Journal of Rural Studies 47 (2016) 254–266

Contents lists available at ScienceDirect

Journal of Rural Studies

journal homepage: www.elsevier.com/locate/jrurstud

Adaptation to climate change and its impacts on food productivity and crop income: Perspectives of farmers in rural Pakistan

Muhammad Abid [a, b, *], Uwe A. Schneider [c], Jürgen Scheffran [a]

[a] Research Group Climate Change and Security (CLISEC), Institute of Geography, University of Hamburg, Grindelberg 7, 20144 Hamburg, Germany
[b] School of Integrated Climate System Sciences (SICSS), University of Hamburg, Grindelberg 5, 20144 Hamburg, Germany
[c] Research Unit Sustainability and Global Change, University of Hamburg, Grindelberg 5, 20144 Hamburg, Germany

ARTICLE INFO

Article history:
Received 26 January 2016
Received in revised form
4 August 2016
Accepted 22 August 2016
Available online 5 September 2016

Keywords:
Climate change
Adaptation
Food productivity
Crop income
Rural Pakistan

ABSTRACT

Evaluation of the ongoing efforts for farm level adaptation to climate change is crucial to understand their effectiveness and to suggest further actions at the policy level. The current study explores the adaptation of wheat farmers to climate change, its determinants and its impact on food productivity and crop income in rural Pakistan. This study is based on a primary dataset of 442 wheat farmers conducted through face-to-face structured interviews from 65 villages across three agro-ecological zones of Punjab Province, Pakistan. The study employs logistic regression analysis to find adaptation determinants and uses the propensity score matching technique to estimate the causal impact of adaptation on food productivity and crop income. The results of the study suggest that wheat farmers were well aware of climate change, but for various reasons did not adapt accordingly. The major adaptation strategies implemented by wheat farmers include changing planting dates, crop varieties and fertilizer types. Moreover, education, farming experience, access to agricultural extension, weather forecasting and marketing information were the factors that significantly affected farmers' adaptation decisions. Adapting wheat crops to climate change significantly and positively affects wheat productivity and net crop income and hence indirectly improves the farmers' wellbeing and local food security. More benefits were achieved by farmers who used a combination of different adaptation strategies. The study suggests to focus on farmers' education, easy access to farm advisory services and information on new adaptation methods for sustainable food production and local food security.

1. Introduction

Projected changes in climate and increasing climatic risks over the 21st century pose serious challenges to agricultural development in developing countries (IPCC, 2014). Pakistan is one of the countries most affected by climate change due to its low adaptive capacity and poor infrastructure (Stocker et al., 2013). Projections suggest a 2–3° increase in temperature and a significant variation in the distribution of rainfall in Pakistan by 2050 (Gorst et al., 2015). The Global Climate Risk Index (GCRI) ranked Pakistan number 8 in a list of countries most affected by climate change and extreme weather events over the period 1995–2014 (Kreft et al., 2016). Due to extreme events and climate variability, rural livelihoods and the productivity of major crops such as wheat, cotton, rice and sugarcane have been greatly affected over the last two decades (Abid et al., 2015). The historic floods during 2010–2014 and severe droughts lasting from 1999 to 2003 indicate the vulnerability of rural households in Pakistan to climate change (Abid et al., 2015).

The resilience of the agricultural sector to climate change is one of the most important concerns for economic development in Pakistan as more than two-thirds of the country's population lives in rural areas and relies on the agricultural sector for their subsistence and livelihood (Abid et al., 2011; WB, 2014). Further, through adverse impacts on cereal productivity and food prices,

* Corresponding author. Research Group Climate Change and Security (CLISEC), Institute of Geography, University of Hamburg, Grindelberg 7, 20144 Hamburg, Germany.

E-mail addresses: Muhammad.abid@uni-hamburg.de, abiduaf@gmail.com (M. Abid), Uwe.schneider@uni-hamburg.de (U.A. Schneider), Juergen.scheffran@uni-hamburg.de (J. Scheffran).

http://dx.doi.org/10.1016/j.jrurstud.2016.08.005
0743-0167/

climate change could have serious implications for local food security in Pakistan, which mainly depends on cereal crops. Wheat alone, which was grown on 8.66 million hectares in 2013, supplies 37% of the total daily calories in Pakistan (Prikhodko and Zrilyi, 2013). However, the current national average wheat yield (2797 kg/ha in 2013) is much lower than the global mean (3268 kg/ha in 2013) (FAO, 2015). According to a recent study, farmers in Pakistan only realize 32% of the potential crop yield (Prikhodko and Zrilyi, 2013). The huge gap between actual and potential crop yields is one of the major factors contributing to the insufficient supply of cereals in the country. For instance, Zulfiqar and Hussain (2014) reported an increasing gap between per-capita wheat demand and supply in Pakistan for the period of 2013–2050 (for details on wheat caloric demand-supply gaps, see Table A.1 in Appendix A). Unsteady agricultural growth coupled with a steadily increasing population may lead to serious consequences for local food security and livelihoods (Sheikh et al., 2012). Climate change may aggravate the situation if not managed adequately and in a timely manner.

To ensure food security and to protect rural livelihoods from the adverse impacts of climate change, effective adaptation at farm level is required (Abid et al., 2015). However, a major challenge at the local level is that farmers, as the key stakeholders, will have to face most of the adaptation burden themselves. Under perfect market conditions, farmers still may be better off and may get compensation for the increased cost of production in term of higher prices. However, this is not always true in the case of developing countries like Pakistan, where prices are mainly controlled by non-market forces (imperfect conditions) and farmers may suffer from increased production cost and lower returns. Hence, there is dire need for public adaptation policy that keeps in mind farmers' intentions and their adaptive capacities. Therefore, it is crucial from a policy perspective to understand the factors that drive farmers' adaptation decisions and the impact of their actions on farm production, which may vary across regions and scales (Niles et al., 2015). Also, it would be worthwhile to investigate the dynamics of gains from ongoing private adaptation measures to climate change. For example, if there are substantial short-term adaptation benefits, it could motivate policy makers to put in more effort to support farmers in the adaptation process by providing access to farm advisory services and technical support (Gorst et al., 2015).

Over the last decade, the literature on climate change and agriculture has evolved from mitigation studies (e.g. McCarl and Schneider, 2001; Metz et al., 2007) to impact assessments (e.g. Schlenker and Lobell, 2010; Seo and Mendelsohn, 2008) and adaptation studies (e.g. Alam et al., 2012; Bryan et al., 2013; Deressa et al., 2011; Mugi-Ngenga et al., 2016). Most of the literature on climate change adaptation in the agricultural sector is either focused on developed countries or developing countries in Africa. However, the adaptation literature showing the perspective of South Asian countries, especially Pakistan, is rare and only a few studies (e.g. Abid et al., 2015; Esham and Garforth, 2013) have analyzed agricultural adaptation to climate change from the farmers' perspective. Most studies of adaptation have highlighted farmers' experiences with changing climatic conditions, their adaptation strategies and determinants and identified relevant constraints for different regions and socio-economic settings. Empirical estimates of the effectiveness of adaptation efforts are scarce and only a few studies (e.g. Bastakoti et al., 2014; Bradshaw et al., 2004) have addressed this aspect at the farm or local level. Thus, more studies focusing on the economic assessment of ongoing adaptation processes may indicate the extent of benefits and suggest policies for actions required to accelerate local adaptation (Abid et al., 2015).

Given this knowledge gap, this study takes the case of wheat farmers and investigates their adaptation to climate change and its impact on food productivity and crop income. Specifically, this study addresses four research questions. First, how do wheat farmers adapt to climate change? Second, how does adaptation vary across various types of farmers? Third, which factors influence wheat farmers' adaptation decisions in response to a changing climate? And fourth, how does adaptation to climate change affect food productivity and net crop income?

The paper is divided into four sections. After the introduction, Section 2 describes the conceptual framework, empirical modeling and methodology. Section 3 presents the results. Finally, Section 4 outlines the conclusion and implications of the results.

2. Material and methods

2.1. Study area and data collection

This study focuses on the Punjab province due to its significance for Pakistan's cereal production (74%) and agricultural gross domestic product (GDP) (53%) (Abid et al., 2015). Punjab is mainly divided into four agro-ecological zones: Irrigated plains, *Barani* (rain-fed) region, *Thal* region and Marginal land. In this study, we selected only three regions and excluded *Thal* region due to budget constraints. All three selected agro-ecological zones have a distinct climate, environment and geography and hence are subject to different kinds of environmental and socio-economic constraints. Fig. 1 shows the map of study areas located in Punjab province.

Further, we focus on wheat farming for two main reasons. First, wheat is the primary source of food in rural Pakistan and accounts for about 50% of the daily per-capita caloric intake in rural areas (Malik et al., 2014). Second, it accounts for about 46% of the total cropland and around 75% of the total area being used for cereals (Farooq et al., 2007). This widespread cultivation allows us to study wheat farmers across different regions to analyze the differences in adaptation strategies and to see how regional characteristics influence the choice of adaptation strategies and associated benefits.

Initially, we interviewed 450 farmers from three agro-ecological zones of Punjab province selected through a multi-sampling technique. Afterwards, we dropped the cases where farmers do not grow wheat crop. The final remaining sample was 442 farmers. The sampling procedure consisted of seven steps. In the first stage, Punjab was selected as the main study area. In the second stage, three agro-ecological zones were selected out of four and in the third stage we randomly selected three representative districts from the three agro-ecological zones; irrigated plains (Toba Tek Singh), marginal land (Rahim Yar Khan) and *Barani* (rain-fed) zone (Gujrat). Some parts of the Rahim Yar Khan also lie in irrigated plains. In the fourth stage, two sub-district divisions (*tehsils*) were randomly selected from each district. The fifth stage involved the selection of a certain number of rural union councils (UCs) from each sub-district division (*Tehsil)* using stratified random sampling and keeping in view the cropping patterns and distance of the UC to the city and to other UCs. In the sixth stage, a certain number of villages were selected from each UC using simple random sampling. In total, we surveyed 65

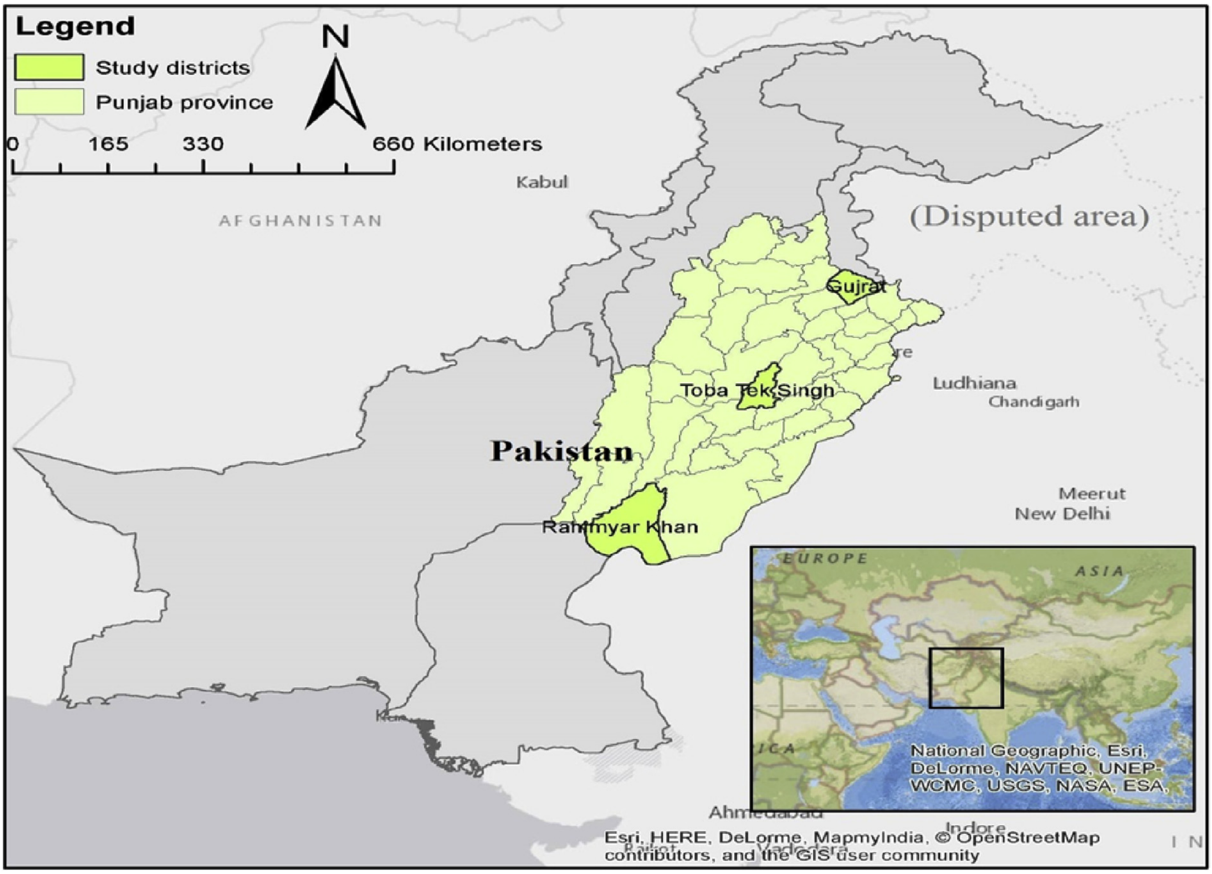

Fig. 1. Map of study districts in Punjab, Pakistan.

villages across the three regions. In the seventh stage, farmers were randomly selected from each village from a list of farmers collected from the revenue department. A pre-tested structured questionnaire was used for face-to-face interviews to collect information on the farmers' socio-economic characteristics, adaptation strategies, access to different institutional services and cropping technologies. The enumerators were trained prior to the survey about the study objectives and data collection tools.

2.2. Conceptual framework

The conceptual framework of this study is based on a top-down approach starting with climate change vulnerability at farm level and ending with implications for farm income and local food security (Fig. 2). As shown in Fig. 2, the study framework consists of three components; climate change vulnerability (left vertical box), adaptation processes (upper horizontal box) and farmers' wellbeing (lower horizontal box). Dotted and straight lines represent the interactions between the three components of the framework. Specifically, the dotted lines show adverse effects such as reduced productivity or farmers' wellbeing while straight lines show positive effects such as improved crop productivity or farm welfare through improved access to food. In this study (as shown in the first vertical box of Fig. 2), we defined climate change as perceived or observed changes in the local environment over the last ten to twenty years or more in terms of occurrence of extreme climatic events such as extreme temperature events, uncertain rains, floods or droughts (Bryan et al., 2013).

Climate change could affect farmers' wellbeing negatively (dotted line) directly or indirectly by affecting food productivity and net crop income through reduced per hectare crop yields (Abid et al., 2015; Antwi-Agyei et al., 2014). Here, food productivity mainly refers to wheat productivity as wheat is the primary staple food in Pakistan. The adverse impact of climate change on food productivity may have direct implications for local food security by limiting the production of wheat grains. However, farmers could reduce losses from climate change by timely management of their crops accordingly. The adoption of certain measures at farm level may not only help farmers to reduce potential losses due to climate change, but it may also have positive impacts on crop productivity and net income. The improved crop productivity and revenue may ultimately improve food security at household level and hence improve farmers' wellbeing. In contrast, the no-adaptation pathway could potentially adversely affect crop productivity and farmers' wellbeing.

2.3. Analytical framework

2.3.1. Adaptation decisions

In this study, we defined adaptation to climate change as a measure to avoid losses due to changes in climatic indicators, temperature and precipitation. A farmer will be considered as an adapter if he implements certain wheat management measures and as a non-adapter if he does not. Following Kato et al. (2011), we use a random utility framework to model adaptation decisions of wheat farmers. We assume that the *i*th farmer will choose to adapt the wheat crop to climate change only if the expected net benefits from adaptation are positive (Abid et al., 2015). The adaptation benefits may include reduced crop losses or improved farmers' wellbeing. This difference in net benefits may be expressed in form of a latent

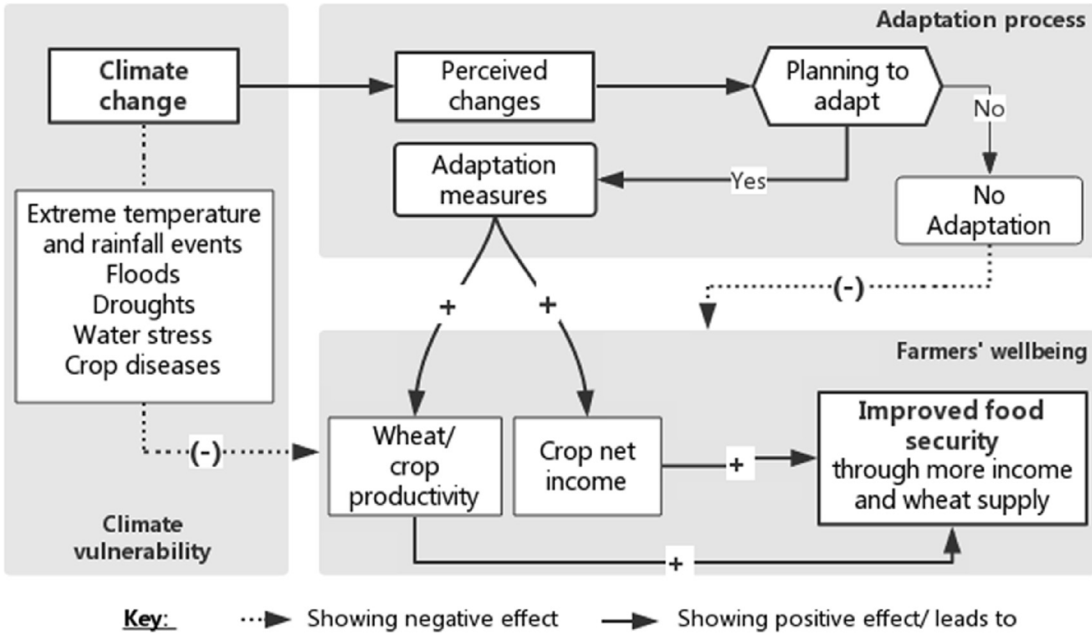

Fig. 2. Conceptual framework of the study showing interactions among climate change, adaptation and farmers' wellbeing.

variable (U_i*):

$$U_i^* = \beta X_{ik} + \mu_i \tag{1}$$

where X_{ik} is the vector of k explanatory variables, β is the vector of logistic regression coefficients and μ_i is the error term. As the latent variable (U_i*) is unobservable, we have only:

$$U_i = \begin{cases} 1 & if \;\; U_i^* > 0 \\ 0 & if \;\; U_i^* \leq 0 \end{cases} \tag{2}$$

where U_i indicates that the ith farmer will adapt his wheat cultivation to climate change ($U_i = 1$) only if the net benefits from adaptation are positive ($U_i^* > 0$). In contrast, the ith farmer will not adapt to climate change ($U_i = 0$) if the net benefits are non-positive ($U_i^* \leq 0$).

Efficient adaptation to climate change could help increase crop productivity and net income and hence could improve farm welfare. However, it might be difficult to differentiate between welfare of adapters and non-adapters. In cases where experimental data are collected through randomization and information on the counterfactual situation is recorded, it would be easy to distinguish the differences between adapters and non-adapters (Ali and Abdulai, 2010). For cross-sectional data, as is the case in this study, when no counterfactual information is available, the direct effect of adaptation could be calculated by looking at the differences in outcomes of adapters and non-adapters. However, these estimates may be misleading and biased.

To measure the net impact of adaptation on wheat productivity and net crop income, the issue of self-selection bias is crucial. To show the importance of self-selection bias, let us assume a reduced-form ordinary least square (OLS) equation that demonstrates the relationship between adaptation and outcome variables:

$$Y_{ij} = \lambda X_{ik} + \Psi U_i + \varepsilon_i \tag{3}$$

where Y_{ij} is the vector of outcome variables such as wheat productivity and net crop income for the ith farmer and ε_i is the error term. Similar to Eq. (1), X_{ik} represents the vector of explanatory variables and λ and Ψ are the regression coefficients. It might be possible that the decision to adapt (U_i), which is assumed to be independent in the above Eq. (3), may be influenced by some unobservable factors e.g. farmer's knowledge, perceptions or managerial skills which are already part of the error term (ε_i) of Eq. (3) (Ali and Abdulai, 2010). In other words, the error term (ε_i) of Eq. (3) may be correlated with the error term (μ_i) of Eq. (1) and the resulting selection bias may yield biased estimates (Kassie et al., 2011; Thoemmes, 2012). The literature shows various methods to address this selection bias. Some studies have adopted the Heckman two-step method that assumes a normal distribution of unobserved variables. Another method employs instrumental variables (IV). This approach usually requires at least one variable in the treatment equation to serve as an instrument for the specification of the outcome equation. Finding valid instruments is a challenge for many empirical analyses (Heckman et al., 1998). Moreover, both OLS and IV procedures restrict the model to take a linear functional form, implying that the coefficients on the control variables are similar for treatment and control groups (Ali and Abdulai, 2010).

2.3.2. Propensity score matching

Another widely used method to deal with the problem of selection bias is propensity score matching (PSM), which is also employed in this study. The PSM technique pairs the treatment (adapters) and control (non-adapters) groups based on the similarity of observable characteristics (Dehejia and Wahba, 2002). In contrast to the OLS and IV techniques, the PSM technique relaxes the assumptions of functional form, normal distribution of unobserved covariates and finding instrumental variables for the specification of the outcome equation. It only requires a set of observable covariates for matching and to determine causal effects of treatment on the outcome variable (Heckman and Vytlacil, 2007). One limitation of PSM is that it does not account for the unobservable variables directly; rather it assumes that selection is based on observable variables. PSM can be a better choice when instruments are weak or not available (Ali and Abdulai, 2010).

Following Rosenbaum and Rubin (1983), we defined PSM as the conditional probability that a farmer adapts to climate change, given the pre-adaptation characteristics. Employing the conditional independence assumption for a randomized experiment, the PSM constructs a statistical comparison group by matching adapters and non-adapters based on the similarity of their predicted probabilities of adapting to climate change (p-score) (Kassie et al., 2011; Thoemmes, 2012). Once this assumption is set or X_{ik} is controlled for all unobserved factors, this implies that adaptation to climate change is random and uncorrelated with outcome variables. The PSM can be represented as:

$$\mathrm{p}(X_{ik}) = Pr[U_i = 1 | X_{ik}] \tag{4}$$

where p shows the propensity scores of pre-adaptation characteristics (X_{ik}), Pr is the probability and U_i indicates the adaptation to climate change. The conditional distribution of X_{ik} is similar to both adapters and non-adapters (Thoemmes, 2012).

In summary, we can divide PSM into five steps. In the first step, a set of pre-test covariates is selected based on theoretical assumptions. The second step involves the estimation of propensity scores (p-value) using a logistic regression where outcome variables are regressed over the selected covariates (Kassie et al., 2011). In the third step, a matching procedure is conducted using the nearest neighbor method (NNM) for matching (Ali and Abdulai, 2010). In the fourth step, causal effects of adaptation on outcome variables are calculated. In the fifth and last step, a sensitivity analysis for matched data is employed to check the adequacy of the results (for more detail on the steps of PSM, please see Figure B.1 in Appendix B). In this study, the whole empirical analysis was conducted using the SPSS and R statistical packages.

2.3.3. Causal effect of adaptation to climate change

The effect of adaptation to climate change on outcome variables may be represented in terms of average treatment effect (ATE) or average treatment effect on the treated (ATT), where treatment refers to adaptation to climate change. The term ATE represents the overall impact of adaptation on the outcome variables considering all respondents, while the term ATT measures the impact of adaptation on the outcome variables only for the treated respondents (i.e. matched adapters and non-adapters). Following Ali and Abdulai (2010), the effect of adaptation on the outcome variables may be expressed as:

$$\tau_{U_{i=1}} = E(\tau | U_i = 1) = E(Y_1 | U_i = 1) - (Y_0 | U_i = 0) \tag{5}$$

where τ is the average treatment effect (ATE) for all respondents (in our case treatment is the adaptation to the climate change) and Y_1 and Y_0 shows the values of the outcome variables for adapters and non-adapter respectively. As discussed above, we do not observe $E\ (\tau |\ U_i = 1)$ directly, although we can estimate the difference $[\tau^e = E\ (Y_1 | U_i = 1) - E\ (Y_0 | U_i = 0)]$ which is a bias estimator. To account for this selection or hidden bias, we can employ the propensity score model (PSM) (Dehejia and Wahba, 2002).

As we are more interested in the average treatment effects on the treated (ATT), so it can be computed after estimating the propensity scores as:

$$T = E\{Y_1 - Y_0 | Ui = 1\} = E[E\{\mathrm{Y}_1 - \mathrm{Y}_0 | \mathrm{Ui} = 1,\ \mathrm{p(X)}\}]$$
$$= E[E\{Y_1 | Ui = 1,\ \mathrm{p(X)}\} - E\{Y_0 | Ui = 0,\ \mathrm{p(X)}\} | Ui = 0] \tag{6}$$

where T indicates the ATT and $p(X)$ indicates the propensity scores as explained in Equation (4). As discussed above, we here employed the NNM method which involves selecting individual cases (wheat farmers) from both groups of adapters and non-adapters as matching partners based on their closeness to each other. The closeness is measured by using propensity scores. The NNM method matches the adapters and non-adapters and excludes the unmatched cases from both groups (Smith and Todd, 2005). In other words, we could say that ATT is acquired after subtracting the effect of selection bias (the inherent differences between the adapters and non-adapter) from the ATE.

2.3.4. Sensitivity analysis

The key purpose of the PSM is to stabilize the estimated distribution of covariates across the groups of adapters and non-adapters (Lee, 2013). If there are some unobserved factors that simultaneously affect the adaptation decision and outcome variables, a hidden bias problem might arise and matching estimates will not be robust (Rosenbaum, 2002). Hence, after matching, we perform a series of model adequacy tests to ensure that there are no systematic differences in the distribution of the covariates between groups of adapters and non-adapters (Ali and Abdulai, 2010). Available indicators include pseudo R^2, F-statistics, the Hosmer and Lemeshow test and standardized mean differences before and after matching. Further, we also use the Rosenbaum (2002) bound test to check the sensitivity of the estimated average adaptation effects (ATT) to hidden bias by calculating the Wilcoxon signed rank. The p-value of the Wilcoxon signed rank test tells us how significant the treatment effect is (Keele, 2010; Rosenbaum, 2007). If the p-value is less than the usual 0.05 threshold, we reject the null hypothesis of no treatment (adaptation) effect.

3. Results and discussion

3.1. Farm and household descriptive statistics

Table 1 presents the description and summary statistics of the variables used in the study. The differences in characteristics of adapters and non-adapters show how important these factors are to understand local adaptation to climate change. The table shows that wheat yield, net crop and farm income were found to be slightly higher in the case of adapters than of non-adapters. Likewise, adapters had more farming experience, education and more land under cultivation compared to non-adapters. These results are in line with the findings of other studies (e.g. Abid et al., 2015; Antwi-Agyei et al., 2014; Bastakoti et al., 2014), which found that educated and experienced farmers adapted more compared to less educated and less experienced farmers. It might be possible that educated and experienced farmers were more observant and better informed than less educated and less experienced ones about the ongoing changes in the environment and ultimately adapted more. Likewise, adapters had larger-scale farms and more access to institutional services (e.g. extension, credit and market information, weather forecasting) than non-adapters. These findings confirm that access to institutional services may have a positive

Table 1
Description, units and statistics of variables used in the study.[b]

	Adapters	Non-adapters	Difference[a]
Wheat yield (tons/hectare)	4.08	4.05	0.03
Wheat net returns (thousand PKR/hectare)	75 ($743)	74 ($733)	1 ($9.9)
Total returns from wheat crop (thousand PKR)	278 ($2752)	276 ($2736)	2 ($17)
Total farm income (thousand PKR)	1050 ($10,395)	1041 ($10,308)	8.8 ($87)
Farming experience (years)	26.55	23.31	3.25
Education (years of schooling)	9.62	7.95	1.68
Household (HH) size (numbers)	9.91	9.58	0.33
Household head (1 if farmer is HH's head, zero otherwise)	0.76	0.77	−0.01
Agricultural source of income (1 if agriculture is the main income source, 0 otherwise)	0.62	0.63	−0.01
Wheat area (hectares)	9.34	5.18	4.16
Tenancy (1 if farmers is owner-cultivator, zero otherwise)	0.73	0.85	−0.11
Tube well (1 if farmer owned a tube well, zero otherwise)	0.68	0.61	0.07
Soil fertility (1 if soil is fertile, zero otherwise)	0.56	0.67	−0.10
Credit services (1 if farmer had access, zero otherwise)	0.10	0.09	0.01
Extension services (1 if farmer had access, zero otherwise)	0.27	0.25	0.02
Market information (1 if farmer had access, zero otherwise)	0.70	0.65	0.05
Weather forecasting information (1 if farmer had access, zero otherwise)	0.92	0.79	0.13
Rahim Yar Khan (1 if farmer belonged to the district, zero otherwise)	0.35	0.31	0.04
Toba Tek Singh (1 if farmer belonged to the district, zero otherwise)	0.21	0.40	−0.19
Observations	149	293	

[a] The difference is calculated by subtracting averages of non-adapters from averages of adapters.
[b] Here we used the average exchange rate for year 2013 (1 $ = 101.01 PKR), when the survey was actually carried out.

impact on the farmers' adaptation decision. These results agree with the results of Bastakoti et al. (2014) and Bryan et al. (2013). However, non-adapters were found to have a larger household size and greater dependence on agricultural income. This implies that higher dependency of a household on agriculture may restrict farmers from adapting to climate change.

3.2. Farm level perceptions of and adaptation to climate change

To investigate the farmers' current understanding of climate change and farm level adaptation processes, we jointly assessed the perceptions of farmers along with planned and actual adaptation measures to perceived changes in climate across three study districts (Fig. 3). Results show a substantial reduction in farm-level responses moving from perception to planning and adaptation. On average, 80% of the farmers perceived changes in climate over the past 10–20 years. Still 75% of farmers planned some adaptive measures to observed changes but only 37% of the farmers actually implemented adaptation measures for wheat cultivation. The same trend can be seen in all three study districts. The difference between perceptions, planning and actual adaptation may be due to some internal or external constraints that limit adaptation to climate change in the study districts.

Farmers adopted various measures to adapt their wheat crop to climate change across the three study districts (Fig. 4). Overall, the major strategies were changing planting dates, changing crop variety and changing fertilizer types such as urea, diammonium phosphate, nitrophos and single superphosphate. Modified planting dates include both early and delayed sowing depending on weather conditions. As discussed earlier, the majority of the adapters use weather forecasting information from different sources to adjust management options, particularly the wheat planting

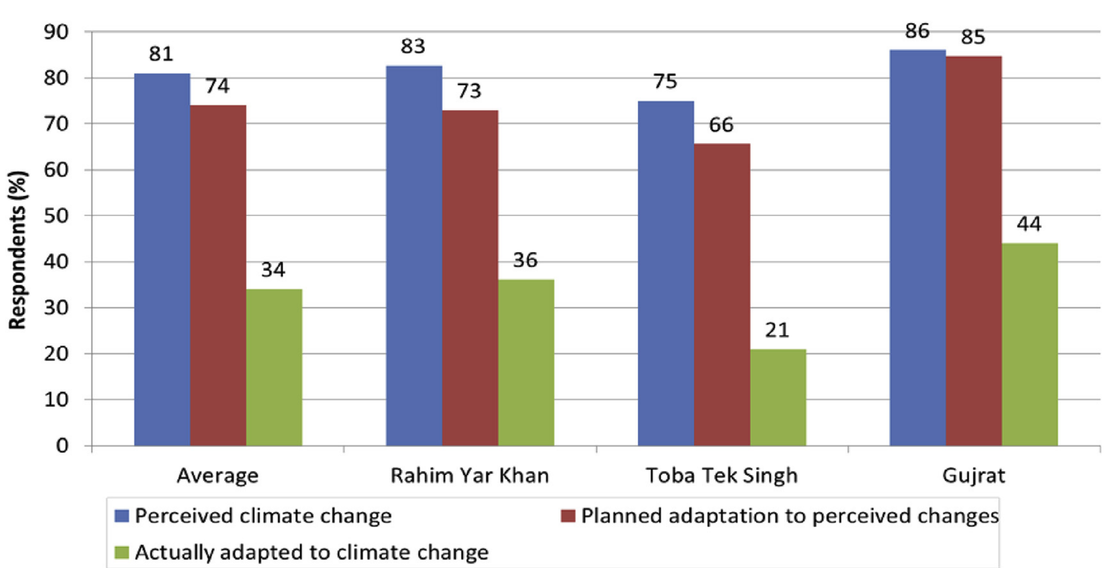

Fig. 3. Average difference between perceptions, planning and actual adaptation to climate change.

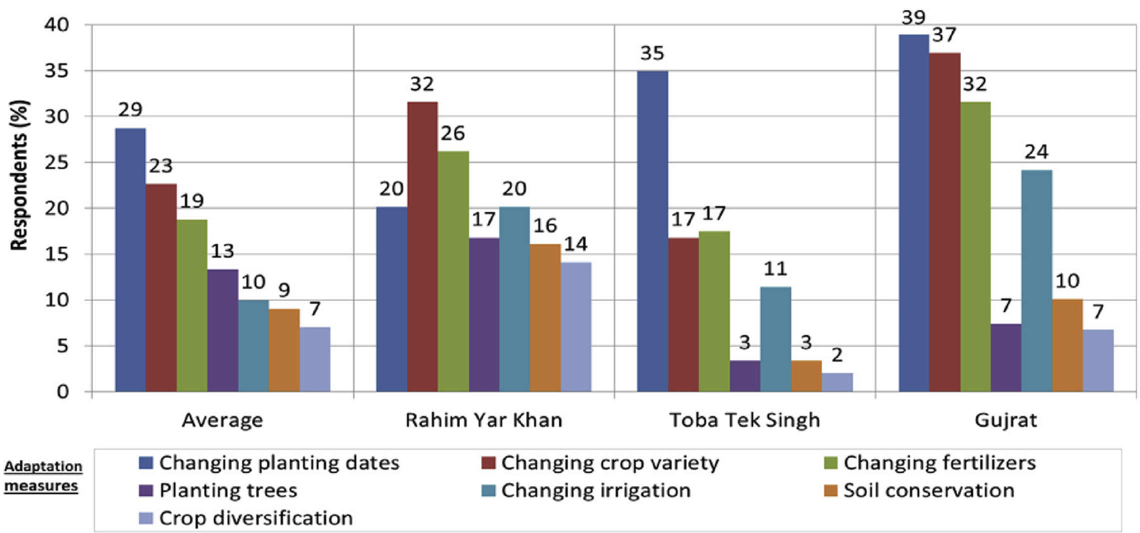

Fig. 4. Adaptation measures used by wheat farmers in three study districts of Punjab. Note: The sum is greater than 100 because some adaptation measures can be selected simultaneously.

dates. For instance, farmers in the *Barani* (rain-fed) region used this technique more often due to their higher dependence on rainfall for wheat sowing. Further, crop variety adaptation includes switching from traditional wheat varieties to heat and drought-tolerant varieties to protect the crop from increasing temperature and water shortage. The implementation of adaptation measures by farmers in the three study regions differs according to regionally relevant crop needs and environmental problems. For instance, in Rahim Yar Khan, changing crop variety was the primary adaptation measure adopted by farmers while changing planting dates was the major adaptation measure adopted by farmers in Gujrat and Toba Tek Singh. These findings may be supported by the findings of other studies (e.g. Asif, 2013; Bukhari and Sayal, 2011), which reported an increasing water shortage in rain-fed (including Gujrat) and semi-arid regions (including Toba Tek Singh) due to ongoing climate change. Similarly, Ahmad et al. (2013) also reported a shift in planting dates in rain-fed regions due to climate change. Interestingly, most of the adaptation measures implemented by wheat farmers were of short-term nature. Long-term measures such as crop diversification and soil conservation were the measures adopted least often by farmers across all three study regions. This may imply that either farmers do not have sufficient funds to implement advanced measures or they do not have proper knowledge about advanced measures. Several other studies (e.g. Bryan et al., 2013; Deressa et al., 2009; Gbetibouo, 2009) have identified the existence of various resource and financial constraints that restrict farmers to effectively adapt their crops to climate change.

Further, we analyzed the farm level adaptation measures across different categories of farmers, i.e. the size of their land holdings and their educational level (see Fig. 5 (a, b)). Concerning farm size, farmers were divided into three categories: 1) small-scale farmers, who owned up to 2 ha of land; 2) medium-scale farmers, who owned 2–5 ha of land; and 3) large-scale farmers, who owned more than 5 ha of land. Regarding their educational level, farmers were divided into two categories: 1) illiterate or less educated

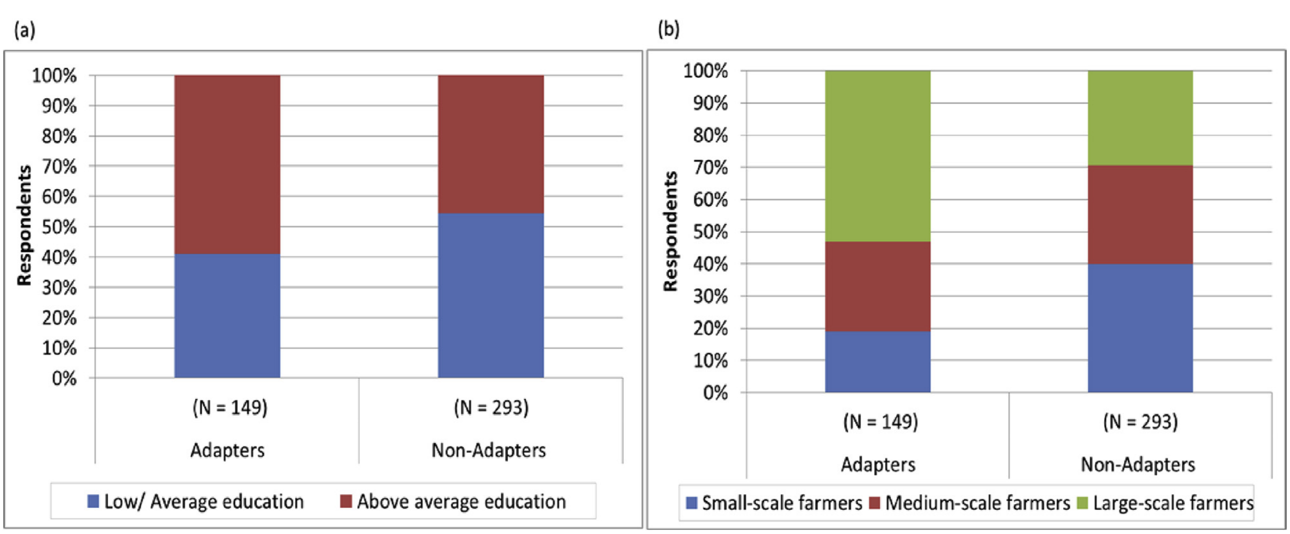

Fig. 5. (a)–(b) Distribution of adapters and non-adapters with respect to their education and size of land holding (% of group sample).

farmers with less than eight years of schooling and 2) educated farmers with eight or more years of schooling.

The results in Fig. 5a show a positive association of adaptation decisions with education level. About 39% of the farmers with above-average education adapted to climate change, while of the farmers with below-average education, only 27% adapted to climate change. Similar positive associations of adaptive behavior with education were reported by Wood et al. (2014) and Bryan et al. (2013). Furthermore, Fig. 5a shows a higher rate of adaptation for large-scale farmers compared to the small-scale farmers. The share of large-scale farmers was 53% among adapters but only 29% among non-adapters. The proportion of medium-scale farmers was similar for adapters and non-adapters. Small-scale farmers, on the other hand, comprised only 19% of the adapters but 40% of the non-adapters. This suggests that large-scale farmers faced fewer restrictions to adapt to climate change. These results are in line with findings of Sahu and Mishra (2013) who reported a positive relationship between land holding and adaptation to climate change. These results are in line with the findings of previous studies on farm level adaptation (e.g. Bryan et al., 2013; Silvestri et al., 2012), which indicated a positive relationship between education and adaptation to climate change.

3.3. Empirical results

3.3.1. Results of propensity score matching

As described above, the matching process starts with the estimation of propensity scores for the treatment variable. For this purpose, we used a logistic regression model, where the probability of adapting to climate change was regressed to a number of covariates. The results of estimation of the propensity score are reported in Table 2.

The results indicate that many of the households and farm-specific variables influence the probability of climate change adaptation. In particular, farming experience, education, an agricultural source of income, market information and weather forecasting information have positive coefficients and tend to expedite adaptation to climate change. These findings confirm our expectations from before the survey and also agree with the findings of other studies (e.g. Bryan et al., 2013; Deressa et al., 2009; Hassan and Nhemachena, 2008; Nabikolo et al., 2012). On the other hand, tenancy status (if the farmer is the owner-cultivator), soil fertility, farm credit and location of the farmer in either Rahim Yar Khan or Toba Tek Singh have negative coefficients. Unlike the findings of some studies (e.g. Fosu-Mensah et al., 2012; Iheke and Agodike, 2016) mainly conducted in Africa, a negative coefficient of tenancy status in this study implies that owner-cultivators were less likely to adapt to climate change compared to the tenants or sharecroppers. The differences in adaptation intentions between tenants and owner-operators may be due to the differences in their educational status, household dependency and resource access. For instance, here in this study the tenants were found to be more educated and have larger households than the owner-operators, which may be the cause of their higher adaptation intentions. Another potential reason may be the tenants' plan to maximize their profit to offset the land rents and to sustain a larger household. Similar to our findings, Javed et al. (2015) and Nabikolo et al. (2012) also reported a negative association of land tenancy and adaptation behavior. According to Javed et al. (2015), higher dependency on farm income and payment of land rents may be the main reasons behind tenants' adaptation intentions (Javed et al., 2015). The negative coefficients for regional dummies imply that farmers in both districts (Rahim Yar Khan and Toba Tek Singh) were less likely to adapt to climate change compared to the farmers located in Gujrat district. This may be due to the fact that farmers in Gujrat were more concerned about climate change as their farming is more dependent on climatic factors, particularly rainfall.

Table 2
Estimation of propensity scores through logistic regression.

	Estimate	Standard error	z-value
Farming experience (years)	0.04	0.01	3.46***
Education (years)	0.13	0.03	4.16***
Household size (numbers)	0.02	0.02	0.94
Household head (dummy)	−0.15	0.29	−0.54
Agricultural income source (dummy)	0.56	0.29	1.94**
Area under wheat crop (hectares)	0.00	0.01	−0.09
Tenancy status (dummy)	−0.84	0.28	−3.00***
Tube well (dummy)	0.29	0.24	1.18
Soil fertility (dummy)	−0.33	0.25	−1.32
Farm credit (dummy)	−0.12	0.40	−0.29
Agricultural extension (dummy)	0.11	0.29	0.36
Market information (dummy)	0.65	0.27	2.39**
Weather information (dummy)	0.86	0.36	2.38**
District R.Y. Khan (dummy)	−0.77	0.37	−2.08**
District T.T. Singh (dummy)	−1.61	0.38	−4.24***
(Intercept)	−2.88	0.70	−4.11***
Number of observations		442	
Hosmer p-value		0.33	
Pseudo R-squared		0.23	

***, ** and * show the significance at 1%, 5% and 10% probability levels, respectively.

3.3.2. Farm level adaptation impacts on food productivity and crop income

After calculating the propensity scores, the nearest neighbor matching (NNM) method was employed to match the control group of individuals (non-adapters) to the treated group (adapters) based on similar propensity scores. During the matching process, the NNM discards the unmatched non-adapters and hence, it leads to the reduction in sample size from 442 to 298 for the post-matching impact analysis (Figure B.2 in Appendix B show the distribution of propensity scores of matched and unmatched individuals in both groups). In the next step, we calculated the average adaptation effects on the wheat productivity (t/ha) and per hectare net crop income before matching (ATE) and after matching (ATT) (Table 3).

The post-matching results reveal that adaptation tends to positively and significantly affect wheat productivity and crop income. The values of ATT illustrate that adapters produced 0.14 t/ha more wheat than non-adapters. Further, adaptation generates PKR 5142 ($51) per hectare more returns for adapters. However, the ATE values depict larger yield gains (0.23 t/ha) and higher crop income improvements (PKR 7370 ($73) per hectare) compared to the ATT estimates. Mainly, the difference between the ATT and ATE values is due to the selection bias that comes from the effect of other observable factors and was removed using the propensity score matching technique. If the matching procedure was not performed before the estimation of adaptation impacts, the results might be biased and misleading.

Higher productivity and higher crop income for adapters also implies a positive impact of adaptation on overall farmers' wellbeing. In addition, the higher yield impacts of adaptation (0.14 t/ha) may lead to the supply of extra 457,800 kcal per hectare which could indirectly improve the local food security situation to some extent by reducing the gap between supply and demand of food calories. These results are generally in line with the findings by Gorst et al. (2015) for different regions of Pakistan, where adaptation shows a positive impact on wheat, cotton and rice yields.

Table 3
Impact of adaptation on wheat productivity and net crop income.

	Wheat yield (tons/ha)	Net crop income (PKR/ha)
Number treated (Adapters)	149	149
Number control (Non-adapters)	149	149
ATE	0.23 (0.002)*	7370 (1.86)*
ATT	0.14 (0.003)*	5142 (1.37)*
Wilcoxon signed rank (WSR) P-value	0.04	0.02
Confidence interval for treatment effect (C.I.)	1.05–1.10	1.10–1.15

* shows the significance at 10% probability level.

Table 4
Indicators of covariate balancing before and after matching.

Indicators of covariates balancing	Before matching	After matching
Pseudo R2	0.23	0.05
p-value of Likelihood ratio	0.00	0.72
F-stat value	81.42 (0.00)	11.40 (0.29)
Hosmer and Lemeshow test values	11.14 (0.33)	9.18 (0.19)
Mean standardized difference	0.18	0.07
Total% bias reduction	–	61

Values in parenthesis show the significance level (p-value).

As discussed earlier, different measures were used to ensure the adequacy of the results. Table 4 demonstrates the indicators of the matching quality from the matching model. The results indicate a decline in the model goodness of fit (pseudo-R2) after matching, which implies that after matching there is no systemic difference in the distribution of covariates between adapters and non-adapters and therefore any difference in the outcomes of both groups would only be due to the adaptation. Further, the significance level (p-value) for the likelihood ratios shows a shift from a highly significant model to a highly insignificant model after matching, which depicts that the covariates are no more associated with adaptation decisions after matching. The F-value of models also demonstrates the overall insignificance of the model after matching and the same applies for the Hosmer and Lemeshow test which shows a decline in model estimation power after matching. The mean standardized difference for distance has also declined, and matching shows overall 61% reductions in selection bias. All results reveal that substantial reduction in bias was obtained through matching and the model is no more dependent on observable factors as it was before matching.

The results of the Rosenblum's sensitivity analysis for the presence of hidden bias are shown in Table 3. Generally, the results agree with findings from other studies (e.g. Faltermeier and Abdulai, 2009; Kassie et al., 2011). For instance, for the impact of adaptation to climate change on wheat yield, the sensitivity analysis recommends that at confidence interval (CI) = 1, the mean difference in the per hectare wheat yields between adapters and non-adapters is 0.14 t/ha if there is no selection bias. Furthermore, at CI = 1.15, the causal inference of the significant treatment (adaptation) effect needs to be critically observed, which implies that the significance of the treatment effect on wheat yield may be questionable if individuals (farmers) differ in their odds of adapting to climate change by a factor of 15%. The critical value of CI for the adaptation impact on wheat net crop income is 1.10, which implies that the treatment (adaptation) effect may change if the covariates differ by 10% from current values. Hence, based on the results of the sensitivity analysis, we can reject the null hypothesis of no treatment

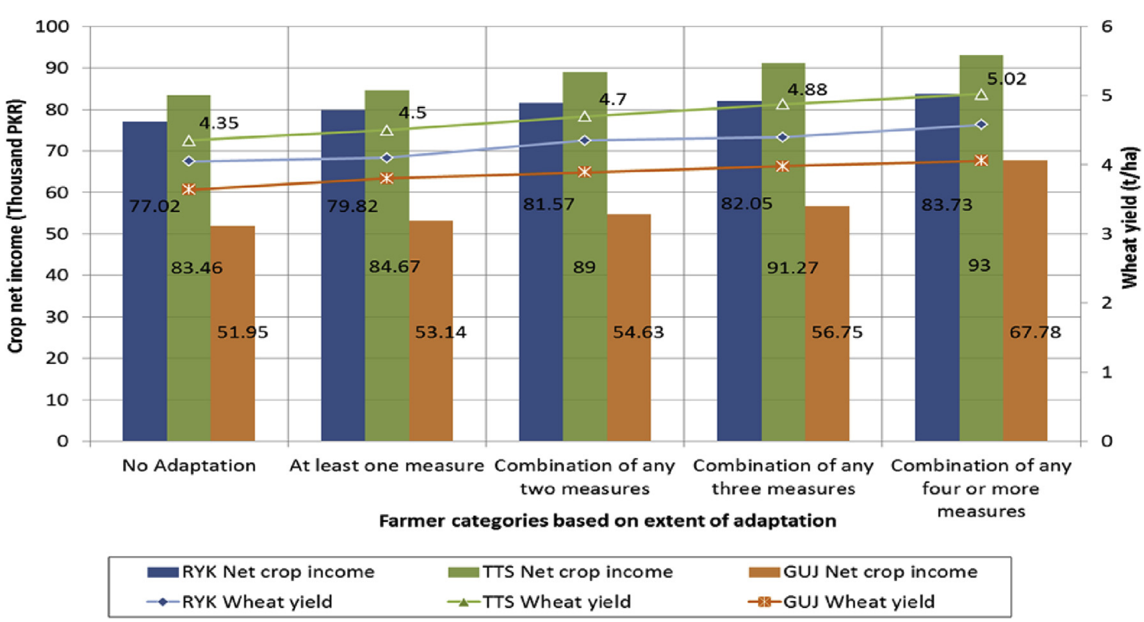

Fig. 6. Wheat productivity and net crop income among farmers' categories based on the extent of adaptation. * here RYK, TTS and GUJ stand for Rahim Yar Khan, Toba Tek Singh and Gujrat respectively.

(adaptation) effect on outcome variables. We can conclude that adaptation has a significant positive impact on crop yield and net crop income.

Furthermore, we compared the wheat productivity and net crop income of different categories of farmers based on their extent of adaptation or number of adaptation measures (Fig. 6). The results indicate that wheat yield and crop income increases with the increase in the extent of adaptation. This implies that farmers who adopted more adaptation measures achieved higher wheat yields (t/ha) and net income levels (PKR/ha) than non-adapters or farmers who took fewer adaptation measures. These findings are in line with the findings of other studies (e.g. Ahmed et al., 2015; Gorst et al., 2015) conducted in a similar context.

4. Conclusions and policy implications

Climate change is expected to adversely affect agricultural productivity and rural livelihoods in Pakistan. Thus, timely adaptation is desirable to reduce potential losses at the farm level. This case study analyzes wheat farmers from rural Pakistan and provides insights into their adaptation to climate change, their determinants and impacts of adaptation on food productivity and crop income.

The study reveals the extent to which farmers perceive climate change and adapt their wheat crop accordingly. While relatively many farmers recognize climate change as a real and ongoing development, we find a substantial reduction in farm-level responses moving from perception to planning and adaptation given the existence of various information, resources and financial constraints. Farmers adapt their wheat crop to climate change ranging from short-term to long-term measures. The key adaptation measures across all three regions include changing planting dates, crop varieties, fertilizer types and planting trees. However, adaptation decisions are significantly affected by various internal and external factors. In particular, education, farming experience, access to agricultural extension, weather forecasting, marketing information and agricultural income source were the important factors influencing the farmers' adaptation decision. In addition, the study also reveals that large-scale farmers adapt more than small-scale farmers adapt, which also shows the importance of access to resources for adaptation to climate change.

Moreover, the empirical findings of the study confirm that adaptation tends to increase wheat productivity and net income at the farm level. These gains show the effectiveness of adaptation at farm level and its contribution to overall caloric supply to a household. Current adaptation is found to be dominated by short-term and less costly measures and shows room for improvement if proper support and information is provided at the farm level. In addition, the study also finds that adaptation benefits increase with the use of more combinations of different adaptation measures compared to single measures. This also shows that utilizing the full adaptation potential may not only help farmers to enhance their livelihoods but it may also support local food security. To fully utilize the benefits of adaptation, region-specific policies need to be designed, keeping in mind climate-related risks and farmers' needs in the particular area.

Overall, the study confirms and quantifies the claim that farm-level adaptation provides substantial benefits to farmers through improved incomes and to society through improved food security. However, farmers are yet unable to enjoy all the advantages of adaptation due to various constraints and lack of information on improved adaptation options. Here, the government, private sector organizations and non-governmental organizations may play a major role in addressing these constraints through active collaboration for the capacity building and education of farmers, easy access to climate-specific information and awareness on improved adaptation measures. Further, agricultural policies need to be updated based on on-the-ground research and attention should also be given to resource-constrained and small-scale farmers, who account for more than two-thirds of the total farming population in Pakistan. All these implications may lead to better adaptation of food crops to climate change and may be able to support farmers to improve their crop yields and ensure local food security.

Acknowledgements

This study is part of a Ph.D. research at University of Hamburg, Germany at the School of Integrated Climate System Sciences (SICSS). We thankfully acknowledge the funding sources for this research: Higher Education Commission (HEC), Pakistan (Ref: 1-1/PM/OSS-II/Batch-4/Germany/2012/9493); Deutscher Akademischer Austauschdienst (DAAD) (91549521); Kompetenzzentrum Nachhaltige Universität (KNU) (Anschub_34_2013) and the Research Group Climate Change and Security (CLISEC) in the Excellence Cluster "Integrated Climate System Analysis and Prediction" (CliSAP) supported by Deutsche Forschungsgemeinschaft (DFG) (EXC177). We thank to the local agricultural extension departments, farmers and enumerators for their time and cooperation in the process of successful data collection during March and April 2014. The authors appreciate the three anonymous reviewers and the editor for their constructive feedback to improve the quality of the paper. Last, but not least, we thank Ms. Sarah L. Nash for her assistance in the proof-reading of the manuscript.

Appendix A. Gaps between supply and demand of energy calories from wheat grains in Pakistan

Table A.1
Supply and demand of per capita wheat calories in Pakistan.

Year	Population (in thousands)	Annual wheat supply and demand (thousand tons)		Annual per capita wheat calories (Kcal)		
		Total production	Net consumption	Supply	Demand	Gap
2010	184,405	23,311	20,980	372,030	405,480	33,450
2011	187,343	25,214	22,693	396,091	405,480	9,389
2012	190,291	23,473	21,126	363,028	405,480	42,452
2013	193,239	24,211	21,790	368,730	405,480	36,750
2014	196,174	25,286	22,757	379,340	405,480	26,140

Source: (own calculations based on FAO, 2015).
Caption: Annual per capita wheat calories are calculated at rate of 3270 thousand kcal per ton of wheat grain. The supply of per capita wheat calories is derived from net consumption available to the households while the caloric demand is calculated at the annual per capita requirement of 0.125 ton of wheat grains in Pakistan.

Appendix B. Propensity score matching procedure

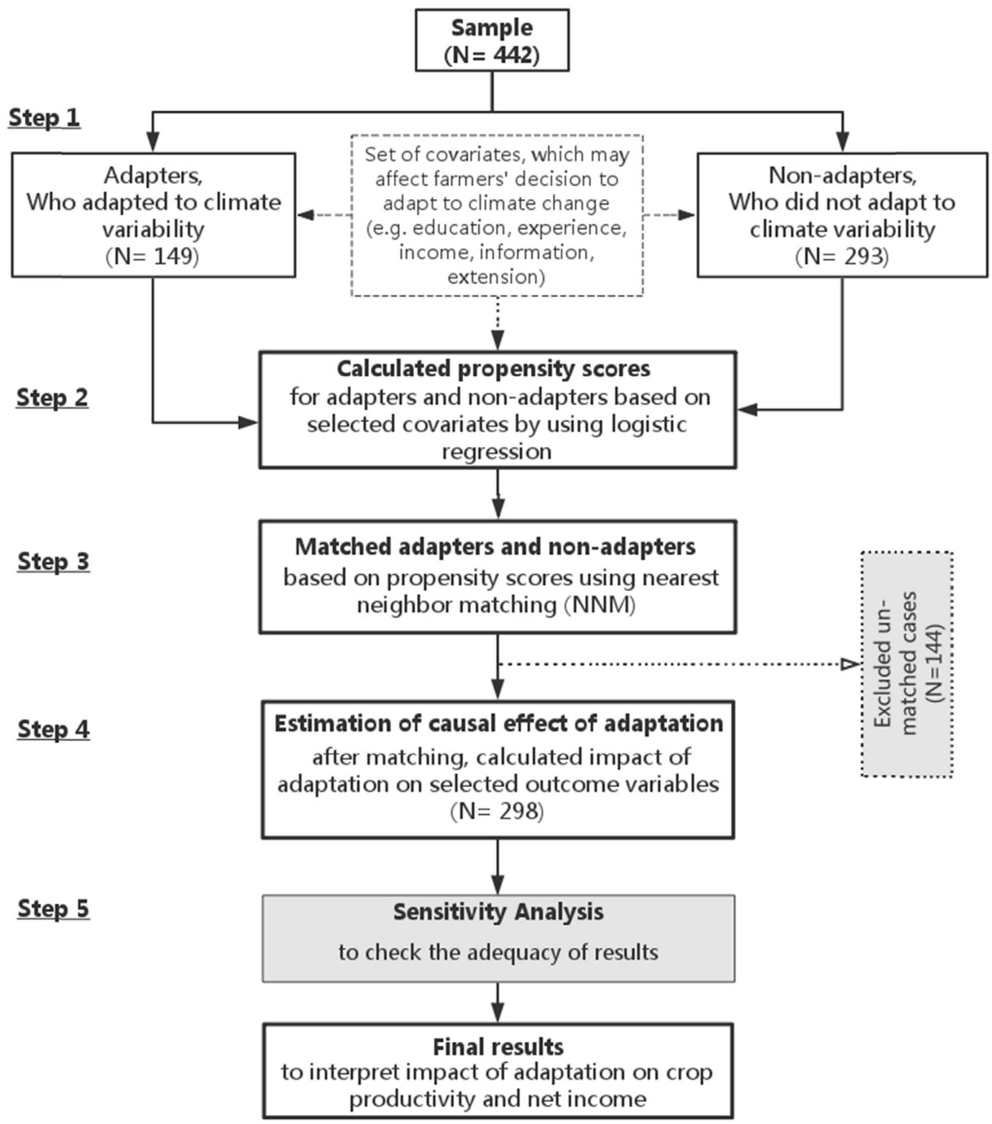

Fig. B.1. Steps involved in performing propensity score matching (PSM).

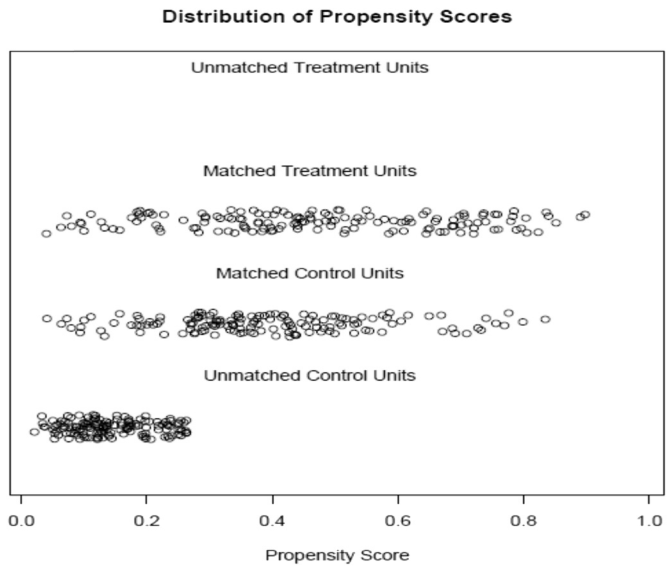

Fig. B.2. Distribution of propensity scores.

References

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

Abid, M., Scheffran, J., Schneider, U.A., Ashfaq, M., 2015. Farmers' perceptions of and adaptation strategies to climate change and their determinants: the case of Punjab Province, Pakistan. Earth Syst. Dyn. 6, 225–243.

Ahmad, M., Iqbal, M., Khan, M.A., 2013. Climate Change, Agriculture and Food Security in Pakistan: Adaptation Options and Strategies, Climate Change Brief. Pakistan Institute of Development Economics, Islamabad Pakistan.

Ahmed, M., Mustafa, G., Iqbal, M., 2015. Impact of Farm Households' Adaptations to Climate Change on Food Security: Evidence from Different Agro-ecologies of Pakistan. Climate change working papers. Pakistan Institute of Development Economics, Islamabad, Pakistan. Available at: http://pide.org.pk/pdf/Climate_Change_6.pdf (Last access: 01.01.2016).

Alam, M.M., Siwar, C., Bin Toriman, M.E., Molla, R.I., Talib, B., 2012. Climate change induced adaptation by paddy farmers in Malaysia. Mitig. Adapt. Strateg. Glob. Change 17, 173–186.

Ali, A., Abdulai, A., 2010. The adoption of genetically modified cotton and poverty reduction in Pakistan. J. Agric. Econ. 61, 175–192.

Antwi-Agyei, P., Stringer, L.C., Dougill, A.J., 2014. Livelihood adaptations to climate variability: insights from farming households in Ghana. Reg. Environ. Change 14, 1615–1626.

Asif, M., 2013. Climatic Change, Irrigation Water Crisis and Food Security in Pakistan. Department of Earth Sciences, Uppsala University, Uppsala, Sweden.

Bastakoti, R.C., Gupta, J., Babel, M.S., van Dijk, M.P., 2014. Climate risks and adaptation strategies in the Lower Mekong River basin. Reg. Environ. Change 14, 207–219.

Bradshaw, B., Dolan, H., Smit, B., 2004. Farm-level adaptation to climatic variability and change: crop diversification in the Canadian prairies. Clim. Change 67, 119–141.

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

Bukhari, M., Sayal, E.A., 2011. Emerging climate changes and water resource situation in Pakistan. Pak. Vis. 12.

Dehejia, R.H., Wahba, S., 2002. Propensity score-matching methods for nonexperimental causal studies. Rev. Econ. Stat. 84, 151–161.

Deressa, T.T., Hassan, R.M., Ringler, C., 2011. Perception of and adaptation to climate change by farmers in the Nile basin of Ethiopia. J. Agric. Sci. 149, 23–31.

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

Esham, M., Garforth, C., 2013. Agricultural adaptation to climate change: insights from a farming community in Sri Lanka. Mitig. Adapt. Strateg. Glob. Change 18, 535–549.

Faltermeier, L., Abdulai, A., 2009. The impact of water conservation and intensification technologies: empirical evidence for rice farmers in Ghana. Agric. Econ. 40, 365–379.

FAO, 2015. FAOSTAT 2015, Database for Wheat Crop, Pakistan. Food and Agriculture Organization of the United Nations, Statistics Division, Rome, Italy.

Farooq, A., Ishaq, M., Yaqoob, S., Sadozai, K.N., 2007. Varietal adoption effect on wheat crop production in irrigated areas of NWFP. Sarhad J. Agric. 23, 807.

Fosu-Mensah, B.Y., Vlek, P.L., MacCarthy, D.S., 2012. Farmers' perception and adaptation to climate change: a case study of Sekyedumase district in Ghana. Environ. Dev. Sustain. 14, 495–505.

Gbetibouo, G.A., 2009. Understanding Farmers' Perceptions and Adaptations to Climate Change and Variability: the Case of the Limpopo Basin, South Africa. Intl Food Policy Res Inst, Washington, D.C.

Gorst, A., Groom, B., Dehlavi, A., 2015. Crop Productivity and Adaptation to Climate Change in Pakistan. Centre for climate change economics and policy Working paper No. 214.

Hassan, R., Nhemachena, C., 2008. Determinants of African farmers' strategies for adapting to climate change: multinomial choice analysis. Afr. J. Agric. Resour. Econ. 2, 83–104.

Heckman, J., Ichimura, H., Smith, J., Todd, P., 1998. Characterizing selection bias using experimental data. Econometrica 66, 1017–1098.

Heckman, J.J., Vytlacil, E.J., 2007. Econometric evaluation of social programs, part II: using the marginal treatment effect to organize alternative econometric estimators to evaluate social programs, and to forecast their effects in new environments. Handb. Econ. 6, 4875–5143.

Iheke, O.R., Agodike, W.C., 2016. Analysis of factors influencing the adoption of climate change mitigating measures by smallholder farmers in Imo State, Nigeria. Analysis 16.

IPCC, 2014. In: Core Writing Team, Pachauri, R.K., Meyer, L.A. (Eds.), Climate Change 2014: Synthesis Report, Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. IPCC, Geneva, Switzerland, 151 pp.

Javed, S.A., Kishwar, S., Iqbal, M., 2015. From Perceptions to Adaptation to Climate Change: Farm Level Evidence from Pakistan. IDRC-PIDE Working Paper 7. Pakistan Institute of Development Economics, Islamabad, Pakistan.

Kassie, M., Shiferaw, B., Muricho, G., 2011. Agricultural technology, crop income, and poverty alleviation in Uganda. World Dev. 39, 1784–1795.

Kato, E., Ringler, C., Yesuf, M., Bryan, E., 2011. Soil and water conservation technologies: a buffer against production risk in the face of climate change? Insights from the Nile basin in Ethiopia. Agric. Econ. 42, 593–604.

Keele, L., 2010. An Overview of Rbounds: an R Package for Rosenbaum Bounds Sensitivity Analysis with Matched Data. White Paper, Columbus, OH, pp. 1–15.

Kreft, S., Eckstein, D., Dorsch, L., Fischer, L., 2016. Global Climate Risk Index 2016: Who Suffers Most from Extreme Weather Events? Weather-related Loss Events in 2014 and 1995 to 2014. Germanwatch eV, Bonn, Germany.

Lee, W.-S., 2013. Propensity score matching and variations on the balancing test. Empir. Econ. 44, 47–80.

Malik, S.J., Nazli, H., Whitney, E., 2014. Food consumption patterns and implications for poverty reduction in Pakistan. In: Annual General Meeting of Pakistan Society of Development Economists (PSDE). Pakistan Institute of Development Economics, Islamabad, Pakistan.

McCarl, B.A., Schneider, U.A., 2001. The cost of greenhouse gas mitigation in US agriculture and forestry. Science 294, 2481–2482.

Metz, B., Davidson, O., Bosch, P., Dave, R., Meyer, L., 2007. Mitigation of Climate Change. Cambridge University Press Cambridge.

Mugi-Ngenga, E., Mucheru-Muna, M., Mugwe, J., Ngetich, F., Mairura, F., Mugendi, D., 2016. Household's socio-economic factors influencing the level of adaptation to climate variability in the dry zones of Eastern Kenya. J. Rural Stud. 43, 49–60.

Nabikolo, D., Bashaasha, B., Mangheni, M., Majaliwa, J., 2012. Determinants of climate change adaptation among male and female headed farm households in eastern Uganda. Afr. Crop Sci. J. 20, 203–212.

Niles, M.T., Lubell, M., Brown, M., 2015. How limiting factors drive agricultural adaptation to climate change. Agric. Ecosyst. Environ. 200, 178–185.

Prikhodko, D., Zrilyi, O., 2013. Pakistan: Review of the Wheat Sector and Grain Storage Issues Country Highlights. Food and Agriculture Organisation, Rome.

Rosenbaum, P.R., 2002. Observational Studies. Springer.

Rosenbaum, P.R., 2007. Sensitivity analysis for m-estimates, tests, and confidence intervals in matched observational studies. Biometrics 63, 456–464.

Rosenbaum, P.R., Rubin, D.B., 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70, 41–55.

Sahu, N.C., Mishra, D., 2013. Analysis of perception and adaptability strategies of the farmers to climate change in Odisha, India. APCBEE Procedia 5, 123–127.

Schlenker, W., Lobell, D.B., 2010. Robust negative impacts of climate change on African agriculture. Environ. Res. Lett. 5, 014010.

Seo, S.N., Mendelsohn, R., 2008. A Ricardian analysis of the impact of climate change on South American farms. Chil. J. Agric. Res. 68, 69–79.

Sheikh, A.T., Elahi, E., Abid, M., Fatima, S., Fatima, N., 2012. Effect of sewage water on the cauliflower productivity in Punjab, Pakistan. J. Agric. Soc. Sci. Pak. 8, 37–40.

Silvestri, S., Bryan, E., Ringler, C., Herrero, M., Okoba, B., 2012. Climate change perception and adaptation of agro-pastoral communities in Kenya. Reg. Environ. Change 12, 791–802.

Smith, J.A., Todd, P.E., 2005. Does matching overcome LaLonde's critique of nonexperimental estimators? J. Econ. 125, 305–353.

Stocker, T.F., Dahe, Q., Plattne, G., 2013. Climate Change 2013: the Physical Science Basis. Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Summary for Policymakers (IPCC, 2013).

Thoemmes, F., 2012. Propensity Score Matching in SPSS arXiv preprint arXiv:1201.6385.

WB, 2014. World Development Indicators 2014. World Bank (WB) Publications.

Accessed from: http://data.worldbank.org/topic/agriculture-and-rural-development (Last access: 16.11.2015).
Wood, S.A., Jina, A.S., Jain, M., Kristjanson, P., DeFries, R.S., 2014. Smallholder farmer cropping decisions related to climate variability across multiple regions. Glob. Environ. Change 25, 163–172.
Zulfiqar, F., Hussain, A., 2014. Forecasting wheat production gaps to assess the state of future food security in Pakistan. J. Food Nutr. Disord. 3, 1–6.