Climate change impacts and the value of adaptation – can crop adjustments help farmers in Pakistan?

Mirza Nomman Ahmed* and
Peter Michael Schmitz

Department of Agricultural and Development Policy,
Institute of Agricultural Policy and Market Research,
Senckenberg Str. 3, 35390 Giessen, Germany
Email: clinca.ahmed@zeu.uni-giessen.de
Email: Michael.Schmitz@agrar.uni-giessen.de
*Corresponding author

Abstract: According to the climate vulnerability index Pakistan is ranked 12th globally and economic losses of approximately 4.5 billion dollars for the entire economy are anticipated. However, all these 'future' estimates of losses for Pakistan do not consider past adaptations by the farmers in their calculations and thus tend to overestimate climate change induced losses. This paper contributes to the literature by studying the effectiveness of households' adaptation and coping measures regarding the prevention of loss and damage using choice-modelling. In order to assess, whether loss and damage is likely to occur in future and to determine, whether crop-cultivating farmers have well adapted, simulations are run. Farmers are found to adjust their crop choices considering climate and expected income. If farmers adapt, benefits exceeding 300 million dollars are possible for the crop sector. In the business as usual scenario, losses between 4 and 12 million dollars (2030/2090) are found. The findings hint towards well-directed adaptations of farmers in Pakistan, preventing loss and damage.

Keywords: developing countries; environmental impact; hedonic; global warming; net revenue and adaptations; agriculture; Pakistan; structural Ricardian model; crop switching.

Reference to this paper should be made as follows: Ahmed, M.N. and Schmitz, P.M. (2015) 'Climate change impacts and the value of adaptation – can crop adjustments help farmers in Pakistan?', *Int. J. Global Warming*, Vol. 8, No. 2, pp.231–257.

Biographical notes: Mirza Nomman Ahmed is a Research Associate at the Professorship of Agricultural and Development Policy within the Institute of Agricultural Policy and Market Research at the Justus Liebig University, Giessen, Germany. Since June 2009, he is coordinating the German foreign ministry funded project 'Climate Change Network for Central Asia' (CliNCA) at the Centre for International Development and Environmental Research, Giessen, Germany. After acquiring his BSc in Agricultural Sciences and Environmental Management in 2006 from the Justus Liebig University, he went on to study transition management, turning attention towards issues related to the development of transitional and developing countries, this with a strong focus on environmental concerns, specifically climate change. His dissertation dealt with the economic impacts of climate change on agriculture in developing countries.

Peter Michael Schmitz is a Full Professor of Agricultural and Development Economics, Director of the Institute of Agribusiness and Chairman of the Board of Directors of the ZEU. Furthermore, he is Honourable Professor and Director of the Institute of European Integration at the Bila Tserkva National Agrarian University (Ukraine) since 2005. His research fields are European and International Agricultural Policies and Policy Analysis, International Agricultural Trade and Trade Policies, Applied Welfare Economics, Transition and Development Economics and Environmental Economics.

1 Introduction

Today, there is a broad consensus on the anthropogenic involvement in climate change. The connection between human activity related green house gas emissions and their impacts on temperature and precipitation regimes has been subject of numerous studies. There seems to be enough evidence that changing climatic patterns will impact on economic well-being (Deschenes and Greenstone, 2007). Harmful effects of climate change are expected worldwide. However, especially to developing countries it poses a far more serious threat as many of their environmental and developmental problems are at risk of being exacerbated (UNFCCC, 2007; Cline, 2007; Mendelsohn and Williams, 2004).

Pakistan, located in the South Asian region between 24–37°N of latitude and 61–76°E of longitude, with agriculture as its mainstay and responsible for almost 70% of the livelihoods of the population, is one such developing country (Ahmed and Schmitz, 2011b). The frequency and the intensity of climate related extreme events in Pakistan have both increased in the recent past. From 1998 to 2002, the province of Balochistan was hit by severe drought conditions, affecting 84% of the population directly, killing 76% of the province's livestock and causing mass migration due to widespread hunger and disease. Of late in 2010, the country was struck and devastated in large parts by epic floods. The LEAD Climate Change Action Plan of Pakistan declares the country to be highly vulnerable to climate change. According to the vulnerability index, Pakistan is ranked 12th globally, economic losses of approximately 4.5 billion dollars are anticipated in the future, grassland productivity and consequently crop and livestock yields are expected to suffer severely from climatic change manifested in significantly higher temperatures and decreased surface water availability and changing precipitation patterns (LP, 2008). Labour in developing countries is highly abundant and relatively inexpensive, thus the economy mainly relies on labour intensive technologies, leaving less room for advanced adaptation options (Mendelsohn et al., 2001). However, all these future estimates of losses and damages for Pakistan do not consider implicit adaptation by the farmers (e.g., through crop switching) in their calculations. These adaptations have taken place since the existence of agriculture and will continue to play a role in the wake of a shift in agro-climatic conditions (Kusters and Wangdi, 2013). Hence, failure to consider the full set of farmer adaptations will lead to overestimations of the damages from climate change. In this context, 'loss and damage' is a relatively new research concept that identifies those negative effects of climate variability and climate change that people have not been able to cope with (Warner et al., 2012). According to Warner et al. (2012), loss and damage can have different pathways. The present study focuses on one of these pathways, that is, the effectiveness of households' adaptation and coping measures regarding the prevention of loss and damage.

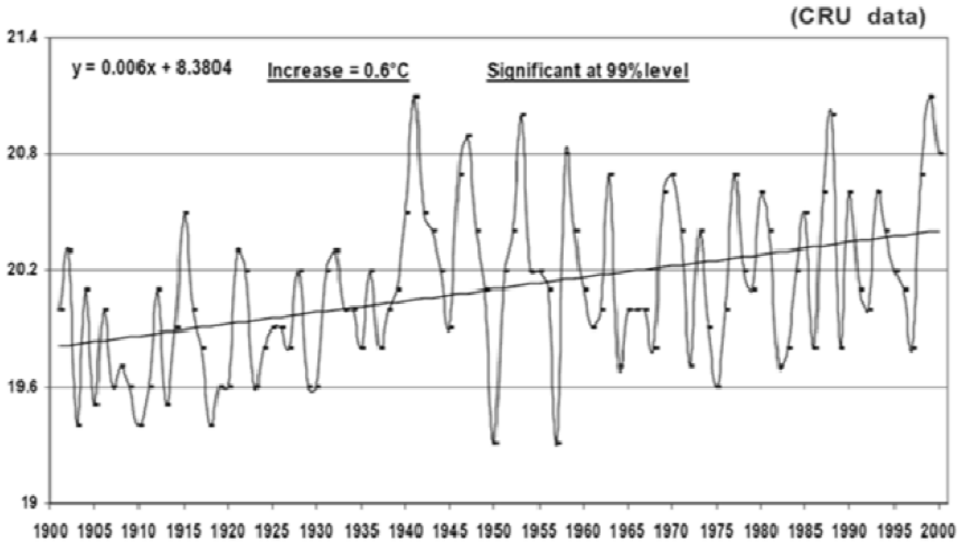
Despite an internationally extensive interest in the measurement of the economic impacts of climate change, specifically on agriculture, the empirical research on Asia remains scarce. Particularly, the quantitative analysis of farmer adaptations (using a choice-approach) and their impact on the overall losses or benefits from climate change has not been carried out for any country in South Asia. This study's mandate is to fill this gap for the crop sector of Pakistan. After sketching the country's vulnerability to climate change and describing the dataset and the study area, an overview on the modelling framework is presented. Ensuing, in a first step, a model is built that helps to understand the impact of climate variables, controlling for other factors (soil, water, education, etc.), on the choice of crops in Pakistan. In other words, to understand how the current crop choices of farmers came about. Once this relationship is established, simulations are run to understand future adaptations that farmers are likely to make. In order to specify possible adaptations and their loss and damage potential, the study applies the structural Ricardian method (Seo and Mendelsohn, 2008a). Hence, to the shortcoming of simple yield-based calculations of welfare changes, in this study climate change induced welfare changes are calculated by including crop switching to see whether the losses are compensated through adaptation. This with the goal to correct for the bias in other studies that do not consider farmer adaptations when assessing the climate change induced welfare effects for the future.

2 Climate change vulnerability in Pakistan

Pakistan is a developing country facing several obstacles to development, including climate change and climate variability. In a nutshell, thus, vulnerability to climate change can be framed as follows: the climate is arid and hot, regularly the country is exposed to risks from extreme weather events (droughts and floods), socio-economic conditions are deteriorating, major income sources of the population (> 170 million) depend on climate sensitive sectors, awareness for environmental protection is missing, warning systems are not in place or are outdated, political instability and capacity to react to abrupt and long-term environmental changes is low. Specifically the agricultural sector is at risk as it is the mainstay of the population, with a total contribution of 25% to overall GDP. The industry of the country is heavily agro-based, with agro-based exports weighing as heavy as 80% in total exports. Moreover, almost two thirds of agriculture are irrigated, requiring sufficient water supplies. On top of the export contribution, agriculture in Pakistan has to fulfil a significant product contribution. As two thirds of the population are engaged in agriculture (direct and indirect), the sector also provides a substantial factor contribution. More than 30% of the population live below the poverty line. GNI per capita is estimated at 3030 $ (PPP) (World Bank, 2013).

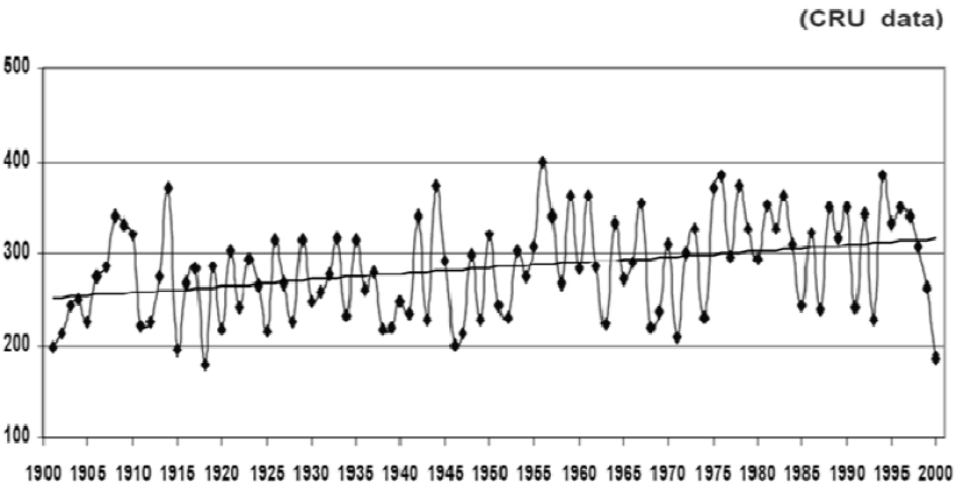
In the framework of the United Nations Development Programme (UNDP) initiated Project 'Climate Systems and Policy' long-term historical data has been studied to assess climatic trends over a period of 40 years (1960 to 2000).

Figure 1 Annual temperature (°C) trend 1901–2000 Pakistan



Source: TFCC (2010)

Figure 2 Annual precipitation (mm) trend 1901–2000 Pakistan



Source: TFCC (2010)

According to the Pakistan Meteorological Department (Chaudhry et al., 2009) during the period 1901 to 2000, the increase in mean annual temperature in the Northern half of Pakistan was found to be higher with a value of 0.8°C as compared to the country as a whole with 0.6°C. Furthermore, data from the Climate Research Unit (CRU) in the UK relative to the national scale indicate a higher increase in mean annual temperature for Northern Pakistan. In addition, based on data from 1951 to 2000 the Task Force on Climate Change (TFCC) report highlights the general warming trend in mean and maximum temperatures for the summer season (April and May), this throughout the country. For the same time period, the Monsoon Season that spans from July to September has generally shown a decreasing trend in temperatures (TFCC, 2010). According to McSweeney et al. (2010), the warming trend is primarily observed for the months from October to December, with precisely 0.19°C per decade. Additionally, the frequency of hot days and nights (days or nights where temperature exceeds a certain threshold by 10%) in Pakistan has increased, whereas the frequency of cold days and nights has decreased respectively.

As far as precipitation is concerned, an increasing trend for precipitation over the last century is revealed. Although the frequency of fluctuations is large the extremes are most evident. As the majority of the annual precipitation is received in the monsoon period, this general rising trend can be explained by the increased variability of the monsoon.

Table 1 Climate related natural hazards in Pakistan (1935–2011)

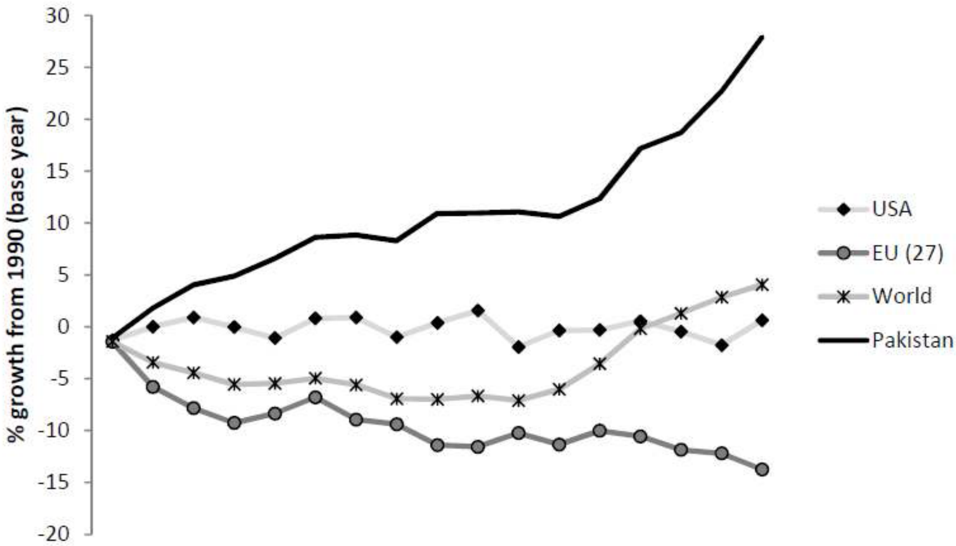
Type of disaster	*Date*	*Death toll*	*No total affected*	*Damage (000 US$)*
Earthquake	31.05.1935	60,000	-	-
	27.11.1945	4,000	-	-
	28.12.1974	4,700	-	-
	08.10.2005	73,338	5,128,309	5,200,000
Flood	1950	2,900	-	-
	August 1973	-	4,800,000	661,500
	02.08.1976	-	5,566,000	505,000
	June 1977	848	-	-
	July 1978	-	2,246,000	-
	15.07.1992	-	6,184,418	-
	08.09.1992	1,334	6,655,450	1,000,000
	02.03.1998	1,000	-	
	22.07.2001	-	-	246,000
	09.02.2005	-	7,000,450	-
	10.08.2007	-	-	327,118
	02.08.2008	-	-	103,000
	28.07.2010	1,985	20,359,496	9,500,000
	August 2011	-	5,800,000	-
Storm	15.12.1965	-	10,000	-
	26.06.2007	-	-	1,620,000
Drought	November 1999	-	2,200,000	247,000

Source: EM-DAT Version 12.07 (2012)

Table 1 based on the Collaborating Centre for Research on the Epidemiology of Disasters (CRED's) data on emergency events presents a timeline of documented major extreme events in Pakistan, dating back as far as 1935 when Pakistan was known as Western India. Climate related natural hazards among others can comprise tornados, hurricanes, floods, cyclones, drought, landslides and heat or cold waves (CBSE, 2006). Pakistan however, has been specifically vulnerable to floods, storms and droughts (Ahmed and Schmitz, 2011a). As shown in Table 1 although the highest death toll was recorded from earthquakes, the highest number of people indirectly or directly affected was estimated for floods and droughts. Regarding the overall economic losses incurred by natural disasters, floods top the list, specifically owing to the magnitude and country wide impact. For instance, in 2010 during the monsoon floods, in total 84 out of 121 districts were affected.

Despite the fact that the country's share in global GHG emissions is marginal, there is enough reason for concern in future when having a look at the annual percentage growth rate of per capita carbon dioxide emissions from 1990 to 2007 (Figure 3).

Figure 3 Per capita CO_2 emissions in selected regions of the world, 1990–2007



Source: Own illustration after CAIT 8.0 (CAIT, 2011)

In 2008, out of 309 million tonnes (mt) of carbon dioxide (CO_2) equivalent total greenhouse gas (GHG) emissions, 39%, were contributed by the agricultural sector (CAIT, 2011; TFCC, 2010). In the following section, detailed aspects related to the assessment of the economic impact of climate change on agriculture, study area and dataset, shall be presented.

3 Materials and methods

3.1 Theoretical approach

As far as the 'Ricardian approach for climate impact assessment' (note: not to be confused with the trade model) is concerned, farmers in different regions are exposed to different climatic conditions, thus the method assumes that they adapt their behaviour to their local climate circumstances (Mendelsohn et al., 1996). The initial approach named Ricardian method for climate impact assessment was developed by Mendelsohn et al. (1994) who analysed the impact of climate change on land values and consequently farm incomes in the USA. The model starts from the observation that farmer decisions are dependent on uncontrollable exogenous factors including climate and that the ‘naïve farmer’ or ‘dumb farmer’ scenario, in which the farmers regardless of occurring changes doggedly continue with their known practices, does not hold. Departing from this observation, and in order to correct for the production function bias, which is the overestimation of damages from climate change by not considering the full set of farmer adaptations, the idea is to compare the net revenues (NRs) or land values [land values = capitalised NRs-as originally observed by Ricardo (1817)] of farmland in different climatic zones, instead of the yields. As the current land values have evolved over a long period of time with climatic and other environmental factors as their determinants, they serve as a practical fundament for the analysis of the long-term phenomenon ‘climate change’. This is a fundamental advantage over the yield-based production function approach that can only model short-term weather changes. The ‘standard Ricardian approach’ for the impact assessment of climate change calculates a change in land values or NRs that results from a change in climate variables. If this change has a positive impact, other things remaining constant, farmers are assumed to have well adapted. Vice versa, a negative change in incomes (land values/NRs) indicates that adaptations were not sufficient to prevent damage. Adaptations in the standard Ricardian setting are treated as a ‘black box’. A new approach termed structural Ricardian model, developed by Seo and Mendelsohn (2008a), provides a solution for the shortcoming of the standard model. The structural Ricardian model is a two stage model. In a first stage, it models farmer choices (e.g., crops, livestock, farm-type), and conditional on the respective choices in a second step calculates the income effects resulting from the specific choice or switch.

A general assumption of the choice model is that farmers make a choice among a set of alternative crops, livestock species or farm types to maximise the NR of their farm. NR (income variable) is calculated by subtracting all costs except household labour from the gross revenue of the farm. The choice that will earn the farm the highest NR will be marked as the primary choice. As farmers in this study have reported more than ten crops, the number of combinations is large and complicates modelling. To these drawbacks, in this study only the primary crop choice is considered, defined as the crop that earns the farm the highest NR. The term choice in this specific setting refers to the alternative that is actually revealed in the survey, which can be thought of as the ‘most preferred’ alternative. Thus, if the dependent variable in the first stage model is the crop chosen in the last growing season, the alternatives might be cotton, wheat, vegetables, fruits, rice, sugarcane and maize. To estimate the choice that the farmer makes, the multinomial logit econonometric model is used. Conditional on the crop choice a second stage model estimates the NR for the farm. The model output can be used to forecast adaptations and impacts for different future climate scenarios, and the value of adaptation can be computed by comparing adaptation and non-adaptation (Mendelsohn and Dinar, 2009). This can help to assess the studied loss and damage pathway.

The theoretical considerations follow Seo and Mendelsohn (2008a, 2008b), Mendelsohn and Dinar (2009). As farmers are assumed to select the desired crop to yield the highest net farm revenue, the net farm revenue of farmer j in choosing crop i from a set of mutually exclusive choices j (j = 1, 2, …, N) is

$$\pi_{ij} = V_i\left(K_j, S_j\right) + \varepsilon_i\left(K_j, S_j\right) \tag{1}$$

with π denoting NR, K representing a vector of the exogenous farm characteristics (e.g., climate, soil types) and S standing for a vector of the farmer's characteristics (household characteristics such as age, education, household size). The observable component of the NR function is V, whereas ε represents the error term. The model assumes that the farmer is well aware of the error term and therefore selects the crop which generates the highest net farm revenue. Thus defining $Z = (K, S)$, the farmer will choose crop i over all other crops if:

$$\begin{gathered} \pi_i^*\left(Z_j\right) > \pi_k^*\left(Z_j\right) \text{ for } \forall k \neq i. \\ \left[\text{or if } \varepsilon_k\left(Z_j\right) - \varepsilon_i\left(Z_j\right) < V_i\left(Z_j\right) - V_k\left(Z_j\right) \text{ for } k \neq i\right] \end{gathered} \tag{2}$$

Briefly, farmer j's problem can be defined as:

$$\arg\max_{i=1\ldots Ii}\left[\pi_1^*\left(Z_j\right), \pi_2^*\left(Z_j\right), \ldots, \pi_I^*\left(Z_j\right)\right] \tag{3}$$

The probability P_{ji} for crop i to be chosen by farmer j is thus given by:

$$P_{ji} = \Pr\left[\varepsilon_k\left(Z_j\right) - \varepsilon_i\left(Z_j\right) < V_i - V_k\right] \forall k \neq i \text{ where } V_i = V_i\left(Z_j\right) \tag{4}$$

Assuming that the error term ε is independently and identically Gumbel distributed and V_k can be written linearly in the parameters such as:

$$V_k = Z_{kj}\gamma_j + \alpha_k \tag{5}$$

the probability that farmer j will choose crop i among I crops is given by (Chow, 1983; McFadden, 1981):

$$P_{ji} = \frac{e^{Z_{ji}\gamma_j}}{\sum_{k=1}^{I} e^{Z_{jk}\gamma_j}} \tag{6}$$

This is the standard derivation of the multinomial logit model, with γ_j as the parameters of the model. From a technical point of view, the issue that arises is that the errors in the selection equation (α_k) and conditional income equation (ε_i) might be correlated, because the profit described in the selection equation is only observed for the chosen crop. To this background, for the estimation of the conditional revenues, which are conditional on the choice of a certain crop, selection bias has to be corrected for in order to receive consistent estimates (Heckman, 1979). If the correction is not applied the OLS estimates become inefficient, as the calculation of income causes a high association between the non-observable characteristics affecting income and those that simultaneously determine the sector in which the individuals are working (Huesca and Camberos, 2010). For instance, the farmers choosing the crop wheat are not a random sample of all farmers that select wheat. Farmers self-select their primary crop. Not all of the reasons for this self-selection are known to the researcher. The researcher does not observe the profits that the farmer would have made had he chosen wheat. Under certain circumstances the omission of potential members of a sample will cause ordinary least squares (OLS) to give biased estimates of the parameters of a model (Curran, 2010). Following Bourguignon et al. (2004, 2007), Dubin and Mcfadden's method (1984) is selected, according to which assuming the following linearity condition

$$E\left(\varepsilon_j \mid \alpha_1, ..., \alpha_J\right) = \sigma \cdot \sum_{j=1}^{J} r_j \cdot \left(\alpha_j - E\left(\alpha_j\right)\right), \text{ with } \sum_{j=1}^{J} r_j = 0, \tag{7}$$

where ε_j is the error from the profit equation in the second stage of the model, α_j is the error from the first stage's choice equation, σ is the standard error of the NR or profit equation, and r_j the correlation between the NR equation and choice equations, the selection-bias corrected conditional NR function for crop choice i can be estimated as follows:

$$\pi_i = X_i \varphi_i + \sigma \cdot \sum_{k \neq 1}^{K} r_k \cdot \left[\frac{P_k \cdot \ln P_k}{1 - P_k} + \ln P_i\right] + \omega_i \tag{8}$$

where X_i is a set of independent variables that include climate variables, socioeconomic variables, hydrological variables and soils; φ_i represents a vector of parameters to be estimated, and ω_i is the error term. After the correction α in equation (5) and ω in equation (8) are independent. Equations (6) and (8) form the core of the two-stage analysis. The expected NR of the farm is the sum of the probabilities across each choice the farmer faces, multiplied by the conditional NR of the selected farm type. Precisely:

$$NR_i(C) = \sum_{k=1}^{K} P_k\left(C_i, Z_i\right) \cdot \pi_k\left(C_i, Z_i\right) \tag{9}$$

As has been argued earlier, either land value or NR can be used as the measure for conditional income (Ricardo, 1817). In this study, a dataset covering detailed information on farming on the household scale for the year 2007 to 2008 is used. Farm NR is the measure for conditional income. The upcoming deliberations discuss the results and their implications.

3.2 Data and study area

A large dataset is constructed by combining the detailed farm-household level information from the Pakistan Living Standards Measurement Survey (PSLM) 2007 to 2008 (FBS, 2009) with climate and soil data from various sources. The PSLM survey covered 106 administrative districts (four provinces) in the country between 2007 and 2008. Farming households in the sample were administered a detailed farm production (input and output) questionnaire. Based on land ownership and data completeness 2,369 farm households were selected covering 79 districts and all agro-ecological zones in the country. When weighted, these household represent a great majority of the crop farmers in the country. The dataset covers the seven most important crops of the country, namely wheat (975 farms), cotton (408 farms), sugarcane (178 farms), rice (507 farms), maize (108 farms), fruits (94 farms) and vegetables (99 farms). Table 2 presents the summary statistics alongside the data source.

Table 2 Summary statistics for the multinomial crop choice model

Variable		*Obs*	*Mean*	*Std. dev.*	*Min*	*Max*	*Source*
Net_Crop_Revenue	$/ha	2,369	233.8699	133.6996	17.08333	1,085.625	FBS (2009)
Summer temperature	°C	2,369	30.60787	2.649737	18.23	34.67	NCDC (2011), FAO (2005)
Fall temperature	°C	2,369	19.27459	3.305058	9.63	24.57	NCDC (2011), FAO (2005)
Winter/spring	°C	2,369	15.68348	3.675906	5.23	21.73	NCDC (2011), FAO (2005)
Accumulated spring	mm	2,369	67.35965	85.0064	5	506.1	NCDC (2011), FAO (2005)
Monsoon precipitation	mm	2,369	31.34104	3.213903	23.1	36.15	NCDC (2011), FAO (2005)
Wheat value	$/kg	2,369	10.52638	4.912004	0	50	FBS (2009)
Cotton value	$/kg	2,369	6.79274	12.9194	0	87	FBS (2009)
Sugarcane value	$/kg	2,369	0.209371	0.8567478	0	25	FBS (2009)
Rice value	$/kg	2,369	4.863233	8.393704	0	62	FBS (2009)
Maize value	$/kg	2,369	1.891938	4.815706	0	30	FBS (2009)
Elevation	m	2,369	420.1144	635.3687	5	3314	FAO (2005)
Household size	Number	2,369	7.896581	4.001565	1	61	FBS (2009)
Education	Years	2,369	3.68721	4.628752	0	23	FBS (2009)
Runoff	mm/year	2,369	38.49388	103.3493	1	627	FAO (2005)
Soil cambisol	%	2,369	0.0889194	0.2142947	0	1	FAO (2003), ESRI (2011)
Soil calcisol	%	2,369	0.5056535	0.3674237	0	1	FAO (2003), ESRI (2011)
Soil fluvisol	%	2,369	0.0834549	0.1161126	0	0.4273678	FAO (2003), ESRI (2011)
Soil rock outcrop	%	2,369	0.0347731	0.1460655	0	1	FAO (2003), ESRI (2011)
Soil sand	%	2,369	0.1348121	0.2717466	0	0.8937818	FAO (2003), ESRI (2011)
Soil regosol	%	2,369	0.0313969	0.1297228	0	0.738439	FAO (2003), ESRI (2011)
Soil leptosol	%	2,369	0.1189034	0.2713905	0	0.9844586	FAO (2003), ESRI (2011)
Weak soil	%	2,369	0.169371	0.2944473	0	1	FAO (2003), ESRI (2011)
Total cultivated land	Acres	2,369	7.499367	13.34708	1	450	FBS (2009)
Irrigated land	%	2,369	0.8111785	0.3835235	0	1	FBS (2009)

Source: Author's own calculations using FBS (2009) dataset

The dependent variable for the second stage income regression net crop revenue per hectare is constructed by valuing all variable inputs (except land) and outputs at the market price, as provided by the Federal Bureau of Statistics Pakistan. Total annual farm income in this paper includes annual earnings from crop farming only. The livestock sector could not be included due to data constraints. Additional earnings by hiring out labour and equipment were only partly reported and therefore are excluded. The total costs are estimated by considering variable costs associated with hired labour, seeds, fertiliser and chemical sprays, tractor charges, irrigation costs, transport/packaging costs, and other incidental farm expenses. NRs per hectare are defined as the difference between revenues and costs divided by the number of hectares farmed. The household data is combined with data on long-term climate normals, soil and hydrological variables alongside socio-economic characteristics. Previous studies have found all agricultural seasons to be important for determining crop choice (Mendelsohn et al., 1994). Therefore, the probability of choosing each crop type as a function of summer, fall and winter temperature, spring, and monsoon precipitation is modelled. The winter season in Pakistan spans from January to March and thus intersects with the spring season. The majority of the precipitation is received during the monsoon season in the country, to this background the emphasis is laid on this particular season for modelling the precipitation impact. However, as most of the crops of the summer season are sown in the months starting from May/June, the accumulated precipitation in the soil is of paramount importance for agriculture. Therefore, the accumulated spring precipitation is separately modelled. Fall and winter precipitation are scarce, agriculture mainly relies on the precipitation that is received during the summer monsoon period, incidentally a separate inclusion of the fall and winter precipitation does not provide sufficient variation and is therefore left out. Various other explanatory variables are also included such as dominant soil types and socioeconomic household characteristics. Furthermore, own prices are used to identify the multinomial choice model. The choice of wheat has been left out of the regression as the base case. Following previous studies, this model also identifies the choice equation using cross prices, annual runoff (proxy for surface water flow) and soil variables (Ekeland et al., 2004).

4 Discussion of results

For assessing the overall goodness of fit of the econometric model, different tests were conducted. Table 3 summarises the three tests for the overall model fit (after Fagerland et al., 2008).

4.1 Sensitivity of crop choice to climate change

Table 4 provides an intuitive interpretation of the parameter estimates in the language of odds or so-called risk ratios which define the probability of choosing one outcome over the probability of choosing the base-case (wheat). The results indicate that crop choice is sensitive to climate. Furthermore, the importance of identifying the model using a multiseasonal approach is revealed. Many of the seasonal climate variables are significant at the 1% level. A positive coefficient implies that the probability of choosing the respective crop increases with an increment in the corresponding variable, whereas the opposite is indicated when the coefficient is negative. The coefficient on education is negative for cotton, sugarcane and vegetables, whereas it is positive for rice and positive significant for maize and fruits. This result implies that educated farmers tend to choose maize, fruits and rice (not significant) over wheat. Education it seems, as in the case of maize and fruits plays an important role when the marketing channels are rather opaque and export potential is high. Educated farmers seem to be better informed about the value of their produce and quality standards to meet export quality requirements (Aujla et al., 2007; Khushk et al., 2006).

Table 3 Measures of fit for multinomial logit model

Log-likelihood Chi^2 test:	
Log-Lik intercept only:	–3,776
D(2237):	2,984
Log-Lik full model:	–1,492
LR (126):	4.569
Prob > LR:	0
Pseudo-R^2:	
McFadden's R^2:	0.605
McFadden's adj. R^2:	0.57
Fagerland et al. statistic:	
Number of observations	2369
Number of outcome values	7
Base outcome value	1
Number of groups	10
Chi-squared statistic	72.051
Degrees of freedom	60
Prob > chi-squared =	0.137

Source: Author's own calculations using STATA 11.2 (StataCorp, 2009)

Table 4 Multinomial logit crop selection model for the farming season 2007–2008

Independent variables	*Cotton*	*Sugarcane*	*Rice*	*Maize*	*Fruits*	*Vegetables*
	Odds	*Odds*	*Odds*	*Odds*	*Odds*	*Odds*
Summer temperature	1.127 (0.230)	1.270 (0.210)	1.964*** (0.251)	1.204 (0.262)	1.495*** (0.179)	1.089 (0.100)
Summer temperature^2	1.040 (0.0774)	0.852* (0.0757)	1.023 (0.0205)	1.066*** (0.0187)	1.050*** (0.0151)	1.001 (0.0134)
Fall temperature^2	0.799 (0.199)	0.663** (0.121)	0.648*** (0.0660)	0.997 (0.0736)	1.065** (0.0277)	0.961 (0.0238)
Winter/spring temperature^2	1.206 (0.224)	1.458*** (0.205)	1.494*** (0.116)	0.970 (0.0637)	0.946* (0.0272)	1.071*** (0.0266)
Spring precipitation	0.971** (0.0114)	1.004 (0.00676)	0.988* (0.00650)	1.027*** (0.00816)	1.027*** (0.00734)	0.992 (0.00542)

Notes: Standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.
Wheat is the omitted choice.

Source: Author's own calculations in STATA 11.2 (StataCorp, 2009)

Table 4 Multinomial logit crop selection model for the farming season 2007–2008 (continued)

Independent variables	*Cotton*	*Sugarcane*	*Rice*	*Maize*	*Fruits*	*Vegetables*
	Odds	*Odds*	*Odds*	*Odds*	*Odds*	*Odds*
Spring precipitation^2	1.000 (6.49e-05)	1.000 (3.84e-05)	1.000 (5.54e-05)	1.000** (1.71e-05)	1.000*** (6.66e-05)	1.000 (1.41e-05)
Monsoon precipitation	1.000 (0.0140)	1.030** (0.0130)	1.010 (0.00589)	1.003 (0.0117)	1.004 (0.00895)	1.010 (0.00770)
Monsoon precipitation^2	1.000 (0.000245)	0.999*** (0.000221)	1.000** (7.19e-05)	1.000 (8.10e-05)	1.000* (0.000203)	1.000 (6.56e-05)
Irrigated land	1.089 (0.0697)	1.722*** (0.323)	1.301** (0.145)	1.241** (0.132)	1.280*** (0.0994)	1.050 (0.0389)
Wheat value	0.765*** (0.0315)	0.846*** (0.0242)	0.876*** (0.0238)	0.739*** (0.0332)	0.845*** (0.0212)	0.778*** (0.0196)
Cotton value	1.208*** (0.0168)	0.989 (0.0118)	0.878*** (0.0234)	1.023 (0.0394)	0.567 (11.97)	1.011 (0.0173)
Sugarcane value	0.238*** (0.0777)	3.121*** (0.487)	0.264*** (0.0793)	0.580 (0.270)	1.430 (0.359)	0.0748** (0.0779)
Rice value	0.927*** (0.0230)	0.990 (0.0175)	1.230*** (0.0179)	0.969 (0.0365)	0.995 (0.0278)	0.943* (0.0312)
Maize value	0.835 (0.0934)	1.011 (0.0368)	0.968 (0.0592)	1.285*** (0.0498)	0.946 (0.0416)	0.910* (0.0443)
Elevation	0.995** (0.00196)	0.998*** (0.000847)	0.995*** (0.000882)	1.000 (0.000744)	1.002*** (0.000407)	1.000* (0.000285)
Household size	1.774** (0.450)	1.233 (0.297)	1.123 (0.232)	0.849 (0.290)	0.865 (0.239)	1.435 (0.403)
Education	0.995 (0.0273)	0.983 (0.0252)	1.002 (0.0211)	1.060* (0.0357)	1.100*** (0.0288)	0.986 (0.0295)
Runoff	1.015 (0.00928)	0.973 (0.0244)	1.016*** (0.00414)	1.001 (0.00201)	0.998 (0.00290)	1.003 (0.00220)
Soil cambisol	0.992 (0.0355)	0.990 (0.00783)	1.013*** (0.00275)	0.994** (0.00308)	0.993 (0.00648)	0.996 (0.00399)
Marginal soil	0.728 (0.363)	1.116 (0.511)	0.153*** (0.0632)	0.00370** (0.00807)	1.056 (0.664)	0.654 (0.330)
Farmland area	0.919 (0.0580)	0.563*** (0.106)	0.799** (0.0894)	0.833* (0.0884)	0.786*** (0.0623)	0.971 (0.0352)
Constant	0.0432*** (0.0402)	2.039 (1.241)	0.139*** (0.0805)	0.173** (0.154)	0.393 (0.252)	0.327* (0.215)
Observations	2,369	2,369	2,369	2,369	2,369	2,369
Log likelihood	–1492	–1492	–1492	–1492	–1492	–1492
Pseudo R^2	0.604	0.604	0.604	0.604	0.604	0.604
Chi^2	4570	4570	4570	4570	4570	4570

Notes: Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Wheat is the omitted choice.

Source: Author's own calculations in STATA 11.2 (StataCorp, 2009)

The odds for selecting cotton over wheat are significantly higher for larger households. Precisely, farms with a larger family size are 1.774 times (odds ratio) more likely to grow cotton than farms with smaller household sizes. Cotton picking is a highly labour-intensive activity and also an important source of employment for the women in rural Pakistan (Ashfaq et al., 2012). Maize on the other hand, with the increasing cultivation of spring varieties has experienced mechanisation, thereby reducing the manual labour input (Muhammad, 2005). The wheat crop since the green revolution has experienced a widespread adoption of tractors and related tillage equipment in Pakistan. Mechanised threshing of wheat has also been widely adopted.

Similar results have also been obtained by Seo and Mendelsohn (2008a) for South America, where the findings showed that larger farm families are less likely to choose maize and wheat, because of the relative ease they are mechanised with. As far as the different soil types are concerned, when the share of marginal soils (calcic, rock, sand) is higher, the farmers are significantly less likely to choose rice and maize over wheat. Rice in Pakistan is grown on the better soils of the country (cambisols). The odds of picking rice over wheat on cambisols are clearly positive significant. Surface water availability on the district level as measured by the annual mean runoff is highly significant and positive for rice. This implies that with a higher abundance of surface water farmers are likely to foremost opt for rice cultivation. All of the own prices are significant. Farmers are more likely to choose these crops over wheat when their prices are higher. Especially sugarcane with an odds ratio of 3.121 for its own price is a very lucrative source of income. The coefficients for elevation are found to be significantly affecting the crop choice for all crops except maize. The odds for selecting cotton, sugarcane and rice over wheat with higher elevation are only marginally negative significant. Thus, only very cautiously it can be inferred, that with increasing elevation wheat is chosen over cotton, sugarcane and rice, whereas fruits and vegetables are as well as likely to be chosen. Higher altitude areas in Pakistan are mainly rain fed, approximately 55% of the cultivated area is cultivated under rain fed conditions; wheat is the primary crop for rain fed areas of the country (Majeed et al., 2010).

Many of the modelled crops have several highly significant temperature coefficients. Especially for sugarcane, rice, maize and fruits, temperature sensitivities are confirmed. Sugarcane choice is sensitive to all seasonal temperature variables.

Because the coefficients of the choice model (linear and squared terms) can be tedious to interpret and present, the conditional marginal impacts have been calculated to understand the effect that the changes in the respective climate variable would have on the choice of a crop. For the multinomial choice model, the marginal impacts on the probability of crop choice can be computed by differentiating equation (6) in the following way.

$$\frac{\partial P_i}{\partial Z_c} = P_i\left[\gamma_i - \sum\nolimits_{k=1}^{I} P_k \gamma_k\right] \tag{10}$$

With P_i denoting the probability of crop i to be chosen, γ_i representing the model parameters and k specifying the exogenous farm characteristics.

Table 5 reports the calculated marginal effects of a slight change in temperature (1°C) and precipitation (1 mm) on the probability of choosing a certain crop. The change is estimated for a uniform increase of 1°C in temperature and a uniform increase in precipitation of 1 mm over all season that have been modelled.

Table 5 Marginal effects of climate change on crop choice in Pakistan

Crop	*Temperature (°C)*	*Precipitation (mm)*
Wheat	–1.290%	–0.012%
Cotton	0.026%	–0.011%
Sugarcane	0.071%	0.012%
Rice	0.774%	–0.004%
Maize	0.031%	0.007%
Fruits	0.010%	0.001%
Vegetables	0.369%	0.007%

Note: Marginal impacts have been estimated at the mean of the corresponding climate variable.

Source: Author's own calculations based on parameter estimates from the choice model

The marginal effects are evaluated at the mean climate. As temperature marginally increases, farmers clearly choose wheat less often, whereas the likelihood of selecting all other crops increases. The rainfall effects are weaker. When the average annual mean rainfall increases by 1 mm, farmers less often select wheat and cotton, whereas they clearly prefer to grow maize and vegetables.

4.2 Sensitivity of income to climate change

In a second stage of the empirical analysis conditional NR functions are estimated by regressing the net crop revenue per hectare for each selected crop type on climate, soil, water and socio economic variables. As already explained, to correct for sample selection bias Dubin-McFadden selection bias correction is used (Bourguignon et al., 2004). The second stage conditional NR model also relies on the same seasonal climate specification that was used for the first stage choice model regressions. The parameter estimates are presented in Table 6. The findings confirm the climate sensitivity of the incomes for the six crops wheat, cotton, sugarcane, rice, vegetables and fruits. Many of the seasonal climate variables are highly significant, especially the squared terms, indicating a nonlinear relationship between farm income and climate. As in the second stage model, each sample is treated individually and sample selection bias correction is applied, a much smaller sample size is left over for analysis, which explains a lower frequency of significant coefficients as compared to the choice analysis.

Table 6 Conditional income by crop regression for Pakistan

Independent variables	*Wheat*	*Cotton*	*Sugarcane*	*Rice*	*Maize*	*Fruits*	*Vegetables*
	Coefficient	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*
Summer temperature	0.0744***	0.0908	0.266***	0.126**	–0.156	0.00440	0.193**
Summer temperature^2	0.0105*	–0.0716	–0.190**	–0.0240	0.00405	0.0835	0.00814
Fall temperature^2	–0.0250**	–0.194*	–0.108**	0.0845*	–0.0310	–0.125	0.0822
Winter/spring temperature^2	0.0299***	0.154*	0.0861**	–0.0730**	0.00555	0.104*	–0.0737
Spring precipitation	0.00317**	–0.00713	–0.00447	0.00349**	–0.000484	–0.0150	0.0259**
Spring precipitation^2	–3.55e-06	0.000256	–3.52e-06	4.81e-05**	7.21e-06	1.08e-05	–7.49e-05
Monsoon precipitation	0.00274***	0.0278	0.00307	0.000474	0.00325	0.0190**	0.00323
Monsoon precipitation^2	–5.26e-06	0.000442	–0.000376**	9.75e-06	–3.00e-05	–0.000392	4.87e-05
Irrigated land	0.0330***	0.172**	0.286***	0.0925**	0.145	0.0319	–0.0226
Crop value (price)	–0.0140*	0.00856**	–0.00939	0.00476	0.0588		
Household size	0.104***	0.00502	–0.0112	0.0437	0.00227	–0.0802	–0.257
Education	0.00329	0.00572	0.0130	0.000929	0.0228	0.0218	–0.0172
Soil cambisol	0.000393	–0.536**	0.000941	0.000497	–0.00450	–0.0297*	0.00535
Weak soils	–0.407***	0.571**	0.339	0.303*	–3.073	1.543	–0.257
Farmland area	–0.0393***	–0.180***	–0.306***	–0.104**	–0.150	–0.0468	–0.0178
Selection terms							
Wheat-selection	–0.211	–0.958	0.907**	0.483	–0.579	–1.662	3.571**
Cotton-selection	–0.477*	0.393*	1.434**	1.635***	1.828	1.255	–1.590
Sugarcane-selection	–0.561**	0.426	0.394***	0.842*	–0.683	0.0447	–0.149
Rice-selection	–0.580*	–0.895	0.384	0.401**	0.843	–1.226	–1.132
Maize-selection	0.0506	–5.498	–2.227	5.722	0.381	–7.727*	5.741
Fruits-selection	0.635	–1.058	1.490	3.250**	–0.303	0.119	–0.874
Vegetables-selection	1.794***	–1.791	–0.689	–1.357	–1.170	–2.382	–1.154

Notes: Standard errors are presented in the ANNEX; ***p < 0.01, **p < 0.05, *p < 0.1.
The dependent variable is the log of net farm revenue $/ha.

Source: Author's own calculations

Table 6 Conditional income by crop regression for Pakistan (continued)

Independent variables	*Wheat*	*Cotton*	*Sugarcane*	*Rice*	*Maize*	*Fruits*	*Vegetables*
	Coefficient	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*
Anciliary							
Sigma2	0.726	3.846	3.625	1.436	1.306	6.594	5.575
rho1_Wheat	–0.247	–0.626	0.611	0.403	–0.649	–0.647	1.513
rho2_Cotton	–0.560	0.257	0.966	1.365	2.051	0.489	–0.674
rho3_Sugarcane	–0.658	0.278	0.266	0.703	–0.766	0.0174	–0.0631
rho4_Rice	–0.680	–0.585	0.258	0.334	0.946	–0.477	–0.480
rho5_Maize	0.0593	–3.595	–1.500	4.775	0.428	–3.009	2.431
rho6_Fruits	0.745	–0.692	1.004	2.712	–0.340	0.0463	–0.370
rho7_Vegetables	2.105	–1.171	–0.464	–1.133	–1.313	–0.928	–0.489
Adjusted R^2	0.3591	0.2772	0.1493	0.3024	0.4621	0.6038	0.5896
Observations	876	408	178	507	71	78	91
Constant	9.460***	7.506***	10.38***	10.00***	8.158*	8.044***	14.90***

Notes: Standard errors are presented in the ANNEX; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
The dependent variable is the log of net farm revenue $/ha.

Source: Author's own calculations

Table 7 Marginal effects of climate on conditional net farm revenue in Pakistan

Crop	*Temperature (°C)*					
	Coef.	*Std. err.*	*z*	*P>z*	*[95% conf. interval]*	
Wheat	0.0794176***	0.0214078	3.71	0	0.037459	0.1213761
Cotton	0.050922	0.0617314	0.82	0.409	–0.070069	0.1719133
Sugarcane	0.2444618***	0.0615745	3.97	0	0.1237781	0.3651456
Rice	0.1371188**	0.0609876	2.25	0.025	0.0175854	0.2566522
Maize	–0.181494	0.2824985	–0.64	0.521	–0.7352	0.3722
Fruits	–0.018	0	–0.11	0.913	–0.333	0
Vegetables	0.2010075**	0.0940891	2.14	0.033	0.0165962	0.3854188
	Precipitation (mm)					
	Coef.	*Std. err.*	*z*	*P>z*	*[95% conf. interval]*	
Wheat	0.0059087***	0.0011259	5.25	0	0.0037019	0.0081154
Cotton	0.020704	0.0427306	0.48	0.628	–0.063046	0.1044544
Sugarcane	–0.001396	0.0089335	–0.16	0.876	–0.018905	0.0161133
Rice	0.0039672*	0.0021637	1.83	0.067	–0.000274	0.0082081
Maize	0.0027697	0.0185036	0.15	0.881	–0.033497	0.0390361
Fruits	0.0039743	0.0080887	0.49	0.623	–0.011879	0.0198279
Vegetables	0.0291716***	0.0086032	3.39	0.001	0.0123097	0.0460335

Again, as the model includes seasonal and quadratic terms that are not straightforward to interpret in terms of a single effect, marginal impacts of a change in climate or crop NRs are estimated and presented in Table 7. Table 7 shows that if climate marginally changes (a uniform change of 1°C in annual mean temperature and 1 mm in annual mean precipitation) from the current mean state, then gains in income (statistically significant) for wheat and particularly sugarcane, rice and vegetables can be expected. Losses in income are revealed for maize and fruits with a marginal warming. As far as the marginal change in precipitation is concerned, statistically significant benefits are found for wheat, rice and vegetables. Almost all coefficients for the marginal precipitation change are positive, as expected for a dry country like Pakistan. To check the consistency of the first and second stage estimations, the marginal effects for the choice regression (Table 5) and the income regression (Table 7) can be compared. Except for wheat, the income effects for sugarcane, rice and vegetables are clearly consistent with farmers' choices. For a temperature increase, the results indicate that farmers substitute sugarcane, rice and vegetables for wheat. For precipitation, the results are not clear and inferences are difficult to draw from a marginal change only, as mentioned before, this shortcoming will be addressed in the subsequent chapter on climate change simulations.

5 Simulations

Using the parameter estimates from the structural Ricardian regressions, the consequences of climate change are simulated. Basically, the initial model is re-estimated using the new climate dataset for each time period. Country level climate change scenarios depicting changes for a ten year average for 2030, 2060 and 2090 under the SRES A2 scenario family are used. The dataset by the UNDP climate change country profile project reports observed trend and projected changes averaged over the whole country and provides spatial variations in change across the country on a 2.5 × 2.5° grid level. These grids contain the ensemble range and ensemble median. The median is used as the reference value for creating a district level dataset using a geographic information system (GIS) (Table 8).

Table 8 Pakistani average annual and seasonal climate change scenarios 2030–2090

	Obs	*Temperature (°C)*	*Precipitation (%)*
2030			
Annual	2,369	1.521992	4.89%
JFM	2,369	1.652469	–15.50%
AMJ	2,369	1.644407	2.71%
JAS	2,369	1.457282	3.91%
OND	2,369	1.599831	–4.89%
2060			
Annual	2,369	3.086661	6.91%
JFM	2,369	3.14943	–15.47%
AMJ	2,369	3.094344	6.67%
JAS	2,369	2.952216	17.20%
OND	2,369	3.089194	–10.11%
2090			
Annual	2,369	5.075728	3.75%
JFM	2,369	5.236809	–32.66%
AMJ	2,369	5.025791	7.58%
JAS	2,369	4.446813	18.86%
OND	2,369	5.098227	2.78%

Note: Values denote deviations from the normal climate!

Source: Author's own calculations based on amended dataset using McSweeney et al. (2010)

The idea is to first measure the change in welfare that results from a change in climate from one point in time to the other, where the base period represents long-term normal climate for the country. The following equation presents the measurement of the climate change induced welfare change.

$$\begin{aligned}\Delta W &= \left[V\left(C_1, Z_i\right) - V\left(C_0, Z_i\right)\right] \cdot L_i \\ &= \sum_{k=1}^{K}\left[P_k\left(C_1\right) \cdot \pi_k\left(C_1\right) - \sum_{k=1}^{K} P_k\left(C_0\right) \cdot \pi_k\left(C_0\right)\right] \cdot L_i\end{aligned} \tag{11}$$

where C_1 denotes the new climate and C_0 represents the initial climate, L_i is the amount of land at each farm i, π_k is the conditional land value of a particular farm type and P_k stands for the probability of each choice the farmer faces.

In case of the structural model, the welfare change captures two different effects. On hand, as the climate changes, the probabilities of crop choice are likely to alter and on the other hand climate change will thereby also impact on the conditional incomes from the chosen crops. To assess the value and thus importance of adaptation regarding loss and damage, the expected income [equation (11)] of climate change without adaptation can be compared to the expected income in the case with adaptation. Equation (12) presents the case when farmers do not adapt.

$$W(C) = \sum_{k=1}^{K}\left[P_k\left(C_1\right) \cdot \pi_k\left(C_0\right) - \sum_{k=1}^{K} P_k\left(C_0\right) \cdot \pi_k\left(C_0\right)\right] \cdot L_i \tag{12}$$

Without adaptation measures farmers will continue to make the same choices that they were making under the initial climate. However, as the incomes of each choice also change, farmers will be made worse off than if they adapted. The value of adaption is given by the difference between equations (11) and (12).

From these new estimates, the probabilities of selecting a certain crop were extracted to compare them with the probabilities of the initial model. Table 9 shows the changes in the probabilities of selecting a certain crop for each climate scenario.

Table 9 Predicted probability change of selecting each crop under different scenarios

Probability	*Obs*	*Current climate*	*2030*	*2060*	*2090*
Wheat	2,369	41.16%	0.1579%	–0.3169%	–0.6416%
Cotton	2,369	17.22%	–0.0312%	–0.0129%	–0.0687%
Sugarcane	2,369	7.51%	0.3340%	0.2832%	–0.0141%
Rice	2,369	21.40%	–0.4679%	0.1406%	0.5830%
Maize	2,369	4.56%	0.0128%	0.0497%	0.1032%
Fruits	2,369	3.97%	–0.0113%	–0.0134%	–0.0167%
Vegetables	2,369	4.18%	0.0057%	–0.1302%	0.0549%

Note: Probabilities have been obtained from the multinomial logit regression estimates.

Source: Author's own calculations

Although the predicted changes seem to be weak, they to some extent highlight the importance of examining agro-climatic zone specific scenarios as precipitation increases can possibly offset, at least to a certain extent, damages and pressure from additional warming. The model does not claim to be correct on the decimal and absolute value level; however, it does claim to accurately reflect the direction of the expected changes. In spirit of this claim, the probability results are interpreted. As climate changes in the short-term (2030) (combined temperature and precipitation change) farmers are more likely to select wheat and sugarcane, whereas they are slightly also more likely to select maize and vegetables. On the other hand, they are reluctant to choose rice, cotton and fruits. Rice especially, as has been explained earlier in the interpretations for the structural Ricardian model, has a U-shaped relationship with summer precipitation (rice growing season), thus minimum levels of precipitation are essential for the crop to flourish. By 2030, the change in temperature is evident over most of the country, however in the rice growing regions of the Punjab, precipitation levels do not change. Thus, from a relative point of view, under the 2030 scenario farmers are more likely to switch from rice, cotton and fruits to wheat, maize, and foremost sugarcane. Under the midterm scenario (2060) farmers clearly move away from wheat, vegetables, fruits and cotton towards maize, sugarcane and foremost rice. In the mid-term scenario, the precipitation gains in the Punjab province and the even stronger precipitation increases in the Sindh province, both major rice producing provinces of the country, seem to benefit rice cultivation, finally exceeding the minimum required precipitation amount for the cultivation of rice. Sugarcane, although also more selected in 2060s, when compared to 2030s shows a weaker positive effect (on probability), whereas the negative effect for cotton is relatively also smaller. In the long-term scenario (2090) farmers clearly switch away from wheat, cotton, fruits and newly also sugarcane to rice, vegetables and maize, clearly showing the effect of the strong increase in precipitation and at the same time temperature. Thus, when it is hot and precipitation is available, other things remaining constant (see parameter estimates for structural model for the other variables), farmers select rice, vegetables and maize. The long-term scenario results also hint towards increasing adaptations as warming progresses. How things change when other variables change, such as surface water availability, will be discussed in combination with the following deliberations on welfare and the value of adaptation. As the structural model is a two stage model, the changes in net income are also shown in Table 10. For obtaining these results, all models were re-estimated using the AOGCM scenarios for 2030, 2060 and 2090. Most of the income simulations are consistent with the choices that are made by farmers with a changing climate.

Table 10 Welfare change in Pakistan resulting from different climate scenarios

Farmer response	*2030*	*2060*	*2090*
	Welfare US$/farm	*Welfare US$/farm*	*Welfare US$/farm*
Crops unchanged	–0.966690756	0.142661891	1.261022014
Crop switching	71.08248059	74.92259725	79.82895438
	%-change	*%-change*	*%-change*
Crops unchanged	–0.14%	0.02%	0.18%
Crop switching	10.08%	10.62%	11.31%
Value of adaptation	*70.11578983*	*74.77993536*	*78.56793237*

Notes: The expected income at the current climate is 705$/farm.
Crops unchanged assumes no change in cropping patterns, whereas crop switching assumes farmers to adjust cropping patterns to future climate.
Source: Author's own calculations

After combining the results of both modelling stages the expected change in net income is shown for the selected climate scenarios in Table 10. For the short-term scenario income from crop farming in Pakistan is expected to drop, whereas in the mid-term and long-term slight increases are predicted. If the farmers stick to their current portfolio of crops, revenues are likely to decrease marginally by 2030. In the mid-term and long-term scenarios, a slightly positive effect is observed.

The second and fourth rows calculate the situation, when farmers do adjust their cropping patterns to match future climate. If they adapt, welfare increases by 10% in the short-term scenario, 10.6% in the mid-term scenario and 11.3% in the long-term scenario. As has been mentioned earlier, the simulations model the change in climate only, assuming other factors to remain stable over the course of the next 80 years. This also includes surface water availability. Under these assumptions Table 8.6 shows the value and importance of crop switching as an adaptation measure. Crop switching substantially increases farmers' revenues and thus provides a cushion for other factors that might also change with climate change. Moreover, the fact that farmers, if they do not adapt, are found to have slightly positive revenues in the long-term climate, might be misleading, as the underlying assumption is that everything else remains the same. To see what implications can be expected from a situation, where these other factors change, the following simulation repeatedly exemplifies the importance of adaptation. In the following scenario the assumption is that, farmers continue growing the same crops that they grow under the current climate, however besides climate also new-equilibriums are assumed for surface water availability. The World Bank (2005) predicts Pakistan's water resources to be depleted by 30% to 40% in the long-run. Taking this forecast, the surface water availability proxy variable 'mean annual runoff' is reduced by the proposed percentage. Table 11 presents the results.

Table 11 Welfare change under varying climate scenarios (reduced water availability)

Farmer response	*2030*	*2060*	*2090*
	Welfare US$/farm	*Welfare US$/farm*	*Welfare US$/farm*
Crops unchanged	–2.366609966	–1.525773588	–0.821749152
Crop switching	69.0792512	72.31127141	76.16965436
	%-change	*%-change*	*%-change*
Crops unchanged	–0.34%	–0.22%	–0.12%
Crop switching	9.80%	10.26%	10.80%
Value of adaptation	*66.71264124*	*73.837045*	*76.99140351*

Notes: The expected income at the current climate is 705$/farm.
Crops unchanged assumes no change in cropping patterns, whereas crop switching assumes farmers to adjust cropping patterns to future climate.

Source: Author's own calculations

As expected, reduced surface water availability leads to declines in welfare for all three scenarios. Again, the absolute values do not claim to represent the real and true amount of changes, they however do claim to accurately predict the directional changes. On the basis of these findings, it can be inferred that adaptation is of paramount importance to cope with the adverse effects of climate change in future. This becomes clear, when assessing the results in the second simulation, with reduced surface water availability. Considering the five million farms of the country, the estimates reveal the value of adaptation to be as high as 330 and 380 million dollars (2030/2090) for the country's crop sector. If adaptation does not take place, the losses for the crop-sector range between 4 and 12 million dollars.

The reduced surface water simulations also confirm the apprehension which was hinted at in the deliberations on the climate change only simulations, namely that although the welfare change in the mid and long-term scenarios was not found to be negative, the changes were very close to zero (no change), thus leaving a very thin room for error or changes in factors other than climate, such as surface water availability. Thus, indeed, reducing surface water availability reveals that adaptation is pivotal to cope with climate change, the results in Table 11 show that although less surface water is available, the adaptations made by the farmers cushion the effects of climate change. Thus, although the positive welfare effects are weaker, they are significantly positive.

Although the simulations in general assume a change in climate only, the SRES A2 scenarios account for this shortcoming. It is in general hard to imagine the state of Pakistan in 2090; however, the IPCC storylines are formulated to capture distinctly different future directions. They try to account for underlying uncertainties by including a range of key future characteristics, including demographic change, economic development, and technological change. "For this reason, their plausibility or feasibility should not be considered solely on the basis of an extrapolation of current economic, technological, and social trends" (Nakicenovic et al., 2000). In following the conclusions shall be drawn and possible ways forward shall be elicited.

6 Conclusions and recommendations

This paper in the introduction raised the question, whether the farm households in Pakistan's crop sector were able to efficiently adapt to climate change and thus prevent loss and damage. The findings suggest, indeed, that farmers adjust their crop choices as warming progresses by considering the expected income resulting from the switch. Many of the seasonal climate variables are significant at the 1% level. The marginal effects are evaluated at the mean climate. As temperature marginally increases (by 1°C), farmers clearly choose wheat less often, whereas the likelihood of selecting all other crops increases. The rainfall effects are weaker. When the average annual mean rainfall increases by 1 mm, farmers less often select wheat and cotton, whereas they clearly prefer to grow maize and vegetables. As far as income is concerned, if climate marginally changes (a uniform change of 1°C in annual mean temperature and 1 mm in annual mean precipitation) from the current mean state, then gains in income (statistically significant) for wheat and particularly sugarcane, rice and vegetables can be expected. Losses in income are revealed for maize and fruits with a marginal warming. As far as the marginal change in precipitation is concerned, statistically significant benefits are found for wheat, rice and vegetables. Almost all coefficients for the marginal precipitation change are positive, as expected for a dry country like Pakistan.

Using the Ricardian approach for climate change impact assessment, on the basis of long-term incomes (net crop revenues as proxy for land values – see Kurukulasuriya and Ajwad, 2007) and long-term climate normals, the study reveals that today's choices have come about by taking climate variables into consideration. Hence, farmers have adapted. Using this relationship and utilising the parameters of the choice model, a static comparative approach is applied to simulate future adaptation behaviour of farmers, in case climate would change. Precisely, to see whether, loss and damage is likely to occur in future and to assess, whether crop-cultivating farmers have well adapted in Pakistan, simulations are run.

The simulations reveal some highly interesting findings, i.e., that farmers in Pakistan will react to a change in climate by altering crop choices that have the potential to make them economically better off. The welfare calculations based on the selected sample reveal the value of adaptation (through crop switching only) to be as high as 330–380 million dollars over all five million farms. On the other hand, if adaptations in the crop sector do not take place and water availability decreases by 30%, the estimates reveal losses between 4 and 12 million dollars (2030/2090). The estimates hint towards well-directed adaptations of farmers in Pakistan (found by the structural Ricardian model). Moreover, they reveal that adaptation in any case will benefit the farmers, as by adapting they can cushion the adverse effects from unprecedented extreme weather events or reductions in water availability. As climate warms, farmers in Pakistan are more likely to choose rice, vegetables and maize, whereas they move away from wheat, sugarcane, cotton and fruits. Different crops are revealed to have specific preferred climate ranges, where they grow best. If the optimal ranges are altered crop productivity either falls or increases, dependent on the change in climate. These welfare estimates only consider crops and do not include livestock effects, which could be of high relevance as the livestock sector is an important part of agriculture in Pakistan. In spite of the aforementioned shortcomings, the welfare calculations based on the structural model capture the alteration in the probabilities of choice as well as the impact on conditional income from the chosen crops.

Policy has to be designed to nurture the potential of famers in the crop-sector. Local traditional knowledge has to be tapped when designing adaptation strategies. Farmers have accumulated valuable crop-cultivation knowledge, given their region's specific climate. Hence, learning from these experiences will be a key element in designing a path forward. Crop farmers in Pakistan have generally well adapted to their local conditions by growing a certain primary crop, also considering income as the results of this paper reveal. Thus, if the climate of a region 'A' changes, thereafter making it similar to another region's climate 'B' within the country, then policy makers can draw from the experiences of farmers in region 'B' and facilitate crop-adjustments in region 'A'. This can serve as one possible solution for preventing loss and damage.

References

Ahmed, M.N. and Schmitz, P.M. (2011a) 'Economic assessment of the impact of climate change on the agriculture of Pakistan', *Business & Economic Horizons, BEH*, Vol. 4, No. 1, 2011, pp.1–12, Prague.

Ahmed, M.N. and Schmitz, P.M. (2011b) 'Using the Ricardian technique to estimate the impacts of climate change on crop farming in Pakistan', *European Association of Agricultural Economists 2011 International Congress*, Zurich, Switzerland, 30 August–2 September.

Ashfaq, M., Abid, M., Bakhsh, K. and Fatima, N. (2012) 'Analysis of resource use efficiencies and return to scale of medium sized Bt cotton farmers in Punjab, Pakistan', *Sarhad Journal of Agriculture*, Vol. 28, No. 3, pp.493–498.

Aujla, K.M., Abbas, M., Mahmood, K. and Saadullah, S. (2007) 'Marketing system of fruits, margins and export potential in Pakistan', *Pakistan Journal of Life and Social Sciences*, Vol. 5, No. 1, pp.34–39.

Bourguignon, F., Fournier, M. and Gurgand, M. (2004) *Selection Bias Corrections Based on the Multinomial Logit Model: Monte-Carlo Comparisons*, DELTA Working Papers, No. 20.

Bourguignon, F., Fournier, M. and Gurgand, M. (2007) 'Selection bias corrections based on the multinomial logit model: Monte Carlo comparisons', *Journal of Economic Surveys*, Vol. 21, No. 1, pp.174–205, Wiley Blackwell.

CAIT (2011) *Climate Analysis Indicators Tool Version 8.0*, World Resources Institute, Washington, DC [online] http://cait2.wri.org/wri/Country%20GHG%20Emissions?indicator[]=Total GHG Emissions Excluding LUCF&indicator[]=Total GHG Emissions Including LUCF&year[]=2010&chartType=geo (accessed 26 March 2013).

Central Board of Secondary Education (CBSE) (2006) *Natural Hazards and Disaster Management. Supplementary Textbook in Geography*, UNIT 11: Natural Hazards and Disasters, Preet Vihar, Delhi, pp.1–10.

Chaudhry, Q.Z., Mahmood, A., Rasul, G. and Afzaal, M. (2009) *Climate Change Indicators of Pakistan*, Pakistan Meteorological Department, Technical Report No. PMD. 22/2009, Islamabad.

Chow, G. (1983) *Econometrics*, McGraw-Hill, New York.

Cline, W.R. (2007) *Global Warming and Agriculture: Impact Estimates by Country*, Center for Global Development and Peterson Institute for International Economics, Washington.

Curran, C. (2010) *Sample Selectivity Bias*, The Connexions Project, module m34547, http://cnx.org/content/m34547/1.3/ (accessed 29 December 2012).

Deschenes, O. and Greenstone, M. (2007) 'The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather', *American Economic Review*, Vol. 97, No. 1, pp.354–385.

Dubin, J. and McFadden, D. (1984) 'An econometric analysis of residential electric appliance holdings and consumption', *Econometrica*, Vol. 50, No. 2, pp.345–362.

Ekeland, I., Heckman, J.J. and Nesheim, L. (2004) 'Identification and estimation of hedonic models', *Journal of Political Economy*, February, Vol. 112, No. S1, pp.60–109, University of Chicago Press.

EM-DAT (2012) *The OFDA/CRED International Disaster Database*, Université catholique de Louvain, Brussels, Belgium, Data version, v. 12.07, [online] http://www.emdat.be (created on 30 January 2012).

ESRI (2011) *ArcGis Desktop 10.1*, New York Street, Redlands, CA, USA.

Fagerland, M.W., Hosmer, D.W. and Bofin, A.M. (2008) 'Multinomial goodness-of-fit tests for logistic regression models', *Statistics in Medicine*, 17 January 2008, Vol. 27, pp.4238–4253.

Federal Bureau of Statistics (FBS) (2009) *Pakistan Living Standards Measurement Survey 2007–2008*, Government of Pakistan, Islamabad.

Food and Agriculture Organization (FAO) (2003) *The Digital Soil Map of the World (DSMW) CD-ROM*, Italy, Rome.

Food and Agriculture Organization (FAO) (2005) *New LocClim (incl. CD-ROM)*, Environment and Natural Resources Working paper No. 20.

Heckman, J.J. (1979) 'Sample selection bias as a specification error', *Econometrica*, Vol. 47, No. 1, pp.153–162.

Huesca, L. and Camberos, M. (2010) 'Selection-bias correction based on the multinomial logit: an application to the Mexican labor market', *Mexican Stata Users' Group Meetings 2010*, Stata Users Group.

Khushk, A.M., Memon, A. and Lashari, M.I. (2006) 'Marketing system of selected fruits in Pakistan', *Bangladesh Journal of Agricultural Research*, Vol. 31, No. 1, pp.39–68.

Kurukulasuriya, P. and Ajwad, M.I. (2007) 'Application of the Ricardian technique to estimate the impact of climate change on smallholder farming in Sri Lanka', *Climatic Change*, March, Vol. 81, No. 1, pp.39–59.

Kusters, K. and Wangdi, N. (2013) 'The costs of adaptation: changes in water availability and farmers' responses in Punakha district, Bhutan', *Int. J. Global Warming*, Vol. 5, No. 4, pp.387–399.

LP (2008) *LEAD Climate Change Action Program*, Internal Document, LEAD Pakistan, Islamabad.

Majeed, S., Bhatti, A.A. and Abbas, G. (2010) 'Productivity and profitability of Barani wheat under chemical and organic farming systems', *Pakistan Journal of Agricultural Research*, Vol. 23, Nos. 1–2, pp.5–16.

McFadden, D.L. (1981) 'Econometric models of probabilistic choice', in McFadden, D.L. (Ed.): *Structural Analysis of Discrete Data and Econometric Applications*, MIT Press, Cambridge.

McSweeney, C., New, M. and Lizcano, G. (2010) 'The UNDP climate change country profiles: improving the accessibility of observed and projected climate information for studies of climate change in developing countries', *Bulletin of the American Meteorological Society*, February, Vol. 91, pp.157–166.

Mendelsohn, R. and Williams, L. (2004) 'Comparing forecasts of the global impacts of climate change', *Mitigation and Adaptation Strategies for Global Change*, Vol. 9, No. 4, pp.315–333.

Mendelsohn, R. and Dinar, A. (2009) *Climate Change and Agriculture: An Economic Analysis of Global Impacts, Adaptation and Distributional Effects*, Edward Elgar Publishing, Inc., Northampton, MA.

Mendelsohn, R., Dinar, A. and Sanghi, A. (2001) 'The effect of development on the climate sensitivity of agriculture', *Environment and Development Economics*, February, Vol. 6, pp.85–101.

Mendelsohn, R., Nordhaus, W. and Shaw, D. (1994) 'The impact of global warming on agriculture: a Ricardian analysis', *American Economic Review*, September, Vol. 84, pp.753–771.

Mendelsohn, R., Nordhaus, W.D. and Shaw, D. (1996) 'Climate impacts on aggregate farm value: accounting for adaptation', *Agricultural and Forest Meteorology*, Vol. 80, No. 1, pp.55–66.

Muhammad, A. (2005) *The Causes and Effects of Agricultural Mechanization and Labor Displacement in NWFP*, PhD thesis, University of Peshawar, Peshawar.

Nakicenovic, N., Alcamo, J., Davis, G. et al. (2000) *Special Report on Emissions Scenarios: A Special Report of Working Group III of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge, UK.

National Climatic Data Center (NCDC) (2011) NESDIS, NOAA-US Department of Commerce, Global Surface Summary of the Day – GSOD, Asheville, NC Dataset Publisher, National Climatic Data Center.

Ricardo, D. (1817) *On the Principles of Political Economy and Taxation*, John, London.

Seo, N. and Mendelsohn, R. (2008a) 'A Ricardian analysis of the impact of climate change on South American farms', *Chilean Journal of Agricultural Research*, Vol. 68, No. 1, pp.69–79.

Seo, N. and Mendelsohn, R. (2008b) 'Measuring impacts and adaptation to climate change: a structural Ricardian model of African livestock management', *Agricultural Economics*, Vol. 38, No. 2, pp.150–165.

StataCorp (2009) *Stata Statistical Software: Release 11.2/SE*, Stata Corporation, College Station, TX, USA.

Task Force on Climate Change (TFCC) (2010) *Task Force on Climate Change*, Final Report, Planning Commission, Government of Pakistan, Islamabad.

United Nations Framework Convention on Climate Change (UNFCCC) (2007) *Climate Change: Impacts, Vulnerabilities And Adaptation in Developing Countries*, Bonn, Germany.

Warner, K., van der Geest, K., Kreft, S., Huq, S., Kusters, K. and de Sherbinin, A. (2012) *Evidence from the Frontlines of Climate Change: Loss and Damage to Communities Despite Coping and Adaptation, Loss and Damage in Vulnerable Countries Initiative*, Policy Report, Report No. 9, United Nations University Institute for Environment and Human Security (UNU-EHS), Bonn.

World Bank (2005) *Country Water Resources Assistance Strategy-Water Economy: Running Dry*, Agriculture and Rural Development Unit-South Asia Region, Washington.

World Bank (2013) *World Development Indicators 2013*, Washington DC, USA.