Earth Syst. Dynam. Discuss., 5, 1359–1406, 2014
www.earth-syst-dynam-discuss.net/5/1359/2014/
doi:10.5194/esdd-5-1359-2014

Earth System Dynamics Discussions
Open Access

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

M. Abid[1,2], J. Scheffran[1], U. A. Schneider[3], and M. Ashfaq[4]

[1]Research Group Climate Change and Security (CLISEC), Institute of Geography, University of Hamburg, KlimaCampus, Grindelberg 7, 20144 Hamburg, Germany
[2]School of Integrated Climate System Sciences, Grindelberg 5, 20144 Hamburg, Germany
[3]Research Unit Sustainability and Global Change, KlimaCampus, University of Hamburg, Bundesstrasse 55, 20146 Hamburg, Germany
[4]Institute of Agricultural and Resource Economics, University of Agriculture, Faisalabad, Pakistan

Received: 10 September 2014 – Accepted: 23 September 2014 – Published: 17 October 2014

Correspondence to: M. Abid (muhammad.abid@zmaw.de)

Published by Copernicus Publications on behalf of the European Geosciences Union.

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 of 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 households adapted their farming to climate change. Changing crop varieties, changing planting dates, plantation of trees and changing fertilizer 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 of greater investment in farmer education and improved institutional setup for climate change adaptation to improve farmers' wellbeing.

1 Introduction

Climate change is a global environmental threat and development concern. 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

ESDD

5, 1359–1406, 2014

is likely to affect 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 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, 2010), Pakistan is one of the highly affected countries by climate change. Pakistan has 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 (Nomman 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 the 62 % rural population (Abid et al., 2011b; 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 (Nomman and Schmitz, 2011).

Agriculture is the main source of support for 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 term of climate change adaptation in Pakistan is very limited due to the ineffective climate policy, the very low technological and financial capacity of the country in adapting to climate change (OECD, 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

ESDD
5, 1359–1406, 2014

awareness and protection programs may be some important aspects of the adaptation policy to climate change (Schlenker and Lobell, 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 rooms for further advances in existing adaptation setup. 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 farmers' adaptation to climate change across different disciplines in various countries that explored farmers' adaptive behavior and its determinants (Bryan et al., 2009; Deressa et al., 2009; Hassan and Nhemachena, 2008; Thomas et al., 2007). Perceiving climate variability is the first step in the process of adapting agriculture to climate change (Deressa et al., 2011). Hence, understanding how farmers perceived changes in climate and what factors shape their adaptive behavior is desirable for adaptation research (Mertz et al., 2009; Weber, 2010).

Despite internationally extensive research on agriculture adaptation to climate change, a little work is done so far in South Asia. Similarly in Pakistan, the scope of research on 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' perceptions and their adaptive behavior which is imperative to understand climate change adaptation in agriculture because farmers are the primary decision makers and stakeholders in the agriculture sector. The choice of adaptation methods by farmers depends on various social, economic and environmental factors

ESDD
5, 1359–1406, 2014

(Deressa, 2007; Brayan et al., 2013). The exact knowledge of these factors may assist policy to enhance the adaptation in agriculture by realizing these factors and investing in farmer-friendly measures for the improvement of the agricultural sector (Deressa, 2007).

This study mainly seeks to answer the two research questions, i.e. how farmers perceive long term changes in surrounding climate and how they adapt their farming in response to perceived changes in climate? Further, this study also considers factors affecting farm level adaptation methods adopted by farm households in the study area. Most of the factors affecting the farm households' choice of adaptation measures to climate change 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 findings of this study may bridge the gap of knowledge regarding adaptation of the agriculture sector to climate change in Pakistan and may provide a guide to policymakers in designing effective adaptation policies. 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 Sect. 5 we conclude our results and present some policy implications of the study.

2 Conceptual framework and methodology

2.1 Dependent and independent variables

Adaptation is a way to avoid 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 sample farm households in the study area. In order to decide to adapt to

ESDD
5, 1359–1406, 2014

changes in climate, farm households must first recognize their concerns about climate change and perceive changes in long-term climate such as temperature and rainfall patterns in their area (Bryan et al., 2013).

Following the previous studies of Kato et al. (2011) and Bryan et al. (2013), we assume that farm households will choose to adopt certain adaptation measure only if they perceive reduction in risks to crop production and increase in net farm benefits associated with adoption of a particular measure. Consider a latent variable (Y_i^*) which is equal to expected benefits from adoption of certain adaptation measures and depends on X_k:

$$Y_i^* = \alpha + \sum \beta_k X_k + \varepsilon_{Y_i 1*}. \quad (1)$$

In this equation, Y_i^* is latent binary variable and X_k the exogenous explanatory variables that influence farmers' choice of adopting particular adaptation measure. Here 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_i^*) directly. All we observe is:

$$Y_i = \begin{cases} 1 & \text{if} \quad Y_i^* > 0 \\ 0 & \text{if} \quad Y_i^* \leq 0 \end{cases} \quad (2)$$

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

Hence, we may interpret Eq. (2) in terms of observed binary variable (Y_i) as:

$$\Pr(Y_i = 1) = Y_i = G(X_k \beta_k) \quad (3)$$

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

2.2 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 $Y_i = 1$ (which is adoption of particular adaptation measures in our case). But this coefficient cannot explain how much the probability of household i to adopt particular adaptation measure ($Y_i = 1$) will change when we change X_k, i.e. the coefficient (β_k) reveals nothing about the magnitude of the effect of a change in explanatory variable X_k on $\Pr(Y_i = 1)$. Thus, to interpret and quantify the results, we need to calculate either marginal effects or partial-elasticity. Marginal effects (y_i') describe the effect of a unit change in explanatory variable on the probability of dependent variable, i.e. $\Pr(Y_i = 1)$. Derivation of marginal effects is discussed in detail in Appendix A. The final equation of the marginal effect after derivation will be as:

$$y_i' = \Pr(Y_i = 1) \cdot (1 - \Pr(Y_i = 1))\beta_k. \quad (4)$$

Another means to interpret results of logistic regression in a more simple and accurate way is the partial-elasticity which measures the percentage point change in the probability of the regressand or dependent variable (adoption of certain adaptation measure to climate variability) due to 1 % increase in the explanatory variable X_k (see Appendix A for further detail). We may interpret partial-elasticity of the logit model calculated at mean as:

$$\eta_Y(\overline{X_k}) = \beta_k \overline{X_k} \Pr(Y_i = 1)(1 - \Pr(Y_i = 1)). \quad (5)$$

2.3 Description of explanatory variables

The choice of explanatory (independent) variables used in this study is based on data availability and review of literature. The independent variables used in this study

ESDD
5, 1359–1406, 2014

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 agro-ecological factors. In this study, instead of using agro-ecological factors (e.g. temperature and rainfall) directly, we used dummy variables for agro-ecological zones, given the absence of variability in temperature and rainfall for households in the same district.

Prior to the start of the survey, a multinomial logit (MNL) modeling approach was proposed for this study based on a literature review which shows that most of the studies focusing on 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. But in our study it was found that instead of using single adaptation measure, sometimes farm households are involved in adopting more than one adaptation measure simultaneously, which make the MNL approach inappropriate to use for this study even after combining similar measures (Bryan et al., 2013). Furthermore, groupings of similar measures into self-defined groups or categories may lead to the possibility of misinterpretation of key adaptation measures being adopted by surveyed farm households (Bryan et al., 2013). Further the set of explanatory variables influencing the farmers' decision of adaptation were also expected to be different for different adaptation measures. Therefore, we preferred to employ the logistic regression technique to examine the factors that affect farm households' choice to implement certain adaptation measure. Table 1 shows the description and expected signs of explanatory variables used in this study.

2.4 Hypothesis testing for model significance

Before running a complete analysis, we tested all of our models to check for significance and accuracy for predictions. There are many different ways to measure goodness of fit for logistic models. In the first step, we used the classification table method

ESDD
5, 1359–1406, 2014

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 vs. the alternative that at least one of the regression coefficients (β_k) is not zero (Peng et al., 2002):

$$H_0: \quad \beta_k = 0$$
$$H_1: \quad \text{at least one } \beta_k \neq 0.$$

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. Eq. (1), fits significantly better than the model with just an intercept (i.e. an intercept-only model):

$$Y_i^* = \alpha. \tag{6}$$

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

ESDD
5, 1359–1406, 2014

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 thee 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.

2.5 Schematic framework of farmers' adaptation process

A schematic framework of the farmers' adaptation process was developed based on field data analysis (Fig. 1). 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 factors (e.g. environmental or institutional factors). After perceiving climate change, 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 Sect. 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 not to adapt may be explained by various constraints mentioned by farmers who choose not to adapt, even they were intended to adapt in the 2nd stage (Fig. 3). 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

ESDD
5, 1359–1406, 2014

lines represent positive and negative relations of variables with dependent variables (perceptions, intentions or adaptations) respectively while dotted line represent a weak link, and full lines shows a significant relationship.

3 Materials and methods

3.1 Sampling and data collection

To investigate the farm level perceptions and choice of adaptation methods to climate change in Punjab, our study was conducted in three districts of Punjab, Pakistan. The selection of study districts took into account different agro-ecological zones (AEZs), cropping patterns, irrigation source networks and climate. The study districts are selected from a range of AEZs including irrigated plains; rain-fed regions and marginal lands. 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 the 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, Punjab was selected as 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, a criterion was developed for the selection of union councils. According to this criterion, the union councils with the urban population were excluded from the list, and 20 % of the union councils were selected from the rest as a sample using a random sampling method. 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

ESDD
5, 1359–1406, 2014

farmers were randomly selected from each village. Table 2 depicts the numbers of farmers interviewed from the study areas.

The survey was conducted between March 2014 and April 2014. For the data collection, about 450 farmers irrespective of gender, farm size or tenancy status were interviewed through a farm household survey in selected union councils of three study districts of Punjab. Interviews were conducted for the cropping year 2012–2013 for both *Rabi* (winter) season 2012–2013 and *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 start of the study, pretesting of the questionnaire was done to make it realistic based on local information. The enumerators were given short-term infield training about the study objectives and farm household survey.

3.2 Description of the study area

This study was done in the Punjab province, which is geographically located approximately between 31° N latitudes and 72° E longitudes in the semi-arid 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., 2011a). 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 2 shows the map of study areas located in Punjab province.

The mean annual minimum temperature in Punjab ranges from 16.3 to 18.2 °C over the period 1970–2001. Mean annual maximum temperature in Punjab ranges from 29.3 to 31.9 °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

ESDD
5, 1359–1406, 2014

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 mm annually. The 2nd study district, Toba Tek Singh is located in the central mixed zone, which receives average rainfall ranging between 219.5 and 718 mm annually. The third district is located both in high rainfall and rice zone which receives average rainfall between 697 and 1401 mm annually (Mohammad, 2005).

4 Results and discussion

4.1 Farm level perceptions of climate change

Farmers' perception of long term changes in climate is a crucial pre-indicator in the adaptation process and plays an important role in shaping farmers' behavior (Adger et al., 2009). Various studies have explored the importance of perceptions of risk and the cognitive process of primary decision makers for the adoption of different adaptation decisions (Frank et al., 2011; Grothmann and Patt, 2005). In this study, we defined climate change as observed or perceived changes in the local environment over the period of 10–20 years or more in terms of occurrence of extreme environmental events such as droughts, floods, extreme high or low temperatures, human or animal diseases; perceived changes in average summer and winter temperature; changes in rainfall and growing season length (Bryan et al., 2013). Respondents were asked how they perceive long-term changes in climate in their area.

The study results (Fig. 3a) indicate that majority of large number of farmers perceived a slight increase in temperature for both summer (56.9 %) and winter seasons (39.3 %).

About the precipitation trends, 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 (Fig. 3b). 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 (Fig. 3b).

4.2 Farm level adaptation process

In our study, we also analyzed the whole adaptation process across all three study districts (Fig. 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 (75 %). In the 2nd stage (intention stage), overall 73 % 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 respondent 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 an 8.2 % reduction was observed in responses while from intention stage to adaptation stage, responses of farm households were reduced by 22.6 %. Overall decrease in responses from perception to adaptation stage was 29 %. From the results, it can be determined that the number of farmers who adapted to climate change is less than the farmers who perceived 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 Sect. 4.3.

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |

ESDD
5, 1359–1406, 2014

4.3 Farm level adaptation strategies and constraints

Farmers who observed long-term variability in the climate over the period of 10–20 year were further asked to describe the farm level adaptation measures undertaken by them 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 Fig. 5, the most commonly adopted adaptation measures were the changing crop varieties (32.2 %), changing planting dates (28.4 %), planting trees (25.3 %) and changing fertilizer (18.7 %) followed by changing crop types (10.2 %), increasing irrigation (9.78 %), soil conservation (9 %), crop diversification (7.56 %), migration to urban areas and renting out land (2.2 %). 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 (Fig. 5). In the Gujrat district, major adaptation measures adopted by farmers were use of different crop varieties (39 %), changing planting dates (36.7 %), planting shaded trees (31.3 %) and changing fertilizer (24 %). The main reason of changing crop variety, planting dates and plantation of shaded trees may due to more dependence of farming on rain and groundwater for cultivation of crops in 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 (17.3 %) and planting shaded trees (17.3 %) were the primary adaptation measures. In Rahim Yar Khan, farmers mainly use changing planting dates (31.3 %), planting shaded trees (27.3 %), changing crop variety (22 %), changing fertilizer (20 %) and changing crop types (18 %) as the adaptation measures in a changing climate (Fig. 5).

ESDD
5, 1359–1406, 2014

Moreover, we identified a number of constraints faced by the farmers who perceived long term changes in climate and were 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 (Fig. 1). The major constraints identified by the majority of the respondents (Fig. 6) were the 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 measures 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 of adaption, even if they plan to adapt to climate variability. Use of farm credit in the study sites is limited, besides access to micro-credit facilities available at town level. High interest rates may be a reason for less interest of farmers in formal credit institutions. Less access to or availability of resources at farm level constrains the capability in adapting to climate change. Here resources mean physical resources which 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 that provision of subsidies on farm inputs; updated farm information services and sufficient irrigation water supply may be the necessary means to enhance the adaptation of agriculture to climate variability in the study area.

ESDD
5, 1359–1406, 2014

4.4 Adaptation to climate variability across regions and different farm characteristics

From the results of the adaptation process explained above in Sect. 4.3 and Fig. 1, we can observe that farm level adaptation processes (perceptions, intentions and adaptation) are influenced by various factors. Theses adaptation measures can be further explored based on different characteristics of farm households or their location. Hence, we assume that perceptions, intentions to adapt and adaptation to climate change differ both in term of extent and decision 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 (Fig. 7). In term 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 Fig. 7, it can be observed that moving from low education level to higher education level leads to an increase in the perception, intention to adapt and final adaptation to climate change in all study districts. Overall, farmers with more than 10 years of schooling perceived (44.2 %) more changes in climate over the last 10–20 years compared to the farmers with less than 10 years of schooling (25.8 %) or no education (11.3 %). In the case of intentions to adapt to climate change, farmers with less than 10 years of schooling (23.6 %) or no education (10.9 %) were less willing to adapt to climate change compared to the 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 are having more than 10 years of schooling, and 18.2 % of the farmers had education between 1 and 10 years. Adaptation to climate change was lowest in case of illiterate farmers who were the only 8.4 % of the total sampled farmers who adapted to climate change.

ESDD
5, 1359–1406, 2014

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 (Fig. 7).

Analysis of adaptation measures across different categories of farmers based on farming experience is explained in Fig. 8. Farmers with more than 20 years of experience perceived (40.9 %) more changes in long term climate compared to the 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 to climate change 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. From the discussion, we can conclude that the higher the level or education or farming experience, the higher will be the probability of adaptation to climate change.

4.5 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 direction of effect of independent variables are presented in Table 4; the marginal effects that explain the effect of a unit change in explanatory variables on the dependent variable are shown in Table 5 and 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.

ESDD
5, 1359–1406, 2014

4.5.1 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 year of experiences 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 the results of the studies by 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.

4.5.2 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). 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 (0.082 %), changing crop variety (0.094 %), changing planting dates (0.173 %), plantation of shaded trees (0.085 %), soil conservation (0.082 %), changing fertilizer (0.15 %) and irrigation (0.091 %) as adaptation measures to climate variability. Various studies (Bryan et al., 2013; Deressa et al., 2009; Maddison, 2007) also found a significant positive relationship between education of household head and adaptation to climate

ESDD
5, 1359–1406, 2014

change that supports the finding of this study. Hence, it can be concluded that farmers with higher years of schooling are more likely to adapt to changes in climate compared to the farmers with little or no education.

4.5.3 Household size

A positive coefficient of household size indicates a positive relationship between household size and probability of adaptation. For instance, a 1 % increase in the size of household would lead to a 0.173 % increase in the likelihood of plantation of shaded trees and 0.045 % increase in choice of soil conservation as adaptation measure. Finding of the studies of Croppenstedt et al. (2003) and Deressa et al. (2009) also supports our findings of a positive relationship between household size and adoption of agricultural technology or adaptation to climate change.

4.5.4 Land area

Land area represents the total land area holds 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 0.011 and 0.06 % respectively (Table 6).

4.5.5 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 indicates that tenants are more likely to adapt their farming to perceived climate change compared to the owner operator farmers. As 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 fertilizer (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 self-operating farmers (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 self-operating farmers (owners).

4.5.6 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 to 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 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.

4.5.7 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 0.053 % in the probability of changing crop type (Table 6).

4.5.8 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 type and increased irrigation and negatively related to the changing crop type, changing planting dates, plantation

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |

ESDD

5, 1359–1406, 2014

of shaded trees, soil conservation, changing fertilizer and crop diversification, although not significantly.

4.5.9 Access to information on water deliveries

Access to information of 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.

4.5.10 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 fertilizer (16.95 %), soil conservation (16.33 %), changing planting dates (15.15 %), changing crop type (11.33 %), and crop diversification (8.17 %).

4.5.11 Extension of crop and livestock production

Agricultural extension is an ongoing process and may be of various kinds. It 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).

ESDD
5, 1359–1406, 2014

Results in Table 4 indicate that extension of crop production significantly and positively relate to changing crop variety and significantly and negatively related to the probability of changing crop type. The insignificant relation may be due to the reason that farmers get poor information over 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 among extension and adaptation measures. These results support the farmers' complaint about lack of updated information on adaptation to climate change by extension department.

4.5.12 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 farmer have access to market information (Table 5).

4.5.13 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).

4.5.14 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

ESDD
5, 1359–1406, 2014

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.

4.6 Partial-elasticity comparisons across regions

We further analyzed and compared the partial elasticities of explanatory variables for all adaptation methods across three study districts (Fig. 9). From the results, it can be observed that elasticity scores range from −0.01 to 0.20 except one exception 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) both for Rahim Yar Khan respectively 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. While the 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

ESDD
5, 1359–1406, 2014

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.

5 Conclusions and policy suggestions

Climate change is a reality which is expected to have significant impacts on Pakistan with an increase in the frequency of environmental disasters like floods, droughts and less uncertain rains. Agriculture is more likely to be affected by climate change due to its direct connection to climate. Hence, the adaptation of agriculture to climate change is needed at micro level. This study shows that farmers do perceive and are concerned about changes in climate and its effects on their farming. The majority of the farmers perceived variability in mean temperature and rainfall for both summer and winter season over the last 10–20 years.

Farmers are more likely to perceive climate change but less likely to intend or to adapt to climate change. Farmers are adapting their farming to avoid climate change vulnerabilities. Most of the farmers choose changing crop varieties, changing planting dates, changing fertilizers and planting shaded trees as adaptation measures to climate change. This study also examined the important factors affecting the likelihood of different adaptation measures in a changing climate. The study revealed that the household characteristics are positively associated with adoption of adaptation measures to climate change. It was found that farmers with higher education level more likely adapt to climate change compared to farmers with less education. Similarly farming experience, farm household size, land area and tube-well ownerships also significantly increases the probability of adaptation to climate change.

On the other hand, tenants more likely adapt compared to self-operating farmers which may be due to the fact that tenants have more burden to keep their farm revenue above the total cost. Moreover, farmers located near to the local market are more likely to change their crops as adaptation measures that may be due to the easy access

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |

ESDD

5, 1359–1406, 2014

Farmers' perceptions of and adaptation strategies to climate change and their determinants

M. Abid et al.

to new information on high yielding varieties and crops. This study also revealed that institutional factors such as extension on crop production, access to information on climate, and access to market information and water deliveries enhance adaptation to climate change. This study also revealed the importance of education and farming experience on perceptions, intentions and adaptation to climate change which increase with increase in the farming experience and education level.

However, farmers' decisions to adapt to climate change are constrained by various factors which include mainly lack of information, lack of money, resource constraint and less irrigation water. The findings of the study depict that most of the constraints faced by farmers are of an institutional nature and can be covered with improving the institutional setup for climate adaptation. This study also reveals the necessity of public-private partnerships to improve this social and institutional structure to enhance the farm level adaptation in agriculture. Policies are aiming for the betterment of agriculture and need to focus more on the distribution of updated information on improved agricultural technologies and climate change adaptation to benefit the farmers to adapt their farming in a changing climate. This study also shows that farmers in different agro-ecological zones are adopting different adaptation measures compared to other zones. Hence, it shows the need of research on agro-ecological zones before designing future adaptation policies especially for the agriculture sector.

Moreover, only 58 % of the farmers in Punjab adopted at least one adaptation measure but only 30 % of farmers adapted two or more adaptation measures. Most of the adaptation measures adopted by farmers are limited to changing crops or varieties and very few farmers adopted advanced types of adaptation measures such as soil conservation, crop diversification, etc. Hence, future policies need to focus more on the enhancement of the advanced adaptation measures at farm-level such as introducing climate smart varieties, promoting soil conservation and new adaptation measures based on different agro-ecological zones.

ESDD
5, 1359–1406, 2014

Besides small-scale adaptation of agriculture to climate change, investment and research are also needed at macro-level adaptation measures which ultimately benefit the small-scale agriculture from both ends.

Appendix A: Marginal effect and elasticity calculations

Let us have a logit function (in term of observed variable Y_i) already explained in Eq. (3) in Sect. 2:

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

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

If we take the partial derivative of Eq. (A1) with respect to explanatory variable X_k, by applying chain rule (Dawkins, 2005), it will give us the marginal effect:

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

As we know that

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

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

$$\begin{aligned} g(X_k\beta) &= \frac{(1+e^{X_k\beta})\cdot e^{X_k\beta} - e^{X_k\beta}\cdot e^{X_k\beta}}{(1+e^{(X_k\beta)})^2} \\ &= \frac{e^{X_k\beta} + (e^{X_k\beta})^2 - (e^{X_k\beta})^2}{(1+e^{X_k\beta})^2} \\ &= \frac{e^{(X_k\beta)}}{(1+e^{X_k\beta})^2}. \end{aligned} \tag{A3}$$

ESDD
5, 1359–1406, 2014

If we put the value of $g(X_k\beta)$ from Eq. (A3) into Eq. (A2) then it becomes:

$$\frac{\partial Y_i}{\partial X_k} = \frac{e^{(X_k\beta)}}{(1+e^{X_k\beta})^2}\cdot\beta_k. \tag{A4}$$

Usually marginal effects are calculated at mean of explanatory variables (X_k) so we may replace X_k with mean value of X_k (Schmidheiny, 2013).

$$= \frac{e^{(\overline{X_k}\beta)}}{\left[1+e^{(\overline{X_k}\beta)}\right]^2}\cdot\beta_k$$

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

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

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

$$= \Pr(Y_i=1)\cdot(1-\Pr(Y_i=1))\cdot\beta_k$$

Partial-elasticity can be easily calculated from marginal effects. As we already know that elasticity is responsiveness of the dependent variable in percentage for a percentage change in the dependent 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:

$$\eta_Y(X_k) = X_k\cdot\frac{\partial G(X_k\beta)}{\partial X_k}. \tag{A5}$$

ESDD
5, 1359–1406, 2014

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

$$\eta_Y(X_k) = X_k \cdot \Pr(Y_i = 1) \cdot (1 - \Pr(Y_i = 1))\beta_k. \tag{A6}$$

Moreover we can conclude partial-elasticity X_k times the marginal effect of the explanatory variable (Rahji and Fakayode, 2009).

In the similar way of calculating marginal effects, partial elasticities are also calculated at mean of explanatory variables (X_k) so we may write Eq. (A6) as:

$$\eta_Y(\overline{X_k}) = \beta_k \overline{X_k} \Pr(Y_i = 1)(1 - \Pr(Y_i = 1)) \tag{A7}$$

where $\Pr(Y_i = 1) = \frac{e^{(\overline{X_k}\beta)}}{1+e^{(\overline{X_k}\beta)}}$.

Acknowledgements. This study is part of a Ph.D. research at the School of Integrated Climate System Sciences (SICSS), University of Hamburg, Germany. This Ph.D. research is made possible under the sponsor of Higher Education Commission (HEC), Pakistan; Deutscher Akademischer Austauschdienst (DAAD); Kompetenzzentrum Nachhaltige Universität (KNU) and the Research Group Climate Change and Security (CLISEC) in the Exzellence Cluster "Integrated Climate System Analysis and Prediction" (CliSAP) supported by Deutsche Forschungsgemeinschaft (DFG). We are very thankful to the Department of Agriculture (Extension wing) Punjab, local farmer representatives for their effective coordination and support in organizing and conducting successful farmer interviews. Further, we would like to thank our survey team members, Muhammad Usman, Muhammad Haseeb Rizwi and Muhammad Ikhlaq Mansoor and farm households in Punjab in helping and supporting our interviews during March and April 2014.

ESDD
5, 1359–1406, 2014

References

Abid, M., Ashfaq, M., Hassan, S., and Fatima, N.: A resource use efficiency analysis of small Bt cotton farmers in Punjab, Pakistan, Pak. J. Agric. Sci, 48, 65–71, 2011a.

Abid, M., Ashfaq, M., Khalid, I., and Ishaq, U.: An economic evaluation of impact of soil quality on Bt (*Bacillus thuringiensis*) cotton productivity, Soil Environm., 30, 78–81, 2011b.

Adger, W. N., Dessai, S., Goulden, M., Hulme, M., Lorenzoni, I., Nelson, D. R., Naess, L. O., Wolf, J., and Wreford, A.: Are there social limits to adaptation to climate change?, Climatic Change, 93, 335–354, 2009.

Ashfaq, M., Zulfiqar, F., Sarwar, I., Quddus, M. A., and Baig, I. A.: Impact of climate change on wheat productivity in mixed cropping system of Punjab, Soil Environm. (Pakistan), 30, 110–114, 2011.

Bryan, E., Ringler, C., Okoba, B., Roncoli, C., Silvestri, S., and Herrero, M.: Adapting agriculture to climate change in Kenya: household strategies and determinants, J. Environ. Manage., 114, 26–35, 2013.

Croppenstedt, A., Demeke, M., and Meschi, M. M.: Technology adoption in the presence of constraints: the case of fertilizer demand in Ethiopia, Rev. Dev. Econ., 7, 58–70, 2003.

Curran, C.: Logit and Probit Regressions, available at: http://cnx.org/contents/7cafdabf-7ed1-4a02-b40a-e4c9598f9709@3 (last access: 22 July 2014), 2010.

Dawkins, P.: Derivatives Definitions and Notation, available at: http://tutorial.math.lamar.edu/pdf/Calculus_Cheat_Sheet_Derivatives_Reduced.pdf (last access: 29 August 2014), 2005.

Deressa, T. T.: Measuring the Economic Impact of Climate Change on Ethiopian Agriculture: Ricardian Approach, World Bank Policy Research Paper No. 4342, World Bank, Washington, D.C., 2007.

Deressa, T. T., Hassan, R. M., Ringler, C., Alemu, T., and Yesuf, M.: Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia, Global Environ. Change, 19, 248–255, 2009.

Farooq, O.: Chapter agriculture, in: Pakistan Economic Survey 2012–2013, Ministry of Finance, Government of Pakistan, Islamabad, 2013.

Farooqi, A. B., Khan, A. H., and Mir, H.: Climate change perspective in Pakistan, Pakistan J. Meteorol., 2, 11–21, 2005.

Fernihough, A.: Simple logit and probit marginal effects, in: R, Working Paper Series, UCD Center for Economic Research, UCD School of Economics, University college, Dublin, 2011.

ESDD
5, 1359–1406, 2014

Government of Pakistan: Pakistan Mouza Statistics, Statistics Division, Agricultural Census Organization, Pakistan Bureau of statistics, Islamabad, Pakistan, 1998.
Grothmann, T. and Patt, A.: Adaptive capacity and human cognition: the process of individual adaptation to climate change, Global Environ. Change, 15, 199–213, 2005.
Hanif, U., Syed, S. H., Ahmad, R., Malik, K. A., and Nasir, M.: Economic impact of climate change on the agricultural sector of Punjab, Pakistan Develop. Rev., 4, 771–798, 2010.
Hassan, R. and Nhemachena, C.: Determinants of African farmers' strategies for adapting to climate change: multinomial choice analysis, Afr. J. Agr. Resour. Econ., 2, 83–104, 2008.
Hijioka, Y., Lin, E., Pereira, J. J., Corlett, R. T., Cui, X., Insarov, G. E., Lasco, R. D., Lindgren, E., and Surjan, A.: Asia, in: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, edited by: Barros, V. R., Field, C. B., Dokken, D. J., Mastrandrea, M. D., Mach, K. J., Bilir, T. E., Chatterjee, M., Ebi, K. L., Estrada, Y. O., Genova, R. C., Girma, B., Kissel, E. S., Levy, A. N., MacCracken, S., Mastrandrea, P. R., and White, L. L., Cambridge University Press, Cambridge, UK and New York, NY, USA, 2014.
Hisali, E., Birungi, P., and Buyinza, F.: Adaptation to climate change in Uganda: evidence from micro level data, Global Environ. Change, 21, 1245–1261, 2011.
Hosmer Jr., D. W. and Lemeshow, S.: Applied Logistic Regression, John Wiley & Sons, Hoboken, NJ, USA, doi:10.1002/0471722146.fmatter, 2004.
Hussain, S. S. and Mudasser, M.: Prospects for wheat production under changing climate in mountain areas of Pakistan. An econometric analysis, Agr. Syst., 94, 494–501, 2007.
IFAD: Climate Change Impacts, South Asia, available at: www.ifad.org/events/apr09/impact/se_asia.pdf (last access: 12 July 2014), 2010.
Intergovernmental Panel on Climate Change – IPCC: Climate Change 2001: Impacts, Adaptation and Vulnerability, Contribution of Working Group II to the Third Assessment Report of the IPCC, Cambridge Univ. Press, Cambridge, 2001.
IUCN: Climate Change; Vulnerabilities in Agriculture in Pakistan, available at: http://cmsdata.iucn.org/downloads/pk_cc_agr_vul.pdf (last access: 18 June 2014), 2009.
Kato, E., Ringler, C., Yesuf, M., and Bryan, E.: Soil and water conservation technologies: a buffer against production risk in the face of climate change? Insights from the Nile Basin in Ethiopia, Agr. Econ., 42, 593–604, 2011.

ESDD
5, 1359–1406, 2014

Kreft, S. and Eckstein, D.: Global Climate Risk Index 2014: Who Suffers Most from Extreme Weather Events? Weather-Related Loss Events in 2012 and 1993 to 2012, Germanwatch e.V., Bonn, Germany, 2013.
Leads Pakistan – LP: LEAD Climate Change Action Program, Internal Document, LEAD Pakistan, Islamabad, 2010.
Maddison, D.: The Perception of and Adaptation to Climate Change in Africa, World Bank Policy Research Working Paper, World Bank, available at: http://elibrary.worldbank.org/doi/pdf/10.1596/1813-9450-4308 (last access: 25 July 2014), 2007.
Nhemachena, C. and Hassan, R.: Micro-Level Analysis of Farmers' Adaption to Climate Change in Southern Africa, Intl Food Policy Res Inst, Washington, D.C., 2007.
Nomman, M. A. and Schmitz, M.: Economic assessment of the impact of climate change on the agriculture of Pakistan, Business Econ. Horiz., 4, 1–12, 2011.
Norris, P. E. and Batie, S. S.: Virginia farmers, soil conservation decisions: an application of Tobit analysis, Southern J. Agr. Econ., 19, 79–90, 1987.
Organisation for Economic Co-operation and Development – OECD.: The Economics of Adapting Fisheries to Climate Change, OECD Publishing, Chateau de la Muette, Paris, France, doi:10.1787/9789264090415-en, 2011.
Pakistan Agricultural Research Council – PARC: National Master Agricultural Research Plan, PARC, available at: http://old.parc.gov.pk/Maps/AgroEcoPunjab.html, last access: 21 August 2014.
Pakistan Bureau of Statistics – PBS: Agricultural Statistics of Pakistan, Government of Pakistan, Statistics Division, Pakistan Bureau of Statistics, available at: http://www.pbs.gov.pk/content/agricultural-statistics-pakistan-2010-11 (last access: 1 August 2014), 2011.
Parry, M. L.: Climate Change 2007: Impacts, Adaptation and Vulnerability: Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, 2007.
Peng, C.-Y. J., Lee, K. L., and Ingersoll, G. M.: An introduction to logistic regression analysis and reporting, J. Educ. Res., 96, 3–14, 2002.
Rahji, M. and Fakayode, S.: A multinomial logit analysis of agricultural credit rationing by commercial banks in Nigeria, Int. Res. J. Finance Econ., 24, 97–103, 2009.
Schlenker, W. and Lobell, D. B.: Robust negative impacts of climate change on African agriculture, Environ. Res. Lett., 5, 014010, doi:10.1088/1748-9326/5/1/014010, 2010.

Schmidheiny, K.: Binary Response Models, Short Guides to Microeconometrics, Unversität Basel, Basel, 2013.

Stephenson, B., Cook, D., Dixon, P., Duckworth, W., Kaiser, M., Koehler, K., and Meeker, W.: Binary response and logistic regression analysis, available at: http://www.stat.wisc.edu/~mchung/teaching/MIA/reading/GLM.logistic.Rpackage.pdf (last access: 30 August 2014), 2008.

Swanson, B. and Claar, J.: The history and development of agricultural extension, in: Agricultural Extension: a Reference Manual, edited by: Swanson, B. E., Food and Agricultural Organization of the United Nations, Rome, 1984.

Syngenta: Agricultural Extension. Improving the Livelihood of Smallholder Farmers, available at: http://www.syngentafoundation.org/index.cfm?pageID=594, last access: 5 September 2014.

Task Force on Climate Change – TFCC: available at: http://pc.gov.pk/usefull%20links/Taskforces/TFCC%20Final%20Report.pdf (last access: 10 May 2014), Planning commission, Government of Pakistan, Islamabad, 2010.

ESDD
5, 1359–1406, 2014

Table 1. Description of explanatory variables used in the model.

Explanatory variable	Mean	SD	Description	Expected signs
Years of experience in farming	24.37	11.97	Continuous	(+)
Years of education	8.510	4.256	Continuous	(+)
Household size	9.664	5.133	Continuous	(+)
Land holding	16.06	28.53	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	(+/−)

ESDD
5, 1359–1406, 2014

Title Page
Abstract | Introduction
Conclusions | References
Tables | Figures
◄ | ►
Back | Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

Table 2. 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

ESDD
5, 1359–1406, 2014

Table 3. Hypothesis testing for model significance and predictive power.

Models	Chi-square (χ^2)	df	*P* level	−2·log likelihood	AIC	Model[1] correctness (%)	Nagelkerke pseudo R^2
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 show the statistical significance to reject the null hypothesis (Ho).
AIC (Akaike information criterion) is used to measure the relative quality of statistical model.

ESDD
5, 1359–1406, 2014

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	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.

ESDD
5, 1359–1406, 2014

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	0.0024	−0.0069	0.0025	0.0179	0.0047	0.0033	−0.0001	−0.0004
Land area	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 I 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

ESDD
5, 1359–1406, 2014

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	0.0230	−0.0662	0.0238	0.1729	0.0450	0.0316	−0.0014	−0.0041
Land area	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 input 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

ESDD
5, 1359–1406, 2014

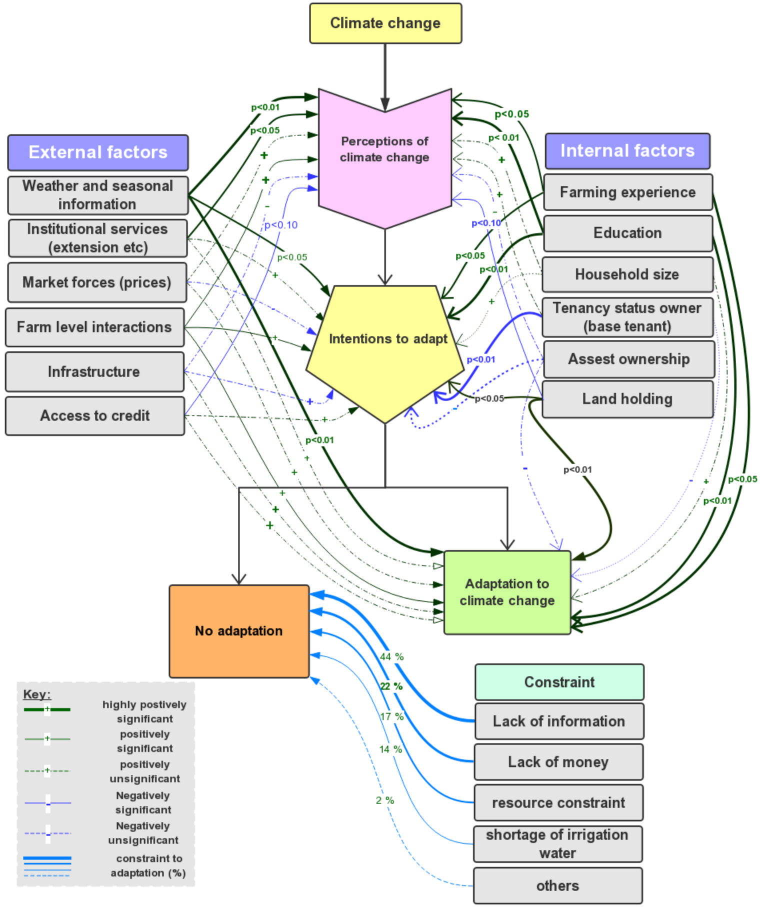

Figure 1. Schematic framework of farmers' adaptation process in Pakistan (own illustration).

ESDD
5, 1359–1406, 2014

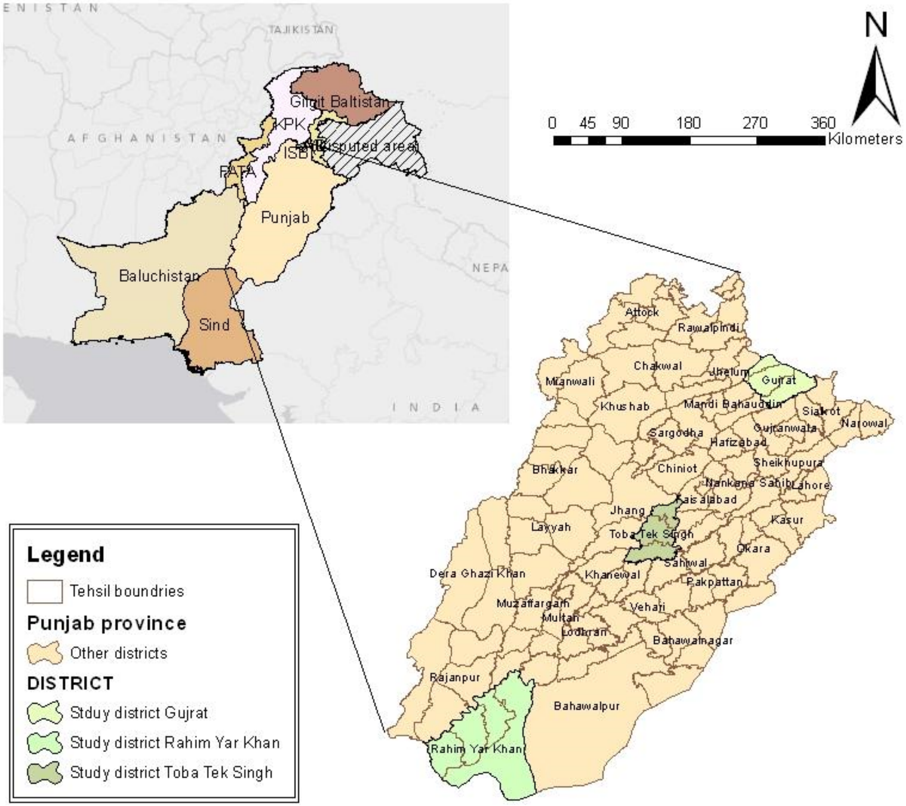

Figure 2. Sample study districts Punjab province, Pakistan.

ESDD
5, 1359–1406, 2014

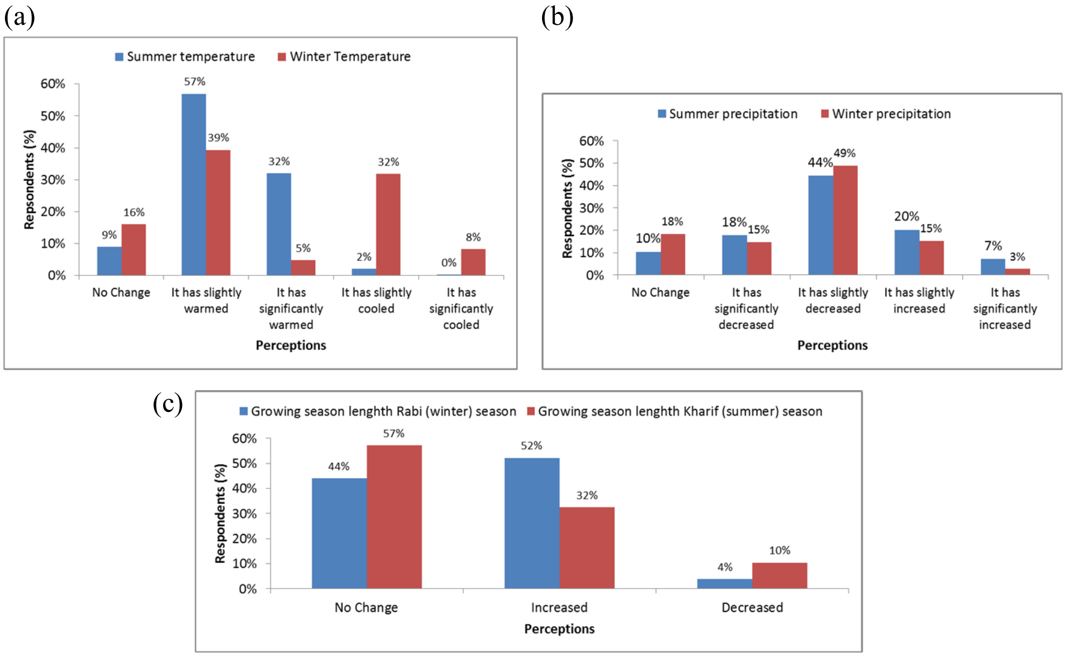

Figure 3. (a)–(c) Farmers' perceptions of climate change in study area Punjab Pakistan.

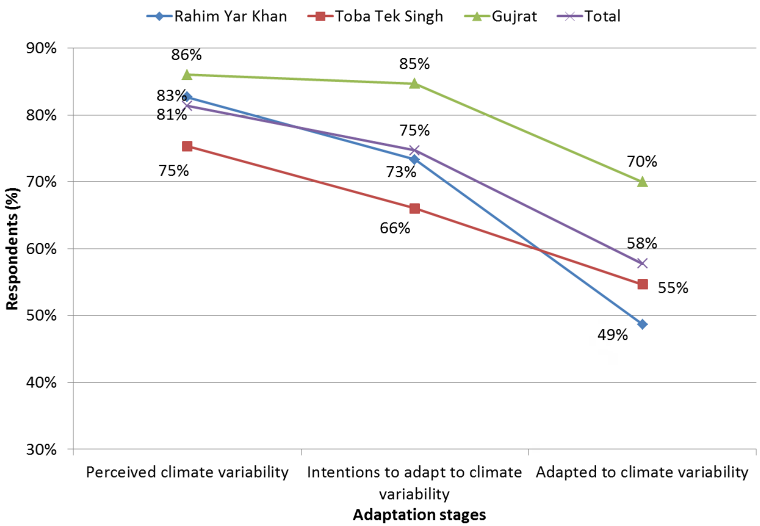

Figure 4. Perceptions, intentions and adaptation to climate change across different study districts.

ESDD
5, 1359–1406, 2014

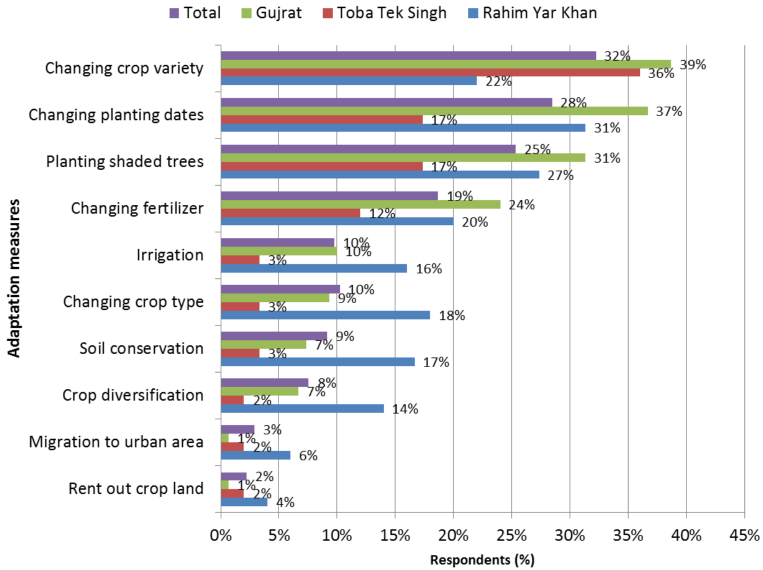

Figure 5. Adaptation measures adopted by farmers across three study areas in Punjab, Pakistan.

ESDD
5, 1359–1406, 2014

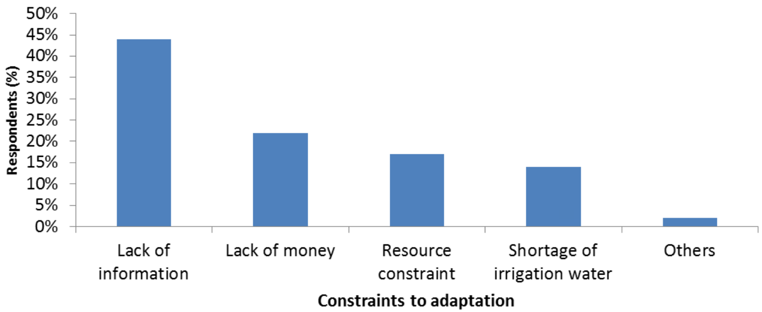

Figure 6. Constraints to adaptation to climate change in the study area.

ESDD
5, 1359–1406, 2014

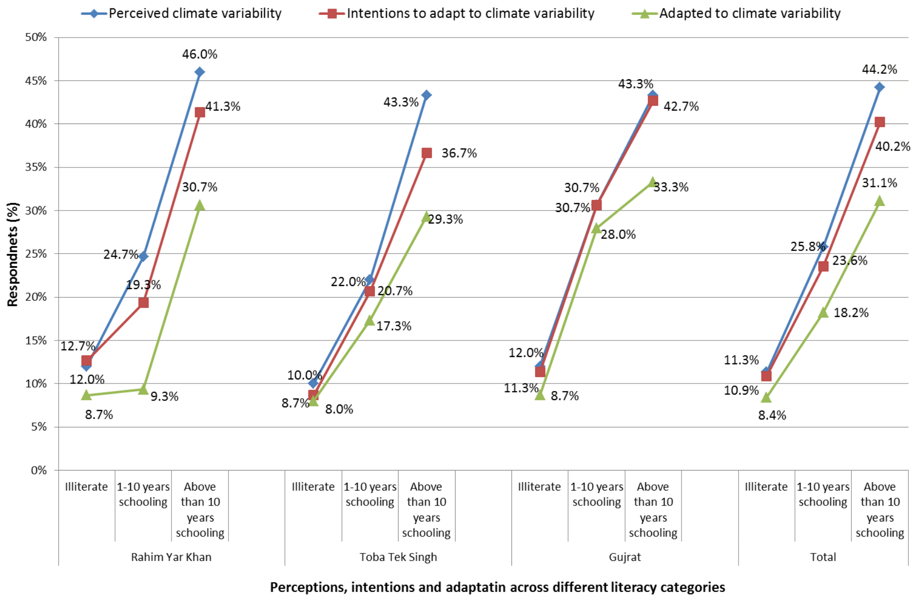

Figure 7. Adaptation to climate variability across different categories of farmers based on education level.

ESDD
5, 1359–1406, 2014

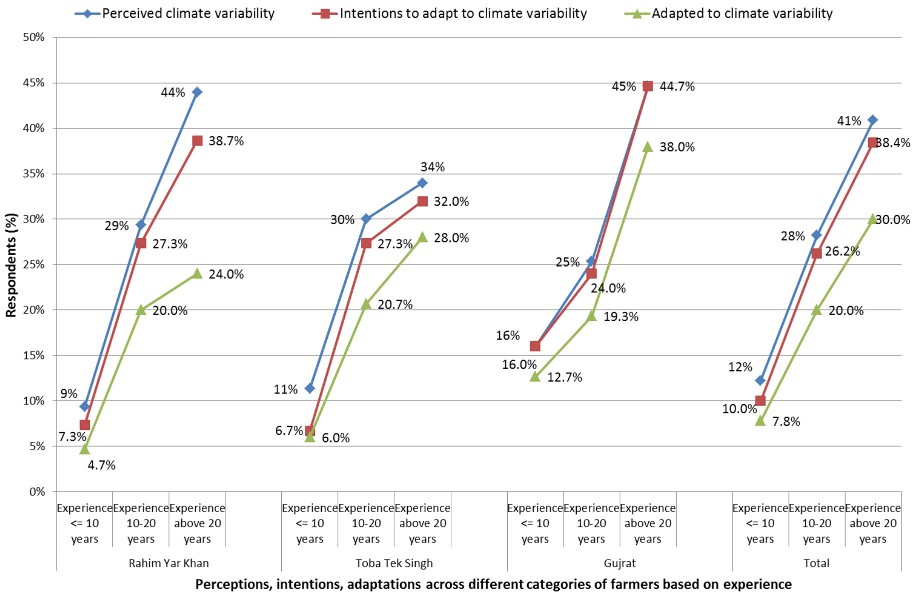

Figure 8. Perceptions, intentions and adaptation to climate change across different categories of farmers on farming experience in Punjab.

ESDD
5, 1359–1406, 2014

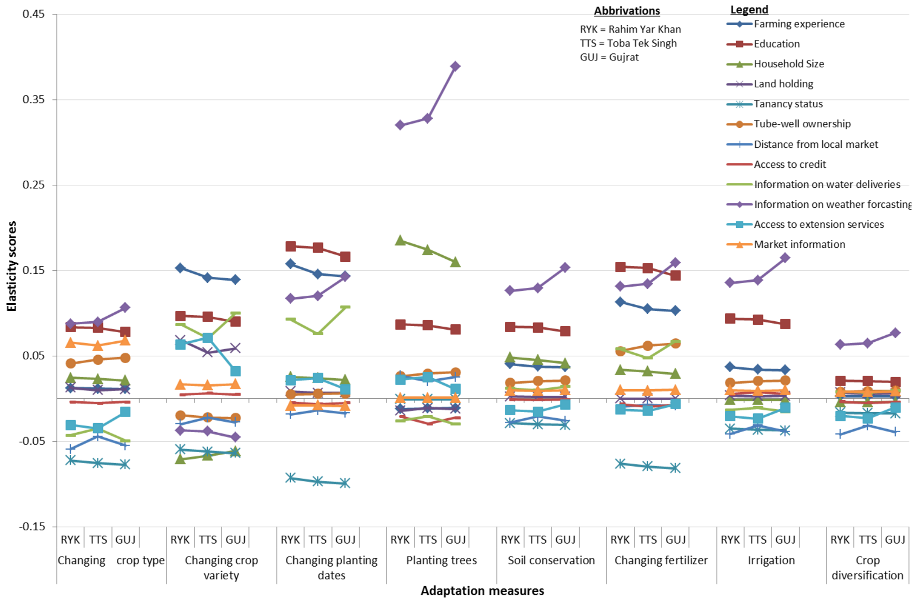

Figure 9. Partial-elasticity calculations across three study districts of Punjab province.

ESDD
5, 1359–1406, 2014