

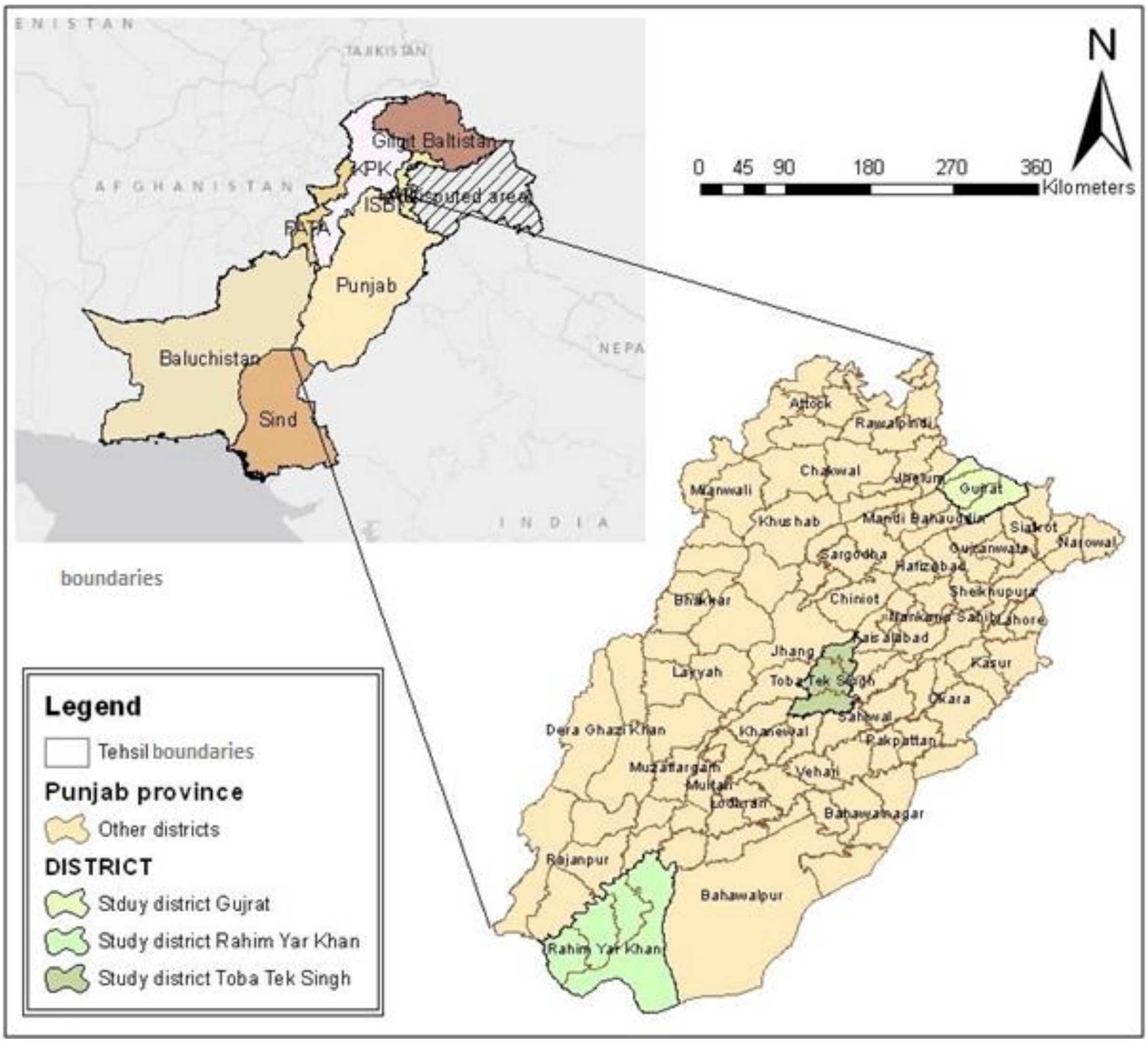

Figure 1. Sample study districts Punjab province, Pakistan

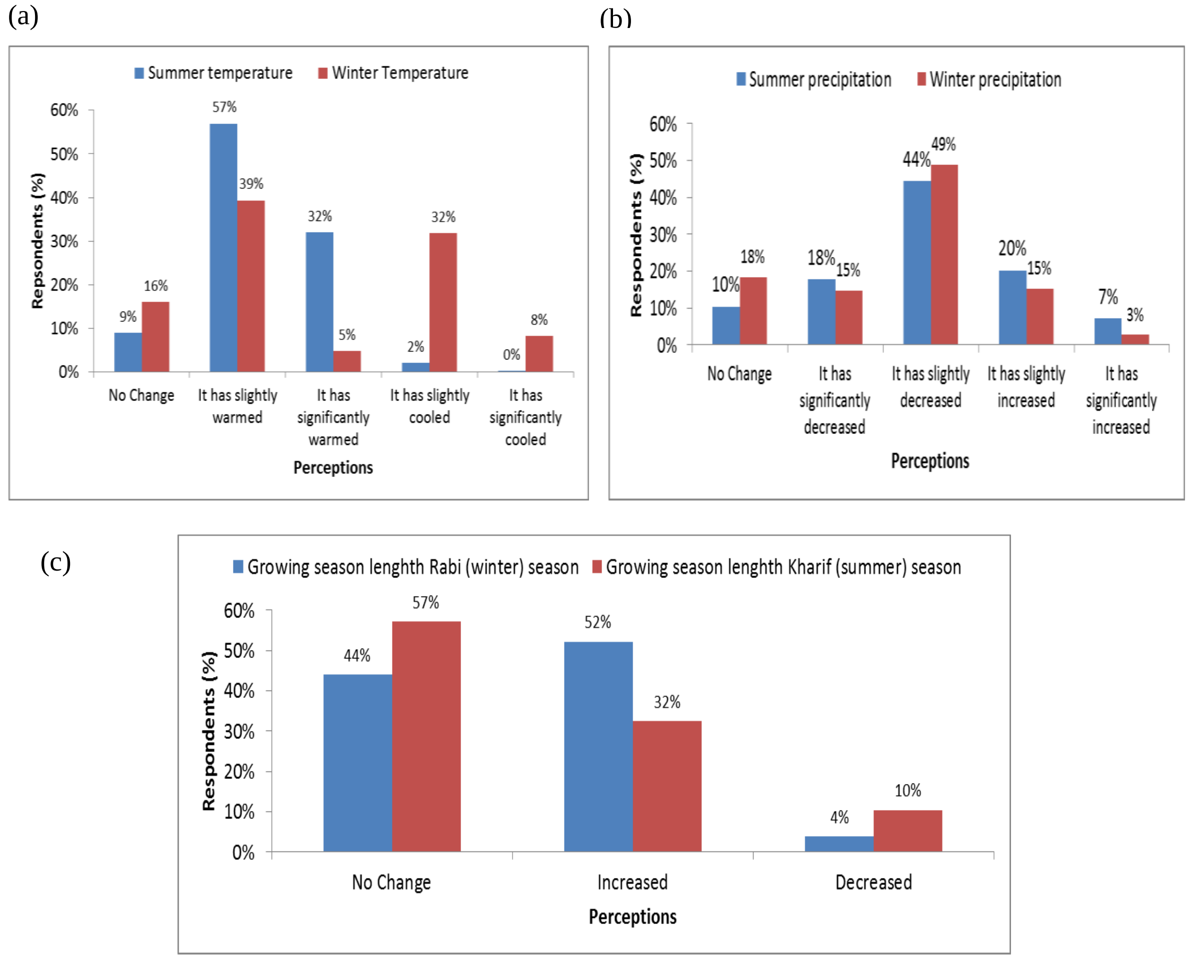

Figure 2 (a)-(c). Farmers’ perceptions of climate change in study area Punjab Pakistan

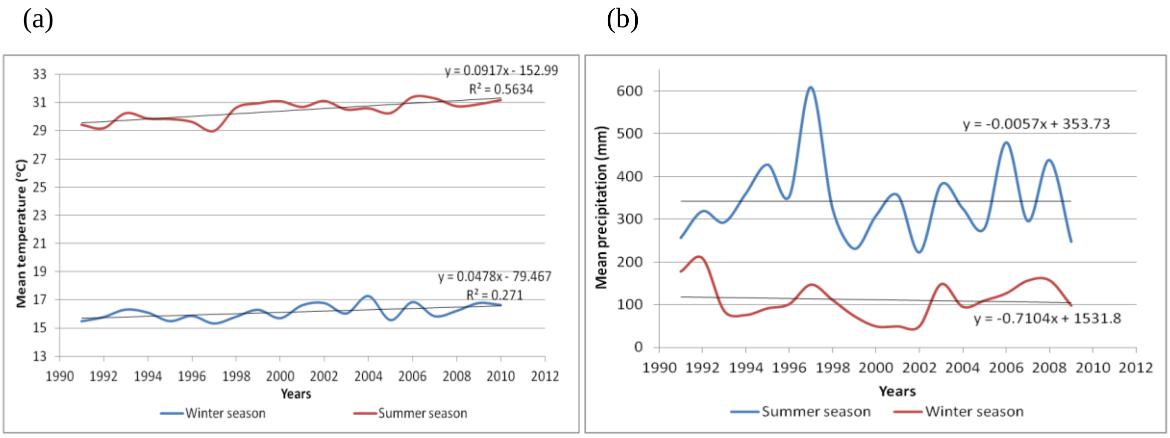

Figure 3 (a-b). Mean temperature and precipitation trends in study area over the period of 1990-2010

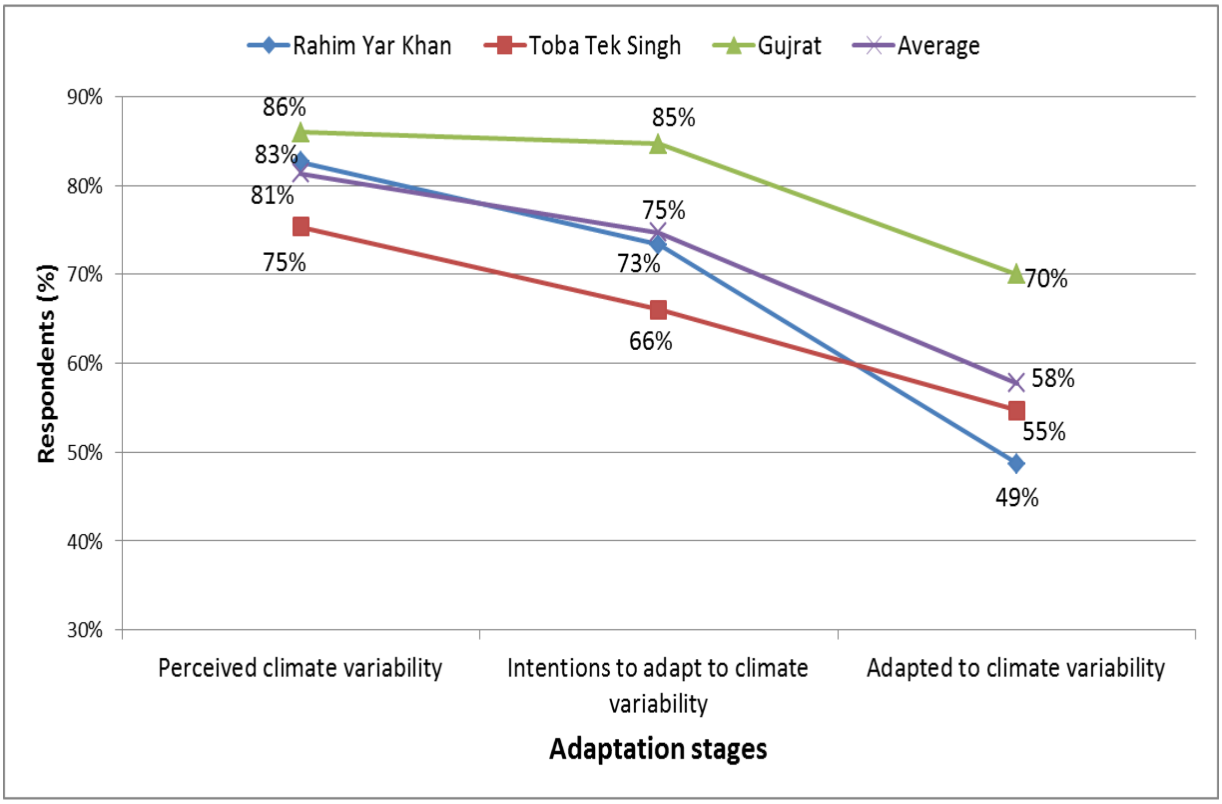

Figure 4. Perceptions, intentions and adaptation to climate change across different study districts

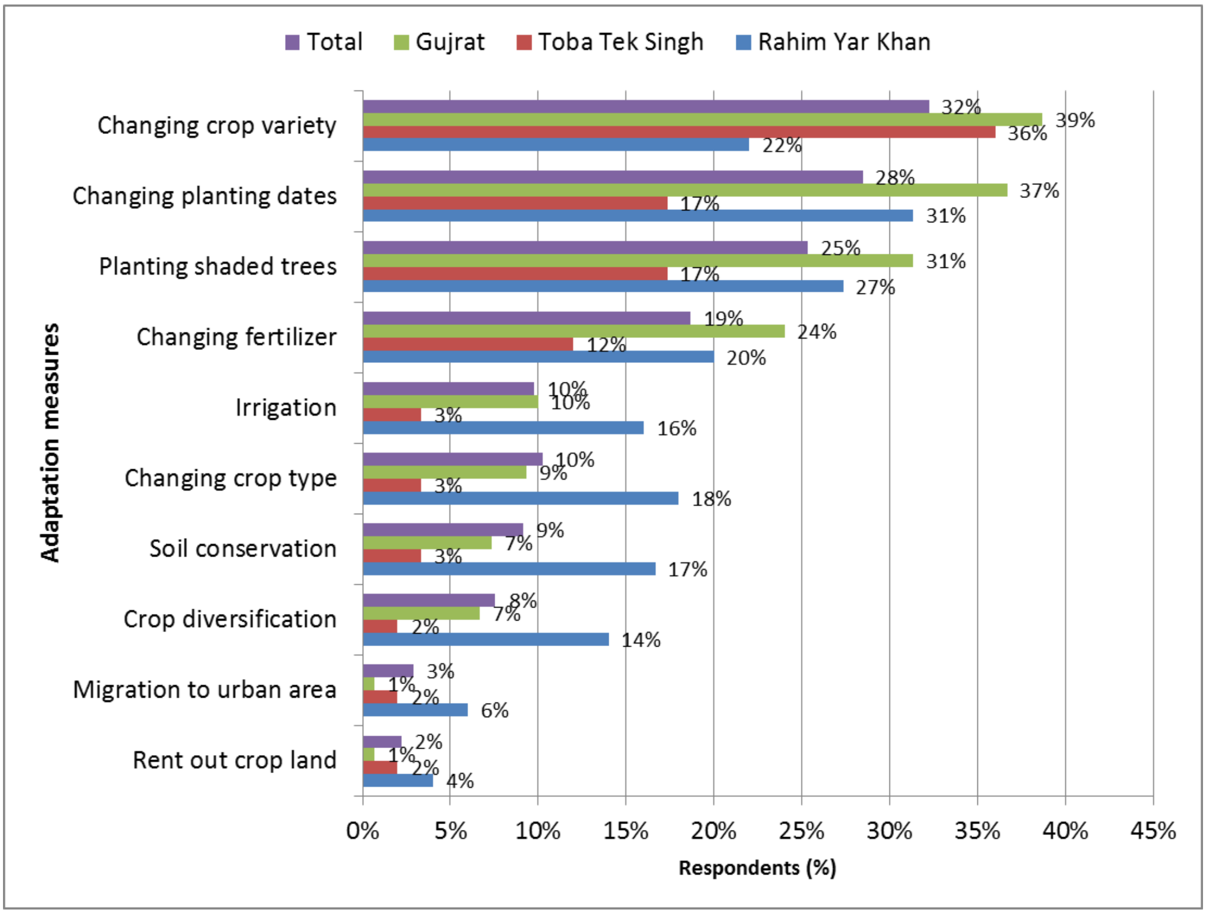

Figure 5. Adaptation measures adopted by farmers across three study areas in Punjab, Pakistan

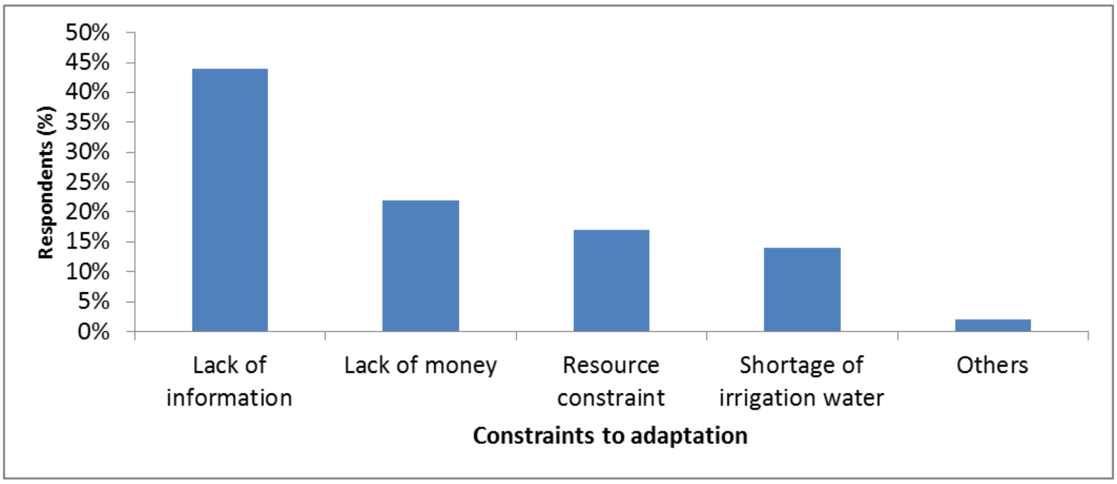

Figure 6. Constraints to adaptation to climate change in the study area

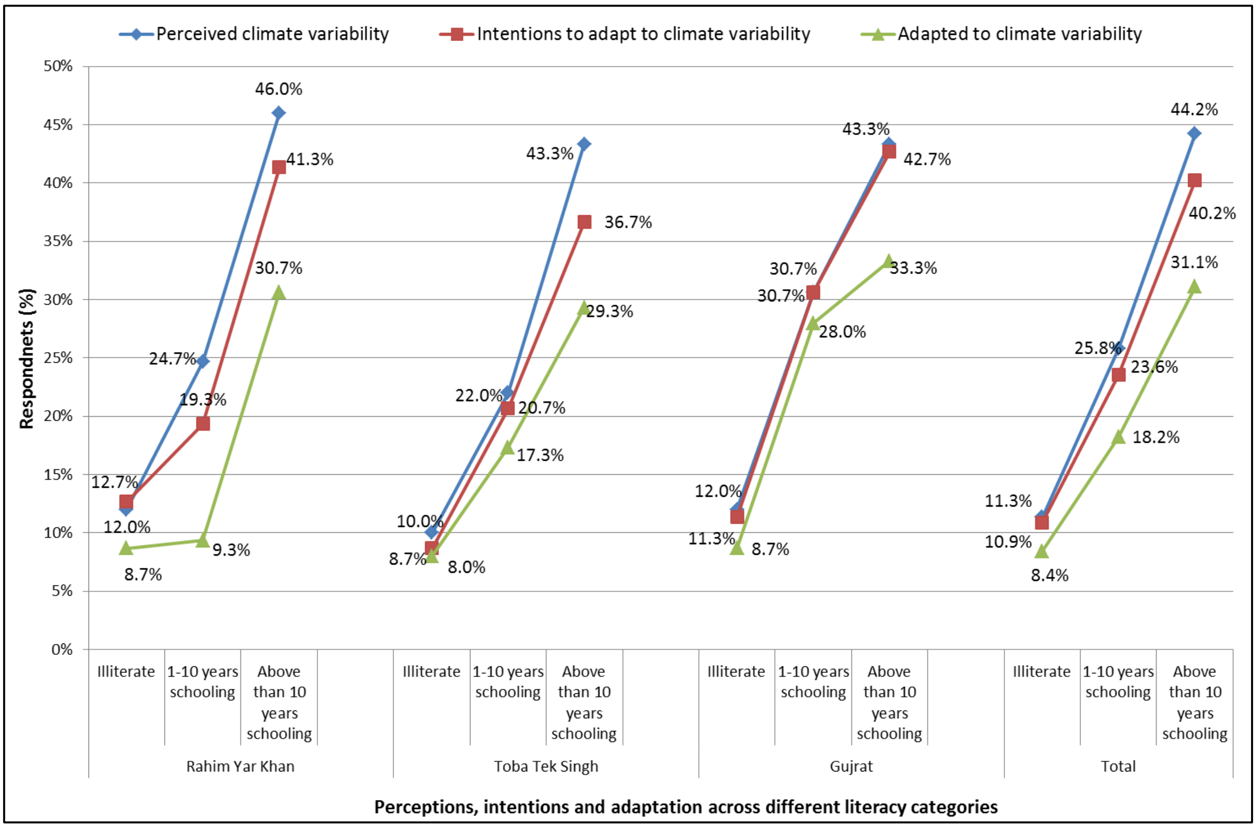

Figure 7. Adaptation to climate variability across different categories of farmers based on education level

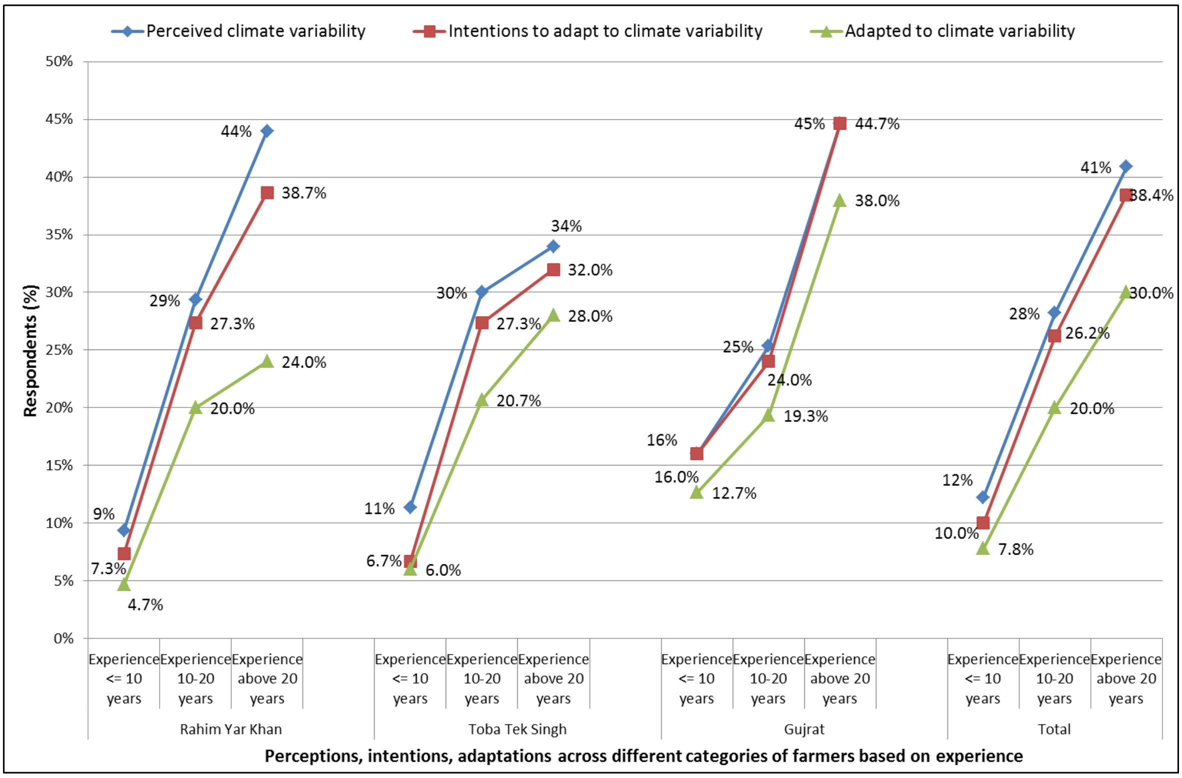

Figure 8. Perceptions, intentions and adaptation to climate change across different categories of farmers on farming experience in Punjab

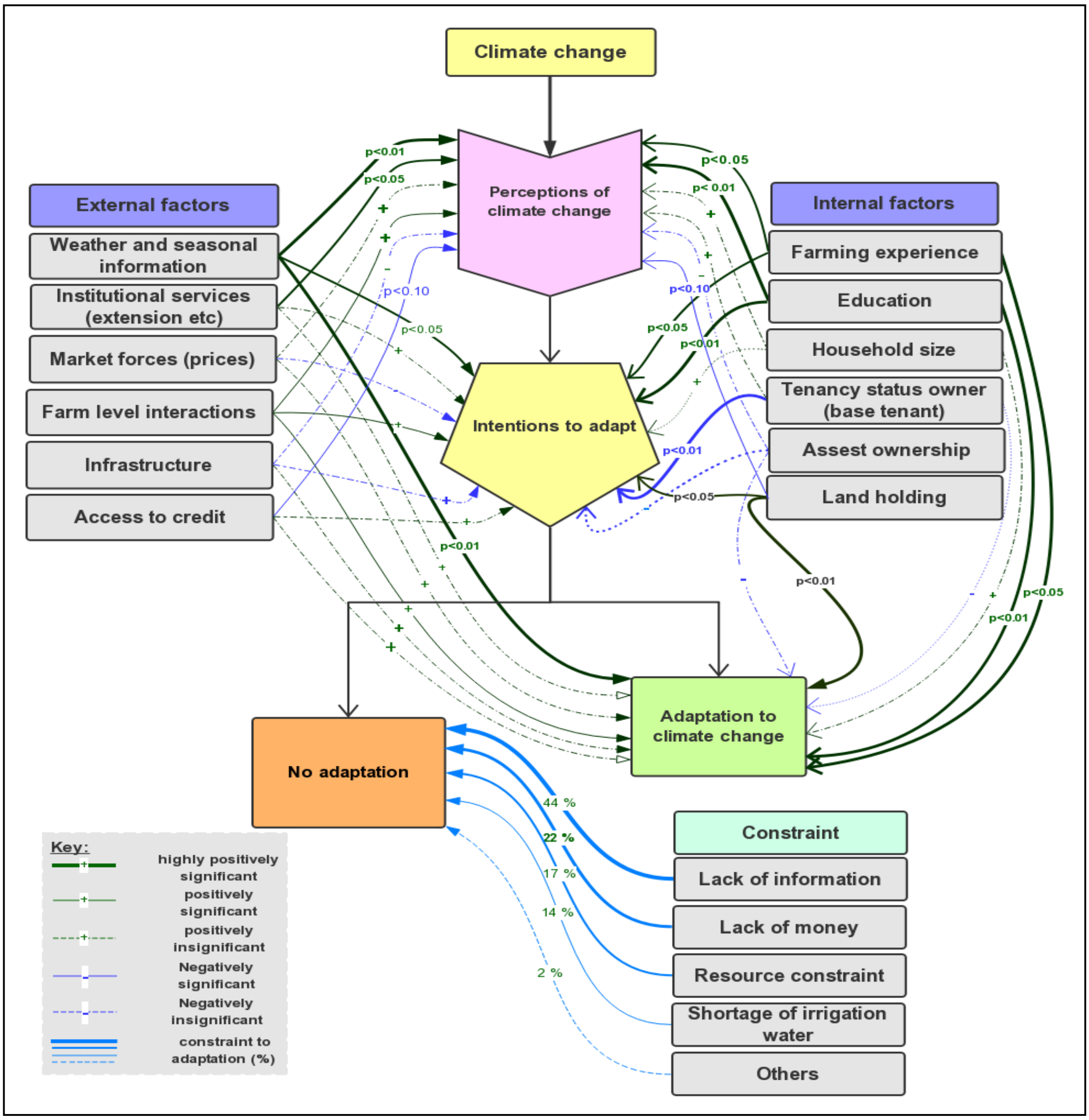

Figure 9. Schematic framework of farmers' adaptation process in Pakistan (own illustration)

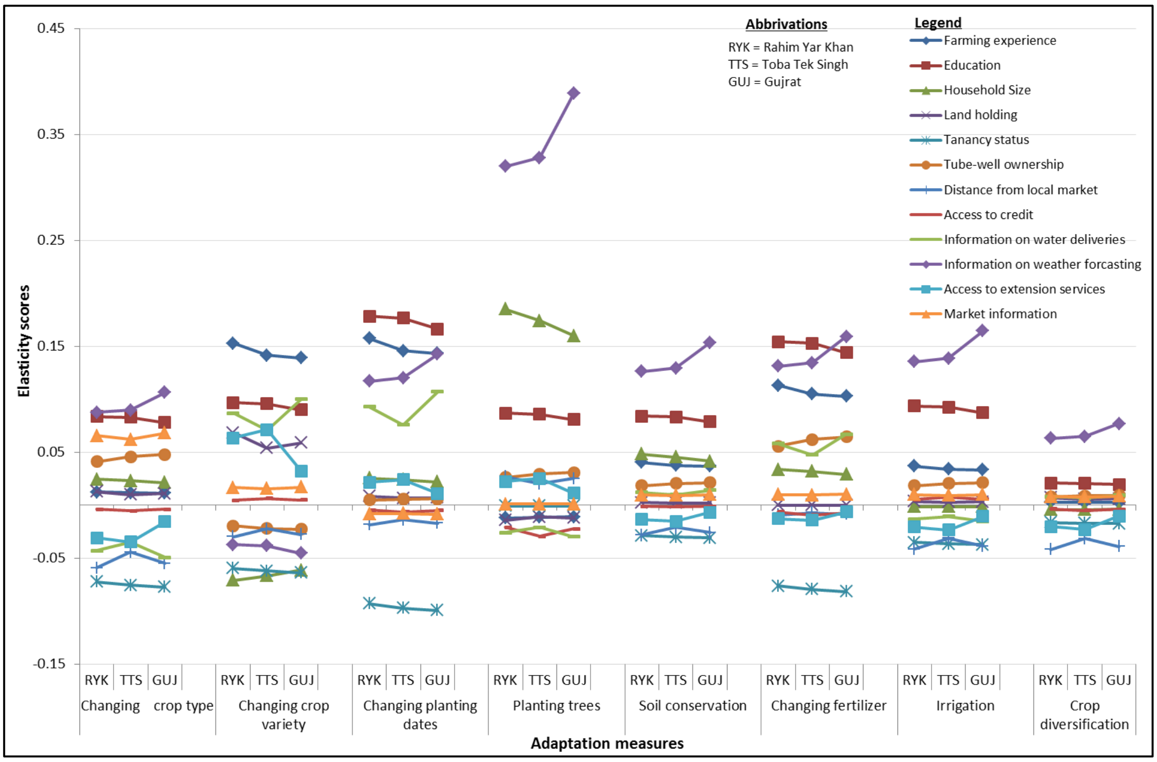

Figure 10. Partial-elasticity calculations across three study districts of Punjab province