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Adaptation to Climate Change in Afghanistan: Evidence on the Impact of External Interventions

Asadullah Jawid and Menusch Khadjavi

Preprint

Climate change is a significant obstacle for farmers in the least developed countries like Afghanistan and adaptation support is exceptionally scarce. This paper provides evidence on the impact of the agriculture-related external support on farmers' adaptation to climate change in the Central Highlands of Afghanistan. To this end, we collected primary data from 1434 farmers whom we interviewed across 14 districts in Bamiyan, Ghazni, and Diakundi provinces. We employ quasi-experimental econometric methods, including an endogenous switching regression analysis, to estimate the treatment effects on various adaptation-related outcomes. We find significant impacts of support interventions on the use of improved types of seeds and farmers' access to irrigation water. Further impacts on the risk of flood, economic and financial as well as government and institutional adaptation constraints appear to be significant, but sensitive to the existence of unobserved factors. We conclude that farmers perceived changes in the climate, and most of them tried to adapt by employing measures available to them. The impact of external support has been partially effective in addressing immediate and short-term farming challenges related to climate change and extreme weather events. They, however, have not been effective in treating long-term fundamental climate change-related risks. Based on our analysis of the past treatments and farmers' selfreported priorities, we provide a list of policy recommendations for adaptation to climate change in farming communities in Afghanistan.

1. Introduction

The literature agrees that global climate has been accompanied by a steady increase in the number and severity of climate-related extreme events, such as drought and flood (Jayatilleke & Yiyong, 2014). Climate change has caused impacts on both natural and human systems (IPCC, Working Group II, 2014; Islam, et al., 2016). Although scientific assessments indicate that the overall impact from climate change is unpredictable (Halkos & Skouloudis, 2016), it has been suggested that a 1-degree increase in temperature may induce a 10% ecosystem transformation and a loss in cereal production of 20-35 million tons (Tamaki, et al., 2017).

Farmers, mostly in least developed countries (such as Afghanistan), are relatively more affected by the impacts of climate change and extreme weather events (Mendelsohn, et al., 2006). Apart from a high level of exposure to the impacts of climate change, limited resources for adaptation is a major contributor to the high vulnerability of farmers in these countries (Khanal, et al., 2017). The literature confirms the crucial need of enhancing farmers' adaptive capacity in order to appropriately address the consequences of climate change, reduce the negative impacts and optimally use the opportunities that it may bring (Khanal, et al., 2018).

Afghanistan is traditionally an agrarian country. Even though the contribution of agriculture to the national GDP is around 22%, it remains an important sector as a source of livelihood for the poor rural population (Haque, et al., 2018). It is estimated that approximately 79% of the population is engaged in farming, herding, or both (UNEP-Afghanistan, 2003; Baizayee, et al., 2014). Furthermore, there has been a consistent policy position that agriculture will be central to Afghanistan's growth and development (Pain & Shah, 2009). Therefore, agricultural adaptation—through enhancing farmers' adaptive capacity to deal with the impacts of climate change and extreme weather events—is crucial.

Evidence suggests that smallholder farmers in many least developed and developing countries have been adjusting their farming practices in response to climate change (Khanal, et al., 2018). In Afghanistan, because of widespread poverty – particularly among farmers (Haque, et al., 2018) -, such autonomous adjustments have not been sufficient to address the current and future consequences of climate change and extreme weather events (Savage, et al., 2009).

In such circumstances, external support provided by the governmental (GO), non-governmental (NGO), and community-based (CBO) organizations for enhancing farmers'

adaptive capacity, is key. Evidence confirms the important role of extension services and community-based organizations in supporting farmers to adapt to climate change (Hassan & Nhemachena, 2008; Deressa, et al., 2009; Khanal, et al., 2017).

In the post 2001 era¹, rural development has been a major focus of the new government in Kabul, its international partners, and NGOs. Agriculture, as a key developmental sector, has been at the heart of all initiatives, interventions, and projects that have been carried out by GOs/NGOs in rural areas² (Savage, et al., 2009; Pain & Shah, 2009). Such support has been, and continues to be, decisive for rural development, poverty reduction, and dealing with consequences of climate change and extreme weather events. Hence, understanding the impact of these interventions is key for further policy development and implementation. Despite this fact, to date the impact of the support provided by these organizations (GOs/NGOs) for farmers' adaptation to climate change has not been documented in the scientific literature³. Evaluating the impacts of such interventions can be costly and laborious - in particular when complex causal links or uncertain framework conditions are involved. However, providing evidence about the possible effects is indispensable to generating knowledge about what works and what does not (Silvestrini, et al., 2015).

Therefore, the central motivation of this study is to contribute to the literature from the point of view of farmers' perception of and adaptation to, climate change in Afghanistan. Specifically, we aim to provide evidence on farmers' perception of and adaptation to climate change and the impact of external support (provided by GOs/NGOs) to their adaptation in the Central Highlands of Afghanistan. To this end, we use household level data and quasi-experiment estimation methods in order to study the farmers' view of the changes in the climate and estimating the effect of external support provided by different GOs/NGOs on farmers' adaptation to climate change.

External support for adaptation (by GOs and NGOs) is defined broadly to cover all kinds of farm-related assistance in the form of projects and interventions that directly or indirectly helped farmers to adapt⁴ to the impacts of the current or expected changes in the climate as well as extreme weather events. Such projects include building dams, providing improved types of seeds, introducing new products, offering workshops/trainings, concreting water

¹ In late 2001, the Taliban regime was overthrown and a new western-backed government was formed in the country.

² For more information from the United Nations Development Programme, see <http://www.af.undp.org/content/afghanistan/en/home/projects/CCAP-Afghanistan.html>

³ We do not rule out the existence of project-based evaluation reports.

⁴ The measures may have been implemented to reduce the adverse effects of climate change or to optimally use the opportunities that it may have provided.

canals, digging water wells, establishing gardens, providing fertilizer and pesticides, digging terraces, and re-greening pasture lands.

Furthermore, we investigate the farmers' perception of climate change and the effect of those changes on their farming business.

In our study, we use primary data that we collected in May-July 2017 from 1,434 farmers across 14 districts in the Central Highlands of Afghanistan. An advanced survey application developed by the World Bank was used to carry out the face-to-face interviews.

Due to the nature of our data, we use quasi-experiment causal inference methods to assess the impact of the external supports provided by GOs/NGOs among the treated farmers. Several past studies (Barth, et al., 2006; Becerril & Abdulai, 2010; Ali & Erenstein, 2017; Antlea, et al., 2018) have employed propensity score matching methods to study the impact of the concerned treatments. The drawback of such an approach is that the propensity score matching estimator only considers observable factors influencing treatment assignment and outcomes of interest. As a result, the estimated treatment effect can be biased. In addition to employing a propensity score matching with kernel ridge regression (KRR), we address this issue by using endogenous switching regression (ESR) to estimate the impact of the treatment on the farmers' adaptation to climate change. To check the robustness of the results from the kernel matching against alternative specifications, we also estimate the effect of the external support using doubly robust (DR), nearest neighbor (NN), and inverse probability weighting (IPW) estimators. Our approach aims to contribute to the literature by providing estimates that are more robust against unbiasedness resulting from unobservable factors, model specification, and different matching estimators.

Our results suggest that nearly all farmers perceived changes in their region's climate in the form of warming and/or a decrease in precipitation. Furthermore, farmers perceived the risk of drought, flood, and cold/heatwaves to be high in their area. The risks of crop failure, crop/animal disease, and pests are also reported to be high. Limited access to irrigation water is the main farming constraint and economic and financial knowledge and awareness, lack of technology and government and institutional constraints are the main adaptation obstacles reported by the farmers. Although some positive impacts of warming has been reported, the majority of farmers believe that their farming business is vulnerable to the current and expected impacts of climate change. In response to the changes in the climate, almost all farmers tried to adopt one or more adaptation measures available to them.

The estimates of the kernel matching show a mixture of significant and insignificant impacts for the past agriculture-related supports provided by the GOs/NGOs. The impact of

the interventions on outcomes such as access to water, and use of improved types of seeds are found to be significant and robust. The treatment impact on risk of flood, economic and financial, and governmental and institutional adaptation constraints are significant but sensitive to the unobserved factors.

We conclude that the risk of climate change related events are high and the majority of farmers have tried to adapt by implementing one or more measures. Furthermore, the support for adaptation (provided by GOs/NGOs) while partially effective in addressing short-term challenges, has not been sufficient to reduce the long-term vulnerability of farmers to the impacts of climate change. In order to build and enhance the adaptive capacity of farming communities, the introduction of improved and drought, pest, and disease-resistance seeds, crops, and trees; and investment in irrigation and water management are recommended.

The remainder of this paper is organized as follows: A summary of climate change and related issues in Afghanistan is provided in Section 2. Section 3 discusses the methods. The study area and the instruments are introduced in Section 4. Results and discussions are presented in Section 5. Sections 6 presents the policy recommendations and concludes the paper.

2. Climate change in Afghanistan

Afghanistan, located in the south part of central Asia, is a mountainous country with generally cold winters and hot summers (Savage, et al., 2009). The country has an extreme continental arid climate that is characterized by desert, steppe, and highland temperature regimes (Shroder, 2014). Afghanistan is divided into five climate regions (Aich & Khoshbeen, 2016): (1) The Hindukush Region; (2) Northern Plains; (3) Central Highlands; (4) Eastern Slopes; and (5) Southern Plateau.

A recent analysis by Aich and Khoshbeen (2016) suggests a significant change in the climate of the country since the 1950s: the average annual temperature has increased by about 1.8 degree Celsius; the average annual precipitation has decreased (with higher variation across seasons and space); and extreme weather events become more frequent. However, Savage, et al., (2009) reported a 0.6 degree Celsius of warming and 0.2mm decrease in average monthly precipitation since 1960. Projections suggest that by 2100 the average temperature over Afghanistan would increase by 2-6 degrees Celsius and the country would

have generally drier condition. Spring rainfall would be significantly reduced. It is estimated that precipitation during March, April, and May would decrease by 10-40mm.

Afghanistan's National Adaptation Program of Action for Climate Change (NAPA⁵) lists drought, flood, warming, heat/cold waves, thunder, and the Monsoon 120 day wind as the main climatic hazards which are exacerbated by climate change⁶ (UNEP; NEPA; GEF, 2009).

With climate change happening, understanding the vulnerability of various sectors and the implications of these changes for development, stability, and food security has become a key research and policy issue. Evidence suggests that agriculture, development, energy, and water are potentially affected by climate change and variability. Agriculture is particularly vulnerable to the impacts of climate change and extreme weather events due to its high sensitivity, inefficient water management, increased soil evaporation, and farmers' limited adaptive capacity (UNEP; NEPA; GEF, 2009; Savage, et al., 2009). Food security among rural households is another major concern that is linked to climate change and extreme weather events. A study conducted jointly by World Food Program (WFP), the United Nations Environmental Programme (UNEP), and Afghanistan's National Environmental Protection Agency (NEPA) shows that incidence of food insecurity is directly linked to extreme weather events, such as drought and flood (WFP; UNEP; NEPA, 2016).

Compared to the degree of vulnerability and magnitude of impacts, current adaptation interventions are limited. Due to the security and economic crisis, adaptation to climate change has not been a central issue for the Afghan government (WFP; UNEP; NEPA, 2016). However, a number of interventions have been implemented that directly or indirectly have contributed to building and enhancing the adaptive capacity of farming communities. Such interventions include the first adaptation project supported under Least Developed Countries Fund (LDCF) (Baizayee, et al., 2014); National Solidarity Program of the Ministry of Rural Rehabilitation and Development/the World Bank (The World Bank, 2017); a range of initiatives and projects by the Ministry of Agriculture, Irrigation and Livestock⁷; and various climate change related projects by World Food Program (Amani, 2018), Action Aid (ActionAid, 2018), and Agha Khan Foundation (AKDN, 2018).

⁵ For more information on NAPA, check the following:

<https://unfccc.int/resource/docs/napa/afg01.pdf>

⁶For more information, visit the following websites:

<https://unfccc.int/topics/resilience/workstreams/national-adaptation-programmes-of-action/napas-received?black=j>

⁷For more information, visit the following websites:

<http://www.af.undp.org/content/afghanistan/en/home/presscenter/pressreleases/2017/12/10/afghanistan-launches-us-71-million-initiative-to-prepare-rural-communities-for-climate-change1.html> and <http://mail.gov.af/en/page/3253/3254>

NAPA has prioritised the sectors that have to be supported under various adaptation intervention. Water management is the sector that needs to be addressed immediately. Frequent droughts have been threatening water resources which are key to agriculture production. Community-based watershed management is one particular sector which is being prioritised by NAPA (UNEP; NEPA; GEF, 2009).

The first climate change adaptation project executed by NEPA and UNEP, was piloted in Bamiyan, Diakundi, Balkh, Badakhshan, and Kabul provinces. Funded by the Least Developed Countries Fund (LDCF) under the Global Environment Facility (GEF), the project aimed to enhance the adaptive capacity of farmers at the intervention sites by addressing water use efficiency and community-based watershed management — in accordance to that which NAPA has prioritized (UNEP; NEPA; GEF, 2009; Baizayee, et al., 2014).

3. Methodology

To analyse the impact of a treatment on certain outcomes of interest, a number of methodologies have been suggested in the literature (Silvestrini, et al., 2015; Khandker, et al., 2010). In non-randomized settings, quasi-experimental methods such as regression discontinuity, time series designs, structural equations modeling, the pipeline approach and propensity score are available to estimate the impacts of a treatment on certain outcomes among treated/non-treated subjects. From these methods, the propensity score estimation method (PSM) fits our case best due to the nature of the data and the design of our study. The basic idea behind PSM is to estimate the counterfactual outcomes using data from a large number of (similar) subjects in a comparison group (Silvestrini, et al., 2015). In the current study, we use a unique dataset of 260 treated and 1,174 comparison farmers from the same area – which allows for a propensity score which is an appropriate method for estimating the treatment effects. To test the reliability of the results, we utilise a number of other methods, such as the doubly robust estimator, and endogenous switching regression.

3.1. Propensity score estimation

To assess the impact of the interventions provided by GOs/NGOs, we employ a quasi-experiment method. Given that inclusion in the treatments was not randomized, the decision

to cover/participate could be endogenous. For instance, the farmers with a larger farm size or those whose primary occupation is farming, might have had higher chances to receive the treatments and that therefore might affected the outcomes. If such observed (and unobserved) factors affect treatment assignment and outcomes of interest (common causes), a naive comparison of means is biased (Hirano & Imbens, 2001). To deal with this problem, we employ quasi-experimental methods (see Wooldridge (2010, pp. 903-981) for a detailed summary). In particular, we use matching and regression adjustment to estimate the counterfactual outcomes—the outcomes realized by farmers being treated, had they not been covered — for the treated farmers (Höfler, 2005).

When evaluating the effect of a treatment T (a dummy variable), interest often lies in the estimation of average treatment effects. Let $Y(1)$ and $Y(0)$ denote the potential outcomes, where $Y(1)$ is the outcome if the farmer receives the treatment, and $Y(0)$ if he does not. Then, the average treatment effect on treated (ATT) is

$$ATT = E[Y(1) | T=1] - E[Y(0) | T=1] \quad (1)$$

The first term in Equation 1 can be estimated by the mean outcome among treated farmers. The term $E[Y(0) | T=1]$, however, is not observed (counterfactual). Generally, $E[Y(0) | T=1]$ is not equal to $E[Y(0) | T=0]$ if treatment assignment is non-random. Nevertheless, conditioning on all confounding factors \mathbf{x} (common causes), T is independent of $Y(0)$ (Frölich, 2004). For estimating ATT, we need an even weaker assumption of mean independence/ignorability in means under no treatment (Wooldridge, 2010, p. 911). That is

$$E[Y(0) | \mathbf{x}, T] = E[Y(0) | \mathbf{x}] \quad (2)$$

If \mathbf{x} contains a few variables, the counterfactual mean can be estimated using nonparametric regression of Y (potential outcome) on \mathbf{x} in the non-treated sample (Frölich, 2004). However, in practice, we are dealing with high-dimensional \mathbf{x} , which makes the earlier method difficult. Rosenbaum and Rubin (1983) suggest using a one-dimensional function of \mathbf{x} , namely, the propensity score. The propensity score (pscore)

$$pscore = P(T=1 | \mathbf{x}=x) \quad (3)$$

is the likelihood of a farmer being treated with given characteristics. For consistently estimating the ATT, Wooldridge (2010, p. 908) suggests that in addition to the mean independence assumption/ignorability in means, given in Equation 2, we should rule out the cases for which the p-score is equal to unity. The condition is called the overlap assumption. The two conditions together form a weak version of the ignorability condition (Wooldridge, 2010, p. 911).

The matching method relies on the concept that each treated farmer is matched to one or more non-treated farmer(s) that is/are closest to it based on the covariate values. Since matching on each covariate in \mathbf{x} is difficult in practice, due to the curse of dimensionality, the p-score can be used instead as defined in Equation 3 (Rosenbaum & Rubin, 1983). Then, matching estimators will compare farmers in the treated group to those in the control group that are closest to them regarding the estimated p-score values. An important issue related to the estimation of the p-score is the selection of the covariates to be included in the p-score model. Since p-scores are used to reduce confounding, the variables that are related to both treatment and outcomes should be included in the p-score model (Melissa, et al., 2014). However, any factor assumed to be affected by the treatment should not be included in the model. Therefore, economic theory has to be relied on as well as past research and knowledge about treatment administration to determine the p-score model (Caliendo & Kopeinig, 2005).

To match using p-score, a number of different methods are available, such as nearest neighbor, caliper or radius, stratification, kernel/local linear, and inverse probability weighting. Making a choice on which method to use is not clear cut (Huber, et al., 2013). For our analyses, we employ a kernel method. kernel matching is non-parametric and, hence, does not pose any functional form assumption, and it uses data on the entirety of farmers in the control group to construct the counterfactual. In kernel matching, a weighted means of all farmers in the control group is used to estimate the counterfactual for each treated farmer. Non-treated farmers with similar p-scores get higher weights. There are several kernel-based matching methods (Frölich, 2004), but we use the kernel ridge regression which Huber, et al. (2014) suggest which has superior finite sample properties. Since we are using the Epanechnikov kernel, according to a rule of thumb, we have set the ridge parameter to .3125 (Frölich, 2004), and employed cross-validation across values of bandwidth and have chosen the one implying minimum mean squared error (MSE). Bootstrap sampling is used to compute the robust standard error of the estimates.

A problem that may arise in using the propensity score method is that the estimator is biased if the propensity score model is not correctly specified. To address this, the literature

(e.g., Wooldridge, 2010, p. 930) suggests combining regression adjustment and propensity score models to achieve some robustness to misspecification of the parametric model. The resulting estimator is called doubly robust (DR) as it only requires either of the models to be correctly specified, not both. In our case, we use the inverse-probability weighted regression adjustment, using the estimated p-scores as the weights.

In order to provide further robustness against alternative matching estimators, we employed two additional propensity score matching methods, namely nearest neighbor matching (where each treated farmer is matched to the three nearest neighbors based on their estimated p-score) and inverse probability weighing methods. Such an exercise is common in the literature propensity score (Becerril & Abdulai, 2010).

Another major concern when using propensity scoring to estimate the treatment effect is the failure to account for all relevant covariates. For addressing this, it is recommended that a sensitivity analysis be run to gauge the robustness of the estimates in terms of possible hidden bias (Rosenbaum, 2002). The idea behind sensitivity analyses is to introduce some hidden bias into the selection process and assess how strong such bias has to be in order to influence the unbiasedness of the matching estimates (Rosenbaum & Silber, 2009). In practice, this is done by computing Rosenbaum bounds suggested by Rosenbaum (2002, p. 269). It should be emphasized that Rosenbaum bounds represent a worst case scenario implying that the confidence interval of the estimates might include zero (DiPrete & Gangl, 2004).

3.2. Unobserved heterogeneity and the endogenous switching model

As mentioned earlier, propensity score-based methods only account for observable factors affecting treatment and the outcome. However, there might be unobservable (or some observables that are not included in the p-score model) factors that might affect both treatment assignment and the outcomes. In such cases, the propensity score-based estimator (such as kernel matching) yields biased treatment effects. To address this problem, it is suggested that endogenous switching regression be used with the treatment determining the endogenous switching point (Di Falco, et al., 2011; Abdulai & Huffman, 2014; Khanal, et al., 2018; Khanal, et al., 2018).

Endogenous switching regression is a two-step estimation approach. First, the farmers are divided into two regimes according to their status of having received external support or not.

In the second stage the outcomes in each regime are estimated separately (Section A.1 in Appendix A provides the theoretical background of the method).

By employing the proposed estimation methods (kernel matching, doubly robust, nearest neighbor, propensity score, sensitivity analysis, and endogenous switching regression) together, we try to ensure that our estimates are robust, consistent, and reliable.

4. Study area and data

4.1. Study area

The study area includes 14 districts in 3 central provinces of Afghanistan. Figure C.1 in Appendix C depicts the study districts. The Central Highlands of Afghanistan is one of the five climate zones in the country (Aich & Khoshbeen, 2016) and traditionally home to Hazaras, an ethnic minority in Afghanistan. The region is widely characterized by deep valleys and mountain ranges up to 6,400m above the sea level (Aich & Khoshbeen, 2016). The Baba mountain range extends from the north-east to the south-west of the region providing the source for many of the country's major rivers, such as Helmand, Kabul, Harirood, and Baghlan. Agriculture, including farming and animal husbandry, is the primary employment and source of income for the inhabitants of the region⁸. Potato, wheat, and almond are the primary products in the study area. Sheep, goats, chickens, and cows are the primary livestock kept by households.

The Central Highlands possesses heterogeneous climate regimes and receives on average about 390 mm of precipitation annually. The amount of rainfall varies considerably across space (Table B.1 in Appendix B presents the average amount of rainfall across 3 provinces) and time (Figure C.2 in Appendix C depicts the amount of precipitation across 12 months). In some districts such as Nili and Kiti, total rainfall is around 260mm while in some districts such as Shibar, Malistan, and Jaghori it exceeds 500mm. The average temperature also varies across space and time. The average temperature in winter can be 0 degrees Celsius in deep valleys in Bamiyan and Diakundi, but as cold as -7 degrees Celsius in the Nahoor plateau. The variation of temperature over time is also high. Figure C.3 in Appendix C depicts the average monthly temperature.

⁸ The statistics are provided in the next section.

4.2. Data and survey instruments

The primary data for our study was collected from farmers in the Central Highlands of Afghanistan from May to July 2017. Our sample consists of 1,434 farmers (260 of whom received adaptation related external support and 1,174 who had not received such as support). A multi-stage systematic random sampling was implemented to choose the subjects. A structured questionnaire⁹ and the World Bank's Survey Solution Application were used to conduct face-to-face interviews with the heads of the farming household.

In addition to the data on adaptation and external support for adaptation, we have collected information on farmers' perception of climate change, climate change-related risks, household's characteristics and implications of climate change for farm production.

The description and summary statistics of the instruments are reported in Table B.2 in Appendix B.

5. Results and discussions

5.1. Sample characteristics

Our sample consists of 1,434 farmers from 14 districts in Bamiyan (37%), Ghazni (33%), and Diakundi province (30%). Nearly 18% of the farmers (260) in our sample have received agriculture-related supports from the GOs/NGOs. The spatial distribution of treated and non-treated farmers is depicted in Figure C.4 in Appendix C.

Farming is the primary employment for 80% of farmers in the sample, and almost 39% of them work only on their farms. The average household size is 9 persons with almost equal distribution over gender. On average 5.4 persons are employed per household out of which 4.1 are working on the farm (2.38 male and 1.72 female members). School attendance is 2.9 persons per household, and 3.7 members are literate. About 64% of the respondents spent some time abroad (mainly in Pakistan or Iran), and 62% of our subjects can at least read and write. The average age in our sample is 46 years, and they have spent almost half of their life (22 years) working on their farms. Most of the farmers (79%) do not own a car. More of them (53%), however, own a motorbike. Because the farmers are mostly poor and the region is predominantly mountainous, motorbike seems to be a preferred mean of transportation. Use

⁹ The English translation is provided in Appendix D.

of the computer is not very common — only 27% have one or more computers at home. Likewise, the use of the internet is low (16%) among the subjects. Watching TV (about 70% have at least one TV at home) and use of mobile (almost 100%) on the other hand, is common. About 70% have access (on average 5 hrs. a day) to electricity. Use of solar panels is still not common, with only 7% of households using them to generate electricity. Due to the particular topology of the region, arable land is minimal. The average farm size per household is 7.6 acre, and 5.7 acres is under cultivation. The average annual net revenue per acre is estimated to be around AFN 69,000 (about USD 900).

Agriculture remains the primary source of income for 76% of farmers and almost 24% of the sale a portion of their agriculture products. Remittances are the primary source of income for about 6% of the farmers, the majority of whom live in Ghazni province. Three systems of irrigation are prevalent in the area. 20% channel water from a river that passes through their villages. A chain of underground canals (known as Karez) is used to supply farmlands with water by about 40% of the households. The remaining 40% channels water from a stream that flows in a nearby valley.

5.2. Climate change perception, impacts, and risks

Evidence suggests that the climate of the study area has changed. An analysis of the weather information from the past 35 years shows that the annual average temperature has increased by about 1.5 degree Celsius and the average precipitation has decreased, although with higher heterogeneity across seasons and regions. Almost all farmers (96%) have perceived changes in the climate, generally in the form of warming (89%) and/or a decrease in snow/rainfall (90%)—consistent with results of our analyses of weather data. The findings are similar to those reported in several past studies, such as Wolka & Zeleke (2017). Almost 2/3 of farmers believe that recent changes in the climate are God’s will and about 10% attribute the changes to human actions (not necessarily economic activities though). About 60% think that the impact of climate change on their farming has been negative and 30% believe that their farming business has improved as a result of climate change. Meanwhile, almost 92% think that their farming business is vulnerable to the future impacts of climate change. About 60% reported a decrease in their farming production compared to 15 to 20 years ago, and 25% reported that their production has increased. All farmers whose farming production has decreased attribute it to climate change (drought and warming). Likewise, all

farmers whose farming production has increased associate it to climate change (mainly warming).

The changes in the climate have been accompanied by the steady increase in the risk of extreme weather events, such as drought, flood, and cold/heatwaves. Risk of drought is particularly perceived to be very high by non-treated farmers. Risks of avalanche and landslide are relatively low among both groups of the farmers. Higher intensity and frequency of extreme events can exacerbate the risk of crop failure and crop/animal disease and pest infestation. The farmers in our sample reported the risk of both of these secondary events to be high. Table 1 reports the summary statistics.

5.3. Adaptation (implementation; constraints; support)

In order to study the adaptation of farmers to climate change and related extreme events, we asked them about the adjustments they have applied to their farming activities in response to climate change. As in many other developing countries, farmers in our sample have tried to adapt by adopting the available measures. Specifically, farmers (especially in Bamiyan) spend more time (compared to 15 to 20 years ago) working on their farms. Use of improved and drought, disease, and pest resistant seeds has also increased. Likewise, around half of the farmers use more fertilizer now. Part-time or an entire shift to other employment other than farming has been reported by about 40% of the farmers (mostly in Ghazni). Seeking relevant information, visiting workshops and training, implementing soil and water conservation measures are the other strategies that farmers implemented in order to adapt to the changing climate.

Adaptation to climate change, however, has not been sufficient compared to the degree of the impacts. Moreover, farmers are bound to various constraints. According to the IPCC's fifth Assessment Report¹⁰, adaptation constraints can be classified as economic and financial, knowledge and awareness, social and cultural, physical and biological, human resources and government and institutional (IPCC, 2014). Adaptation constraints that are reported by farmers include economic and financial constraints (mentioned by 84%: 86% vs 74% among non-treated and treated farmers), government and institutional constraints (mentioned by 65%: 67% vs 55% among non-treated and treated farmers), knowledge, awareness and technology constraints (mentioned by 50%: 48% vs 57% among non-treated and treated farmers), human resources constraints (mentioned by 60%: 60% vs 57% among non-treated

¹⁰ WGII-Chapter 16.

and treated farmers), and environmental (physical and biological) constraints (mentioned by 42%: 42% vs 43% among non-treated and treated farmers).

To investigate the external adaptation support and its impact on farmers' adaptation, we asked farmers which farming and adaptation related support they received from either GOs or NGOs or both. About 18% of the farmers in our sample (treated subjects) have received external support for their adaptation. Support provided includes offering workshop and training on various agriculture-related topics (8%), providing improved types of seeds (13%), providing extra fertilizer (9%), providing irrigation related services (5%), and providing different types of fruit trees (6%). Table 1 reports the summary statistics.

5.4. Kernel matching estimates of the treatment effects

The treatment variable in our analysis is a dummy variable which is 1 if the farmer received at least one type of adaptation-related support (outlined in Section 5.3) and 0 otherwise. For ease of estimation $ncbxx$, the outcome variables are divided into four categories. The first category (Category I) includes variables that represent risks of extreme weather events, such as drought and flood as well as risks of pest and disease and crop failure. The second category (Category II) contains variables that represent immediate farming constraints, such as water availability. The third category (Category III) includes adaptation variables, such as spending more time working on the farm and use of improved types of seeds. The fourth category (Category IV) includes variables related to adaptation constraints, such as economic and financial and government and institutional constraints. Summary statistics of the treatment and outcome variables are reported in Table 1.

Table 1: Summary statistics of the treatment and outcome variables

No.	Variable (category)	Mean_0(st. d)	Mean_1(St. d)	p-value
0	Received external support [yes=1]			
1	Risk of drought (I)	3.17 (1.14)	2.74 (1.32)	0.000
2	Risk of flood (I)	2.52 (1.45)	2.26 (1.32)	0.007
3	Risk of cold/heatwaves (I)	2.57 (1.22)	2.60(1.22)	0.730
4	Risk crop failure (I)	2.98 (1.05)	2.76 (0.99)	0.001
5	Risk of disease/pest (I)	2.93 (1.01)	2.86 (1.02)	0.288
6	Farming constraint-availability of irrigation water (II)	.69(.46)	.45(.50)	0.000
7	Adpt. More work on the farm (III)	.65(.47)	.68(.47)	0.459
8	Adpt. Shift to other jobs (III)	.41(.49)	.42(.49)	0.861
9	Adpt. Improved seeds (III)	.29(.45)	.54(.49)	0.000
10	Economic/financial constr. (IV)	.87(.01)	.73(.02)	0.000
11	Government/institutional constr. (IV)	.69(.47)	.56(.50)	0.000
12	Knowledge, awareness, and tech constr. (IV)	.46(.50)	.55(.50)	0.012
13	Human resources constr. (IV)	.60(.01)	.56(.03)	0.302
14	Environmental (physical/bio) constr. (IV)	.43(.02)	.43(.03)	0.945

Note: Mean_0/Mean_1 is the mean value among non-treated/treated farmers. The p-value corresponds to the two-sided t-test of mean. ‘Adpt.’ stands for ‘Adaptation’. Number of observations 1,434.

Table 2: Treatment effects of the provided supports by GOs/NGOs

No	Outcome (category)	ATT (KM)	ATT (DR)	ATT (NNM)	ATT (IPW)
1	Risk of drought (I)	-.11 (.10)	-	-	-
2	Risk of flood (I)	-.27** (.12)	-.23** (.10)	-.34** (.13)	-.24** (.12)
3	Risk of cold/heatwaves (I)	.05 (.11)	-	-	-
4	Risk crop failure (I)	-.03 (.09)	-	-	-
5	Risk of disease/pest (I)	-.07 (.09)	-	-	-
6	Farming constraint-water availability (II)	-.11*** (.04)	-.14*** (.03)	-.09** (.04)	-.14*** (.03)
7	Adpt. More work on the farm (III)	.01 (.03)	-	-	-
8	Adpt. Shift to other jobs (III)	.01 (.04)	-	-	-
9	Adpt. Improved seeds (III)	.09** (.04)	.10*** (.03)	.10** (.05)	.10*** (.04)
10	Economic/financial constr. (IV)	-.10** (.04)	-.09*** (.03)	-.09*** (.04)	-.09*** (.03)
11	Government/institutional constr. (IV)	-.12*** (.04)	-.12*** (.03)	-.18*** (.04)	-.14*** (.03)
12	Knowledge, awareness, and tech constr. (IV)	.02 (.04)	-	-	-
13	Human resources constr. (IV)	-.07 (.04)	-	-	-
14	Environmental (physical/bio) constr. (IV)	-.03 (.05)	-	-	-

Notes: robust standard errors are reported in the parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. KM: kernel matching. DR: doubly robust. NNM: nearest neighbor matching. IPW: inverse probability weighting. ‘Constr.’ stands for ‘constraint’. Number of observation 1,434.

Before applying the kernel ridge estimator, we tested the covariate balance (Section A.3 in Appendix A and Table B.3 in Appendix B discuss and present the results). Furthermore, the overlap of the estimated pscore is tested (Table B.4 in Appendix B and Figures C.5 and C.6 in Appendix C report and depict the results). The results confirm both satisfactory covariate balance and sufficient pscore overlap among treated and non-treated farmers.

With the two assumptions satisfied, we have applied the kernel ridge regression estimator to all outcome variables, summarized in Table 1.

The kernel estimates of the average treatment effects (ATT) of the provided support by GOs/NGOs among treated farmers are reported in column 3 of Table 2.

Category I contains the main climate change related hazards, such as drought, flood, and pest. Evidence suggests that risk of extreme events has increased as a result of climate change (Jayatilleke & Yiyong, 2014). Agriculture in Afghanistan is particularly affected by the extreme events, such as flood and drought (Savage, et al., 2009). Therefore, increasing farmers’ resilience to these events should be a central issue in adaptation interventions (Baizayee, et al., 2014). Our results suggest that apart from the risk of flood, the estimated treatment effect is insignificant on the remaining outcomes in this category. The risk of flood is found to be higher among non-treated farmers. Specifically, the perceived risk of flood is nearly 7% lower among the farmers who received external adaptation support ($p < 0.05$).

Category II contains an outcome that is immediately affected by climate change and extreme events: the availability of irrigation water. Water is one of the sectors that is most susceptible to the impacts of climate change. Uncertainty around precipitation and increased risk of drought and flood affect water resources and agriculture in general. Hence, addressing water resources management, as a key adaptation strategy, can increase the resilience of farming communities to the impacts of climate change (Oki, 2016). Along the same lines, water resources and watershed management has been one of the sectors prioritized by NAPA (National Program of Action for Adaptation to Climate Change in Afghanistan) to be addressed under adaptation related interventions. Our estimates suggest that external support has increased the availability of irrigation water among the covered farmers (the availability of irrigation water is 14% less among non-treated farmers). The difference is statistically significant.

Category III includes outcomes reflecting the adjustments that the farmers applied in response to climate change. The literature points out the importance of adaptation of farming communities (especially in developing countries) to climate change (Khanal, et al., 2018). Adaptation measures include a wide range of physical, behavioral, and ecological adjustments in order for farming business to survive (and thrive) current and expected changes in the climate (Silvestrini, et al., 2015). A key adjustment is crop diversification and the use of improved types of seeds. Considering the traditional way of farming in the study area, such an adjustment can serve as an effective adaptation strategy to the changing climate—as suggested in the literature (Makate, et al., 2016; Lin, 2011). Towards implementing this strategy, the distribution of improved types of seeds has been one of the major projects being run by the Ministry of Agriculture, Irrigation and Livestock. Our results suggest that the number of farmers implementing this measure is greater among the treated. Specifically, the use of improved types of seeds, that are more drought- and pest-tolerant with higher yield, is about 10% higher among the farmers who received external support ($p < 0.05$). The treatment effect on other adaptation measures (such as more work on the farm, and shift to other forms of employments) is found to be insignificant.

The kernel estimates of treatment effects on outcomes in Category IV are also mixed. Outcomes in this category represent adaptation constraints. The IPCC's fifth Assessment Report¹¹ summarizes all categories of constraints to adaptation, including economic and financial, knowledge, awareness and technology. In less developed countries such as Afghanistan where the poverty rate is very high and the literacy rate is very low, both types of constraint are expected to be widespread. In such a setting, it is expected that most of the autonomous adaptation measures are either inappropriate or they are not executed in the right way due to both economic and intellectual deficits. Poverty is widespread among rural farmers, which implies insufficient/no economic means for adopting various adaptation measures. Knowledge, awareness, and technology and government and institutional constraints are other major challenges that the farmers face in the process of applying adaptation measures. Based on the estimations in Table 2, economic and financial and government and institutional constraints pose less challenge to the adaptation process of farmers who were treated. Specifically, economics and financial constraints are 8% less among treated farmers. Similarly, government and institutional constraints are 13% lower

¹¹ The following website provides more information:
https://www.ipcc.ch/site/assets/uploads/2018/02/WGIIAR5-Chap16_FINAL.pdf

among farmers who were covered. The treatment, however, did not have a significant effect on improving and enhancing the farmers' knowledge, awareness and use of technology.

In order to check the robustness of the kernel ridge estimates, we have estimated the significant ATTs using a double robust (DR), nearest neighbor matching (NNM), and inverse probability weighting (IPW) estimators. The results are reported in columns 4-6 of Table 2. The estimates of these estimators are similar (in terms of sign, significance, and up to a large extent, the magnitude) to those of the kernel ridge reported in column 3. Hence, our estimates are robust to different specifications and estimation methods.

An additional concern is the unobserved factors that affect both treatment assignment and the outcomes of interest. In order to gauge the impact of such factors, we run a sensitivity analysis (by computing the Rosenbaum bounds) for the outcomes for which we observed a significant treatment effect (Table 2).

The results of the sensitivity analysis (reported in column 3 of Table 3) suggest that the treatment effect on some outcomes such as risk of flood and economic and financial constraints are sensitive to the existence of unobserved heterogeneity. For instance, in the case of risk of flood, if there exists an unobserved factor that causes the probability of treatment assignment (between treated subjects and farmers in the comparison group) to differ by more than 45%, the estimated impact is undermined. The remaining significant estimates (use of improved seeds, availability of irrigation water, government and institutional constraints) are not sensitive to unobserved factors.

In order to check the robustness of the treatment effects that are significant (reported in Table 2) and are insensitive to the existence of unobserved factors (reported in column 3 of Table 3) against unobservable factors that affect both treatment assignment and the outcomes, we practice the endogenous switching regression (ESR) with known endogenous switching points. Farmers' risk perception and their perception of the main cause of climate change have been used as identification instruments. The estimates of the endogenous switching regression are reported in column 4 of Table 3.

The results of the endogenous switching model (for significant and insensitive outcomes) suggest the presence of a significant treatment effect on the availability of irrigation water and the use of improved seeds. Specifically, the probability that treated farmers face irrigation water constraint is 46% lower than the farmers in the comparison group. Likewise, the probability of using improved types of seeds is 46% higher among treated farmers. The endogenous switching estimate of the treatment effect on government and institutional constraints is not significant.

Altogether, our estimations suggest a robust effect of external support for adaptation provided by GOs/NGOs on improving the availability of irrigation water and use of improved types of seeds among treated farmers.

Table 3: Robustness tests (sensitivity analysis, endogenous switching regression)

No.	Outcome (category)	Sensitivity analysis (Tau)	Endogenous switching ATT
1	Risk of flood (I)	.45 (45%)	-
2	Farming constraint-water availability (II)	1.00 (100%)	.44* (.23)
3	Adpt. Improved seeds (III)	0.65 (65%)	-.44** (.19)
4	Economic/financial constr. (IV)	.20 (20%)	-
5	Government/institutional constr. (IV)	0.90 (90%)	.07 (.17)

Notes: robust standard errors are reported in the parentheses. *** p<0.01, ** p<0.05, * p<0.1. Number of obs. 1,434.

6. Conclusion and policy recommendations

We provide evidence of the impact of adaptation-related supports provided by the GOs/NGOs on farmers' adaptation to climate change using primary data from 1,434 farmers across 14 districts in 3 central provinces of Afghanistan. Furthermore, we present an overview of a range of climate change-related issues, such as risk of extreme weather events, farming constraints, adaptation, and adaptation constraints. Using propensity score matching with kernel ridge regression, we have investigated the causal impact of the interventions on four categories of outcomes. In particular, we investigate the risk of extreme weather events, adaptation measures, and adaptation and farming constraints.

The analysis shows that risks of drought, flood, cold/heat waves, crop failure, and disease/pest are perceived to be high in the area under study. Spending more time working on the farm, use of fertilizer and improved types of seeds are the main adaptation measures exercised by farmers. Water unavailability is reported to be the main farming constraint. Economic and financial, government and institutional, knowledge, awareness and technology are the main adaptation constraints reported by farmers.

The results of the kernel estimates suggest a positive and significant treatment impact on the risk of flood, access to irrigation water, use of improved types of seeds, government and institutional and economic and financial constraints. Doubly robust, nearest neighbor matching, and the inverse probability weighting techniques yield similar estimates of the treatment effect. The treatment estimates of risk of flood and economic and financial constraint are found to be sensitive to the existence of unobserved heterogeneity.

To address an additional concern regarding the impact of unobservable factors, we apply an endogenous switching regression of treatment the outcomes for which show a significant effect and which are not highly sensitive to the existence of unobserved factors. The corresponding outcomes suggest a robust impact of external adaptation support on farmers' access to irrigation water and use of improved types of seeds.

Taking the findings together, we conclude that provided supports by GOs/NGOs have been partially effective in addressing more immediate farming challenges due to climate change. Such support includes providing improved types of seeds (which are more drought- and pest-tolerant and yield higher production) and improving water availability for irrigation (by improving water use efficiency and watershed management). Provided support, however, has not been effective in addressing long-term and more fundamental farming challenges related to climate change such as drought, flood, cold/heatwaves, and the consequent effects.

Given that agriculture is the primary employment sector and source of revenue in the study area, supporting the sector to survive and thrive under current and future impacts of climate change is key. To this end, a systematic intervention that enhances the adaptive capacity of farming communities and increases their resilience to adverse circumstances is crucial. Towards achieving this goal, we formulate a number of policy recommendations based on our analysis in this paper. First, we recommend the introduction of new crop varieties (such as saffron and potato) and improved types of seeds and fruit trees. This recommendation would be welcomed by 82% of the farmers in the study area. Second, we recommend addressing irrigation problems by constructing canals, improving water resources management, water use efficiency and conservation. The second recommendation is

supported by 69% of farmers. Third, we recommend training farmers on advanced methods of farming, adaptation, farming related risks and ways to deal with them—a recommendation which is supported by 58% of the farmers. Fourth, supporting farmers to better process, package, transport, and sell their products is crucial and would be welcome by 42% of farmers.

In addition, we recommend the improvement of the risk bearing capacity of farmers by offering affordable insurance tariffs and encouragement of local universities to conduct systematic research at the district and community levels to improve the availability of relevant data. Such future data collection could address a limitation of our study: the use of cross-sectional data. With panel data collection over longer time horizons, there would be a better opportunity to help solve the pressing problems of farmers in Afghanistan relating to climate change and other obstacles in the long run. More research on the adaptation to climate change in least developed countries such as Afghanistan remains essential for reducing poverty and giving farmers such as those in our study, a chance for survival and prosperity in the 21st century.

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Appendix A:

A.1: Endogenous switching model

As mentioned in Section 3.2, the propensity-based estimators only account for observable heterogeneities by including the relevant factors in the pscore models. But there are unobservable factors that affect both treatment assignment and the outcomes of interest; the pscore-based estimators yield biased treatment estimates. To address this problem, the literature recommends adoption of the endogenous switching regression. To do so, first, a dummy variable—which is 1 if a farmer is treated and 0 otherwise—is defined. Then a simultaneous equations model of treatment (being covered by external support or not) and outcomes of interest with the endogenous switching point is estimated using full information maximum likelihood (Lokshin & Sajaia, 2004).

To do so, a two-stage approach, as summarized by Lokshin & Sajaia (2004), is practiced. In the first stage, a selection model of treatment is estimated. Let 0 be a latent variable that captures the expected benefits from the treatment. Then a dummy variable A_i , which is 1 if the farmer i is treated, is specified as follows:

$$A_i = \begin{cases} 1 & \text{if } A^* = \mathbf{Z}_i\boldsymbol{\gamma} + \eta_i > 0 \\ 0 & \text{if } A^* = \mathbf{Z}_i\boldsymbol{\gamma} + \eta_i \leq 0 \end{cases} \quad (1.A)$$

\mathbf{Z} includes factors that affect the expected benefits of treatment. Variables such as farmers' occupation, household size, and farm size, farming experience, literacy of the household's head, migration background of the household head, irrigation system, climate, and soil are included in \mathbf{Z} .

In the second stage, separate outcome equations are specified for the farmers who received the external support and those who did not.

$$\pi^*_{1i} = \mathbf{X}_{1i}\boldsymbol{\beta}_1 + \epsilon_{1i} \quad \text{if } A_i = 1 \quad (2.A)$$

$$\pi^*_{0i} = \mathbf{X}_{0i}\boldsymbol{\beta}_0 + \epsilon_{0i} \quad \text{if } A_i = 0 \quad (3.A)$$

where π^*_{1i} and π^*_{0i} are the outcomes of the farmers who were treated and the farmers who were not, respectively. \mathbf{X} is a vector of explanatory factors. The error terms in equations

(1.A), (2.A), and (3.A) are assumed to have a trivariate normal distribution, with zero mean and covariance matrix Σ

$$\text{with } \Sigma = \begin{bmatrix} \sigma_{\eta}^2 & \sigma_{\eta 1}^2 & \sigma_{\eta 0}^2 \\ \sigma_{\eta 1}^2 & \sigma_1^2 & . \\ \sigma_{\eta 0}^2 & . & \sigma_0^2 \end{bmatrix} \quad (4.A)$$

where σ_{η}^2 is the variance of the error term in selection equation (1.A), σ_1^2 and σ_2^2 are the variances of the error terms in the outcome models in (2.A) and (3.A); $\sigma_{\eta 1}^2$ and $\sigma_{\eta 2}^2$ represent the covariance of η_i and ϵ_{1i} and ϵ_{0i} . Since π_{1i}^* and π_{0i}^* are not observed simultaneously, the covariance of ϵ_{1i} and ϵ_{0i} is not defined. An important implication of this error structure is that if the error term of the selection equation (1.A), η_i , is correlated with error terms in outcome models in (2.A) and (3.A), the expected values of ϵ_{1i} and ϵ_{0i} conditional on the sample selections not being zero:

$$E[\epsilon_{1i}|A_i = 1] = \sigma_{\eta 1}\lambda_{1i} \quad \& \quad E[\epsilon_{0i}|A_i = 0] = \sigma_{\eta 0}\lambda_{0i} \quad (5.A)$$

where $\lambda_{1i} = \frac{\phi(Z_i\alpha)}{\Phi(Z_i\alpha)}$ and $\lambda_{0i} = -\frac{\phi(Z_i\alpha)}{1-\Phi(Z_i\alpha)}$. If the estimated covariances $\sigma_{\eta 1}$ and $\sigma_{\eta 0}$ are statistically significant, then there are unobservable factors affecting both the treatment and the outcomes. That is, we find evidence to reject the null hypothesis of the absence of sample selection bias.

A.2: *pscore and outcome models:*

As outlined in Section 3.1, the selection of variables in the *pscore* model is a crucial issue in estimating the counterfactual mean. To reduce the confounding effects, ideally, all common causes of treatment and outcomes should be included in the *pscore* model. In this regard, our *pscore* model—defined in Equation 3 (in Section 3.1)—includes variables such as occupation, age, literacy, migration background, farming experience of the household head, farm size, distance to the market, household size, irrigation, soil fertility, change in temperature and precipitation and province. These factors were chosen based on a literature review (Deressa, et al., 2011; Apata, 2011; Lin, 2011; Makate, Tologbonse, et al., 2013; Okonya, et al., 2013; Uddin, et al., 2014; Obayelu, et al., 2014; Ndambiri, et al., 2014; Ullah, et al., 2015; Singh, et

al., 2015; Cisco & Olungah, 2016; et al., 2016; Menike & Arachchi, 2016;) and an analysis of treatment administration.

$$P(T=1 | \mathbf{x}) = F(\text{Main occupation, Second occupation, Irrigation, Household size, Change in temperature, Change in precipitation, log(Market distance), log(Farm size), log(Household size), log(Farming experience), Province, Soil fertility, Migration background, Literacy}) \quad (6.A)$$

To check the robustness of the estimates against the different model specification, we have employed a doubly robust (DR) approach. In this approach, a weighted regression of the outcome—defined in Equation (7.A)—using the pscores, estimated using the model in Equation (6.A), as weights is performed. In the outcome model, Equation (7.A), in addition to the variables included in the pscore model, we have included the variables that affect the outcomes with some interaction terms.

$$Y = G(\text{Main occupation, Second occupation, Irrigation, Household size, Gender, Change in temperature, Change in precipitation, log(Market distance), log(Farm size), log(Household size), log(Farming experience), Province, Cause of climate change, Soil fertility, Migration background, Literacy, Literate member, TV, Main occupation * log(Farm size), Literate members * log(Farm size), log(Market distance) * Main occupation, Literacy * Second occupation, log(Market distance) * Literate members, Cause of climate change * Literate members}) \quad (7.A)$$

A.3: pscore and covariates balance

Following the discussions in Subsection 3.1, to estimate the ATT using the propensity scores, the condition in Equation 2 (Section 3.1) and the overlap assumption should be satisfied. For checking the overlap, we have used a logistic model—as suggested by Rosenbaum and Rubin (1983)—to predict the likelihood of farmers to be treated being given the observed covariates. The summary statistics of the pscores, reported in Table B. 4 in Appendix B, confirm that the overlap condition is satisfied. The distribution of the pscore among treated and non-treated farmers is depicted in Figures C.5 and C.6 in Appendix C.

Unlike overlap assumption, the condition in Equation 2 (Section 3.1) is not directly testable. However, it has a testable implication that can be invoked in practice. The condition in Equation 2 is violated if the covariates are not balanced at a satisfactory level. To check the covariate balance, first (standard difference in means (SD)) and second (Variance Ratio (VR)) moments (given in the following equations) of the distribution are gauged against a rule of thumb.

$$SD = (\bar{X}_T - \bar{X}_C) \left[\sqrt{\frac{(s_T^2 + s_C^2)}{2}} \right]^{-1}, \quad SB = |SD|.100\% \quad (8.A)$$

$$VR = [S_T^2][S_C^2]^{-1} \quad (9.A)$$

Although there is no clear-cut rule on the optimal values of SD/SB and VR, in practice a $|SD|$ less than 0.1 (an SB of less than 10%) and a VR between 0.5 and 2 for each covariate indicate satisfactory covariates balance (Austin, 2011). An SB of larger than 25% is a sign of severe imbalances (Wooldridge, 2010, p. 917).

In order to assess the balance of the covariates, we have calculated the SB and VR for all corresponding covariates under both kernel matching and DR estimator. The results, reported in Table B.3 in Appendix B, confirm a satisfactory balance of the covariates under both kernel matching and doubly robust estimator.

Appendix B: Additional Tables

Table B.1: Average annual precipitation and average annual temperature across 3 provinces

Province	Precipitation	Temperature
	Mean (std. dev) min max	Mean (std. dev) min max
Bamiyan	300 (77) 201 621	2 (2) .7 7.5
Ghazni	570 (108) 342 715	5.5 (2.1) 2.1 9.4
Diakundi	321 (115) 223 668	7.4 (1.4) 4.9 11.2

Notes: The precipitation is in mm. The temperature is in degree Celsius.

Table B. 2: Description and summary statistics of the instruments

Variable	Description	Sample mean (std .Dev)
<i>Treatment variable</i>		
External support	The farmer received at least one type of adaptation related support from GOs/NGOs: dummy	.19(.39)
<i>Outcome variables</i>		
Risk of drought	Perceived risk of drought: categorical (1 no risk to 4 very high risk)	3.0(1.21)
Risk of flood	Perceived risk of flood: categorical (1 no risk to 4 very high risk)	2.9(1.01)
Risk of cold/heatwaves	Perceived risk of cold/heat: categorical (1 no risk to 4 very high risk)	2.6(1.20)
Risk of crop failure	Perceived risk of crop failure: categorical (1 no risk to 4 very high risk)	2.9(1.01)
Risk of disease/pest	Perceived risk of disease: categorical (1 no risk to 4 very high risk)	2.9(1.02)
Farming constraint-water	The availability of irrigation water is a constraint to farming: dummy	.64(.48)
Adaptation-shift to other employments	The farmer has partly or entirely shifted to other employment as a result of impact of	.42(.49)

	climate change on their farm: dummy	
Adaptation-more work on the farm	The farmer spends more time work on his farm compared to 15-to 20 years ago: dummy	.68(.47)
Adaptation-use of improved seeds	Farmer uses improved types of seeds: dummy	.38(.48)
Adaptation constraint-poverty	Farmer's poverty is a constraint for adaptation: dummy	.84(.37)
Adaptation constraint-external support	No/insufficient external support is a constraint for farmer's adaptation: dummy	.60(.49)
Adaptation constraint-knowledge	Farmer's lack of knowledge is a constraint for farmer's adaptation: dummy	.50(.50)
<i>Climate factors</i>		
Winter precipitation	The total precipitation in the traditional winter season: January, February, and March: continues	70 (25)
Spring precipitation	The total precipitation in the traditional spring season: April, May, and Jun: continues	33(17)
Summer precipitation	The total precipitation in the traditional summer season: July, August, and September : continues	2.4(2.5)
Fall precipitation	The total precipitation in the traditional fall season: October, November, and December: continues	24(10)
Winter temperature	The average temperature in the traditional winter season: January, February, and March: continues	-7(3)
Spring temperature	The average temperature in the traditional spring season: April, May, and Jun: continues	10.4(2.3)
Summer temperature	The average temperature in the traditional summer season: July, August, and September : continues	14.4(1.7)
Fall temperature	The average temperature in the traditional fall season: October, November, and December:	0.19(2.8)

continues		
<i>Province</i>	The province where the farmer live: categorical	
Bamiyan		40%
Ghazni		25%
Diakundi		35%
<i>Irrigation water</i>	Irrigation type: categorical	
River		
Stream		.20
Karez		.40
		.40
<i>Change in temperature</i>	Farmer perception of change in average temperature: categorical	
Warmer		88%
Colder		7%
No change		2%
No idea		3%
<i>Change in precipitation</i>	Farmer perception of change in average precipitation: categorical	
Decreased		90%
Increased		6%
No change		1%
No idea		3%
<i>Cause of climate change</i>	Farmer perception of the main cause of climate change: categorical	
God's will		64%
Humans		11%
Nature		22%
Others		3%
<i>Environmental/farm characteristics</i>		
Soil fertility	Soil is fertile: dummy	.57(.50)
Flat	The farmland is entirely/mostly flat: dummy	.40(.49)

	[1=yes]	
External support	Received farming related supports from GO/NGOs: dummy [1=yes]	.18(.39)
Distance to the market	Distance to the nearest market by car/motorbike in minutes: continues	41(43)
Log of the farm size	Log of the farm size (in acre): continues	1.5(.95)
<i>Household head characteristics</i>		
Primary employment	Farming is the primary occupation of the household head: dummy [1=yes]	.80(.40)
Secondary employment	Farming is the secondary occupation of the household head: dummy [1=yes]	.46(.50)
Literate	Household head is literate: dummy [1=yes]	.59(.49)
Gender	Gender of the household head: dummy [1=male]	
Migration background	Migration background of the household head: dummy [1=have been abroad]	.65(.48)
Farming experience	Farming experience of the household head in years: continues	22(14)
Risk perception	General risk perception of the household head: categorical (0:accepts no risk to 4:accepts high risks)	1.6(1.4)
Household size	Household size: continues	9(3.5)
Age	Age of the household head: continues	46.8(15)
TV	Farmer has a TV at home: dummy [1=yes]	.69(.46)
No of literate members	Number of farmer's household who are literate: continues	3.7(2.5)

Table B.3: Standard difference in mean and variance ratio of the covariates

No	Covariate	Standard difference in means (SD)		Variance ratio (VR)	
		KM	DR	KM	DR

1	Primary employment— farming [yes=1]	-.04	.03	1.05	.97
2	Secondary employment—farming [yes=1]	-.03	-.01	1.00	1.00
3	Irrigation water: River=0				
	Stream=1	.05	.02	1.05	1.00
	Karez=2	.0009	-.02	1.00	.98
4	Change in temperature: No change=0				
	Increased=1	.02	.004	.92	.98
	Decreased=2	-.009	-.002	.95	.98
	No idea=3	-.01	-.0007	.90	.99
5	Change in precipitation: No change=0				
	Decreased=1	.02	.001	.95	.99
	Increased=2	-.04	-.02	.87	.94
	No idea=3	.02	.007	1.1	1.05
6	Province : Bamiyan=1				
	Ghazni=2	-.005	.0006	.97	1.00
	Diakundi=3	-.009	-.01	.99	.99
7	Household size	.003	-.005	1.01	1.00
8	Log(Market distance)	.03	-.003	1.01	.98

9	Log(Farm size)	.02	-.004	.69	.69
10	Log(Household size)	.004	-.003	.97	.97
11	Age	.02	-.006	.84	.87
12	Log(farming experience)	.005	-.007	.79	.82
13	Soil fertility [Not fertile=1]	.01	.02	1.00	1.00
14	Migration background [yes=1]	.01	-.006	.99	1.00
15	Literate [yes=1]	-.003	-.03	1.00	1.02

Notes: KM: kernel matching. DR: Doubly robust.

Table B. 4: Summary statistics of the estimated pscores

pscore	Min.	Max.	Mean (st. d)	Mean_0 (St. D) N=1,222	Mean_1 (st. d) N=261
	.015	.67	.24(.12)	.12(.11)	.31(.14)

Appendix C: Figures

Figure C. 1: Study Districts

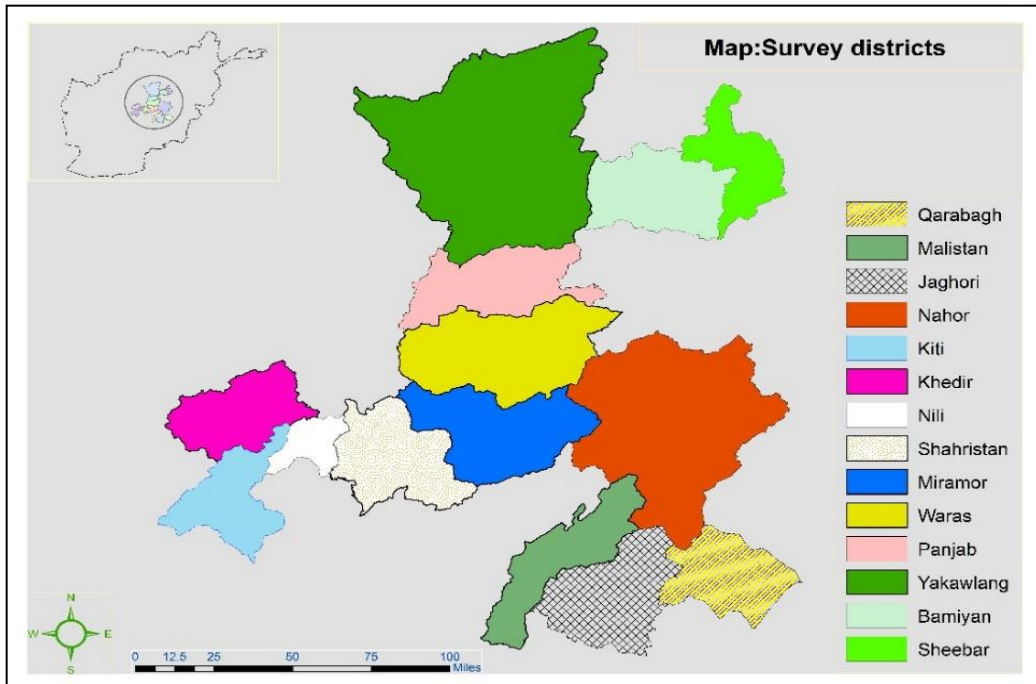
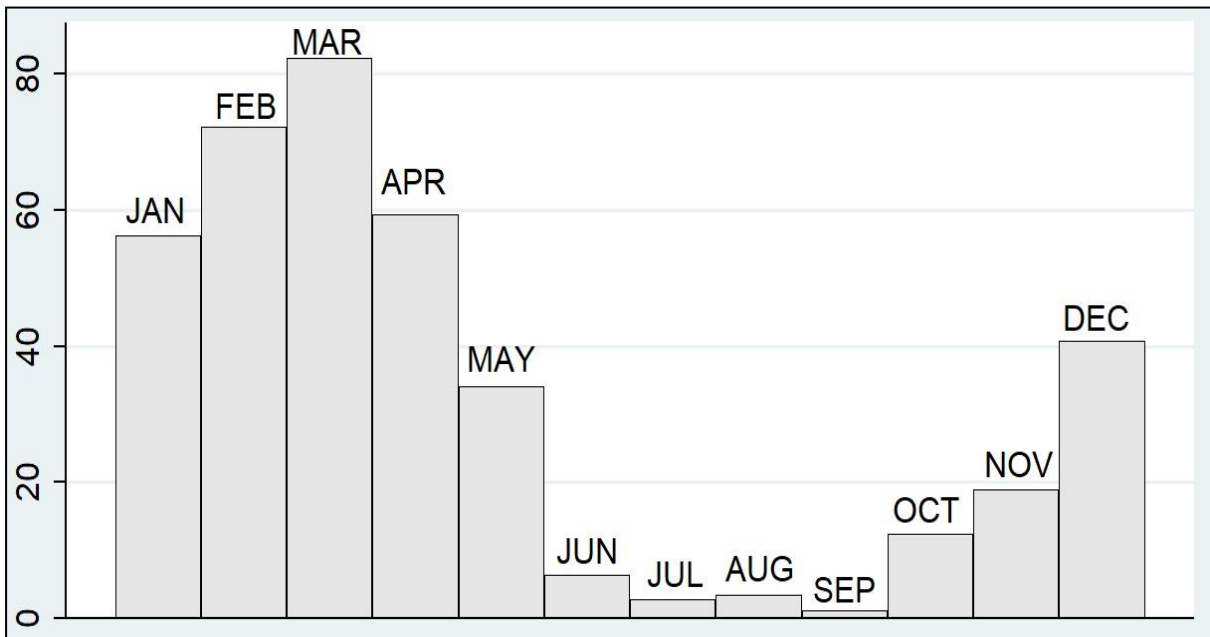
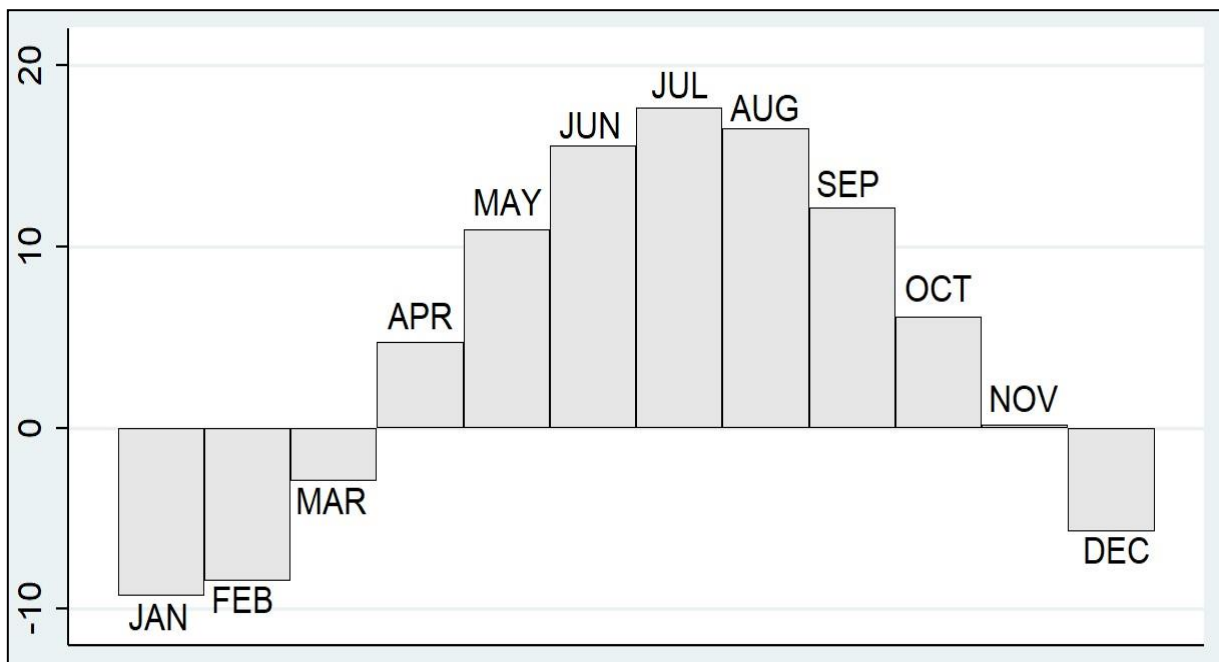


Figure C. 2: Average monthly precipitation (in mm)**Figure C. 3:** Average monthly temperature (in degree Celsius)

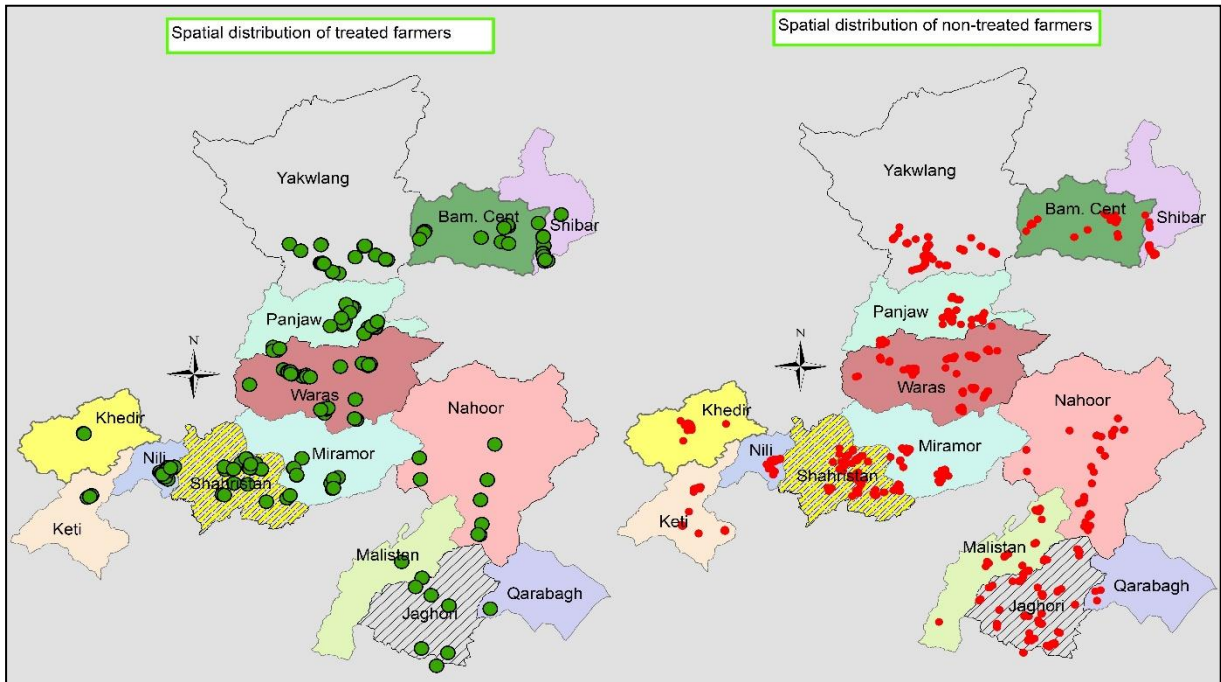


Figure C. 4: Spatial distribution of treated and non-treated farmers

Figure C. 5: Distribution of the estimated *p*score among treated and non-treated farmers

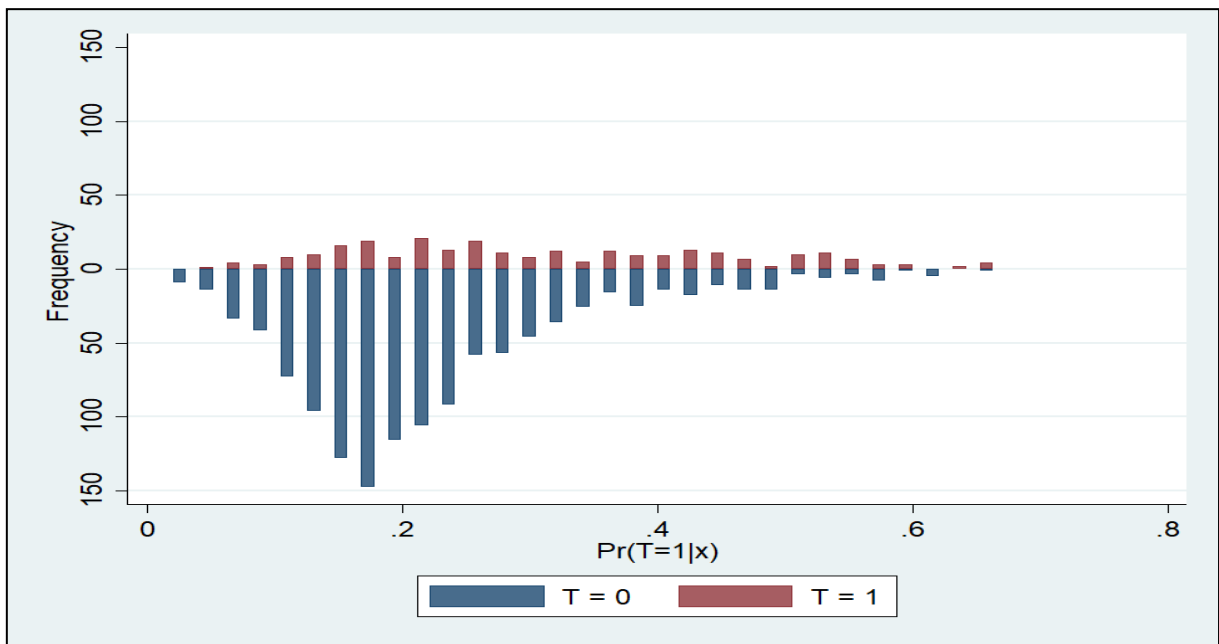
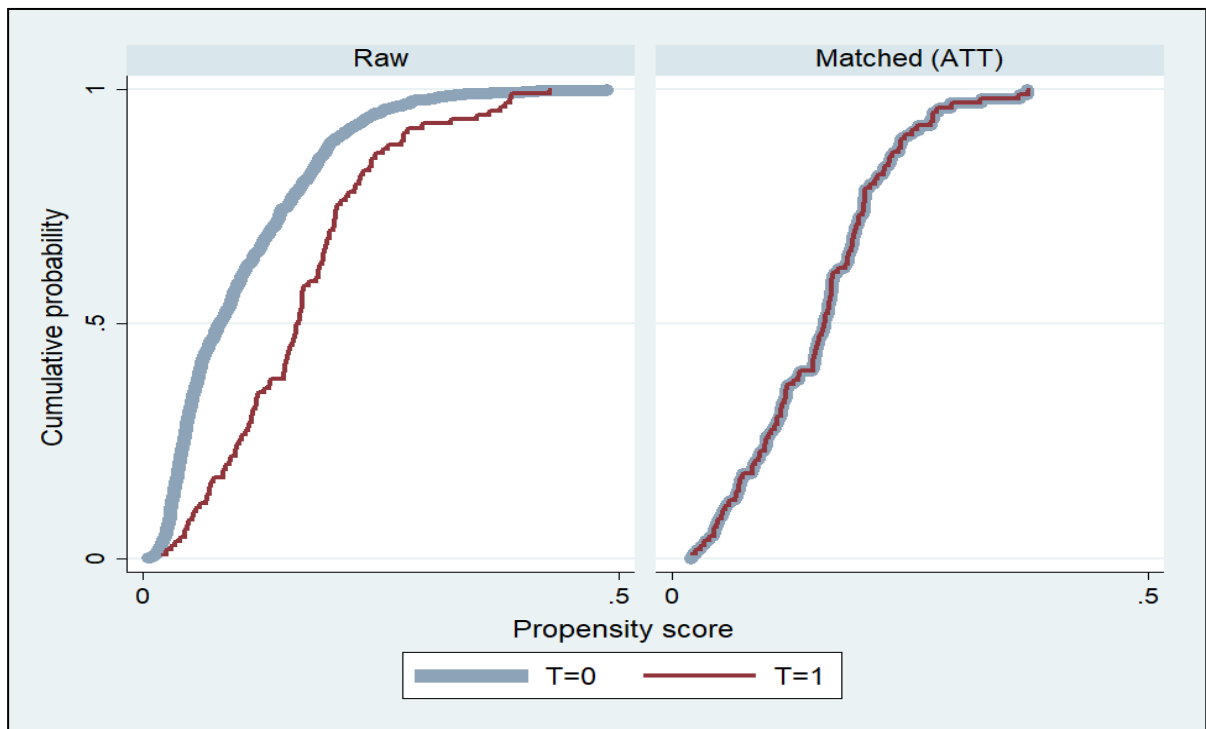


Figure C. 6: Cumulative *pscore* before and after Matching

Appendix D: English translation of the questionnaire

Part I: Personal/household characteristics

- Province: [1: Bamiyan, 2: Ghazni, 3: Diakundi]
- Gender: gender of the household head [male=1]
- Only farming: the farmer is engaged only in farming [yes=1]
- Primary source of income: primary source of income [farming=1]
- Primary occupation: the primary occupation is farming [yes=1]
- Secondary occupation: the secondary occupation is farming [yes=1]
- Literate: household head can at least read and write [yes=1]
- Stayed abroad: household head spent some time abroad [yes=1]
- Farming experience: the number of years the household engaged in farming [continues]
- Age: age of the household head [continues]
- Place of birth: the farmer was born and grown up in the same village [yes=1]
- Risk perception: general risk perception of the household head [categorical (0: accepts no risk to 4: accepts high risks)]
- Household size: the number of family members
- No of literate members: the number of family members who are literate
- TV: TV ownership [yes=1]
- Electricity: hours with access to electricity [continues]

Part 2: Climate change, extreme weather events, adaptation

- Perceived climate change: farmer has perceived climate change [yes=1]
- Change in temperature: average temperature changed [0: no change, 1: increased, 2: decreased, 3: no idea]
- Change in precipitation: average amount of precipitation changed [0: no change, 1: decreased, 2: increased, 3: no idea]
- Main cause of climate change: the main cause of climate change [0: God's will, 1: human, 2: nature, 3: others]
- Overall impact of climate change: overall impact of climate change on agriculture [+1: positive, 0: none, -1: negative]

- Change in farm production: change in farm production as a result of climate change
[+1: increased, 0: no change, -1: decreased]
- Farm vulnerability: farm vulnerability to climate change [0: not vulnerable, 1: vulnerable, 2: very vulnerable]
- Risk of drought: perceived risk of drought [Categorical (1 no risk to 4 very high risk)]
- Risk of flood: perceived risk of flood [Categorical (1 no risk to 4 very high risk)]
- Risk of cold/heatwaves: perceived risk of cold/heat [Categorical (1 no risk to 4 very high risk)]
- Risk of crop failure: perceived risk of crop failure [Categorical (1 no risk to 4 very high risk)]
- Risk of disease/pest perceived risk of disease [Categorical (1 no risk to 4 very high risk)]
- Farming constraint-water scarcity: the availability of irrigation water is a constraint to farming [yes=1]
- Adaptation-shift to other employment: the farmer has partly or entirely shifted to other employment as a result of the impact of climate change on their farm [yes=1]
- Adaptation-more work on the farm: the farmer spends more time working on his farm compared to 15-to 20 years ago [yes=1]
- Adaptation-use of improved seeds: farmer uses improved types of seeds [yes=1]
- Economic/financial constraint: farmer's poverty constrains adaptation [yes=1]
- Government/institutional constraint: limited external support constrains adaptation [yes=1]
- Knowledge, awareness, use of tech: limited knowledge and use of tech constraints adaptation [yes=1]

External support: the farmer received at least one type of adaptation related support from GOs/NGOs [yes=1]

Climate change related constraints: perceived climate change-related constraints for farming [yes=1]

Part 3: Farm characteristics

- Market distance: distance to the nearest market in minutes [continues]
- Farm size: farm size in acre [continues]
- Flat: the farmland is flat [yes=1]

- Sale farm's product: sale a part of the farm products [yes=1]
- Soil type I: rocky land with Lithic Cryorthents
- Soil type II: rocky land with Lithic Haplocryids
- Soil fertility: the soil is fertile [yes=1]
- Irrigation types [0: river, 1:stream, 2: karez]
- Crop net revenue: the difference of total annual income from all crops and total annual expenses (in AFN) [continues]
- Seeds: the amount of money spent annually for varieties of seeds (in AFN) [continues]
- Fertilizer: the amount of money spent annually for fertilizer (in AFN) [continues]
- Pesticides: the amount of money spent annually for different types of pesticides (in AFN) [continues]
- External labor: the amount of money spent annually for external labor (in AFN) [continues]

Part 4: Climate factors

- Winter precipitation: the total precipitation in the traditional winter season: January, February, and March (in mm) [continues]
- Spring precipitation: the total precipitation in the traditional spring season: April, May, and Jun (in mm) [continues]
- Continued on next page
- Summer precipitation: the total precipitation in the traditional summer season: July, August, and September (in mm) [continues]
- Fall precipitation: the total precipitation in the traditional fall season: October, November, and December (in mm) [continues]
- Winter temperature: the average temperature in the traditional winter season (DC): January, February, and March [continues]
- Spring temperature: the average temperature in the traditional spring season: April, May, and Jun (Dc) [continues]
- Summer temperature: the average temperature in the traditional summer season: July, August, and September (DC) [continues]
- Fall temperature: the average temperature in the traditional fall season (DC): October, November, and December [continues]