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# Essays on Environmental and Behavioral Economics

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# **Dedicated to**

*the two most important women in my life, my mother, Mariam Wafae , and my wife, Shamsia  
Jawid.*

# Contents

<b>Acknowledgements</b>	<b>vi</b>
<b>Preface</b>	<b>vii</b>
<b>1 Introduction</b>	<b>1</b>
<b>References</b>	<b>5</b>
<b>2 Climate Sensitivity of Crops Revenue and Adaptation: A Ricardian and Endogenous Switching Analysis of Farms in the Central Highlands of Afghanistan</b>	<b>7</b>
2.1 Introduction . . . . .	8
2.2 Methodology . . . . .	10
2.2.1 The Ricardian Model . . . . .	10
2.2.2 Endogenous Switching Model . . . . .	11
2.3 Study Area and Data . . . . .	12
2.3.1 Study Area . . . . .	12
2.3.2 Data and Survey Instruments . . . . .	14
2.4 Results and Discussions . . . . .	15
2.4.1 Sample Characteristics . . . . .	15
2.4.2 Multicollinearity of Climate Variables . . . . .	18
2.4.3 Ricardian Analysis of the Climate Sensitivity of Crops Net Revenue . . . . .	19
2.4.4 Endogeneity of Farmers' Adaptation . . . . .	24
2.4.5 Climate Simulations . . . . .	27
2.5 Conclusion . . . . .	29
2.6 Appendices . . . . .	31
2.6.1 Appendix A: Additional Tables . . . . .	31
2.6.2 Appendix B: Additional Figures . . . . .	35
<b>References</b>	<b>37</b>
<b>3 Exposure to Climate Change-Related Extreme Weather Events and Risk Preferences: Evidence from Farmers in Afghanistan</b>	<b>40</b>
3.1 Introduction . . . . .	41
3.2 Climate Change and Extreme Weather Events in the Study Area . . . . .	42

3.3	Research Design and Data . . . . .	43
3.4	Results . . . . .	44
3.4.1	Descriptive Statistics . . . . .	44
3.4.2	Exposure to Climate Change-Related Extremes and Risk Preferences . . . . .	46
3.5	Discussion of Possible Mechanisms . . . . .	48
3.6	Conclusion . . . . .	50
3.7	Appendices . . . . .	51
3.7.1	Appendix A: Field Experiment . . . . .	51
3.7.2	Appendix B: Figures . . . . .	52
<b>References</b>		<b>53</b>
<b>4</b>	<b>Adaptation to Climate Change in Afghanistan: Evidence on the Impact of External Interventions</b>	<b>56</b>
4.1	Introduction . . . . .	57
4.2	Climate change in Afghanistan . . . . .	59
4.3	Methodology . . . . .	61
4.3.1	Propensity Score Estimation . . . . .	61
4.3.2	Endogenous Switching Model . . . . .	64
4.4	Study area and Data . . . . .	64
4.4.1	Study Area . . . . .	64
4.4.2	Data and Survey Instruments . . . . .	65
4.5	Results and Discussions . . . . .	65
4.5.1	Sample Characteristics . . . . .	65
4.5.2	Climate Change Perception, Impacts, and Risks . . . . .	66
4.5.3	Adaptation: Implementation, Constraints, Support . . . . .	67
4.5.4	Kernel Matching Estimates of the Treatment Effects . . . . .	67
4.6	Conclusion and Policy Recommendations . . . . .	72
4.7	Appendices . . . . .	74
4.7.1	Appendix A.1: Pscore and Outcome Models . . . . .	74
4.7.2	Appendix A.2: Pscore and Covariates Balance . . . . .	76
4.7.3	Appendix B: Additional Tables . . . . .	78
4.7.4	Appendix C: Additional Figures . . . . .	80
<b>References</b>		<b>81</b>
<b>5</b>	<b>Instruments Description and Questionnaire</b>	<b>85</b>
5.1	Instrument Description and Summary Statistics . . . . .	85
<b>Affirmation</b>		<b>101</b>

# List of Tables

2.1	Summary Statistics of the Instruments . . . . .	15
2.2	Ricardian Analysis of Climate Sensitivity of Crops Net Revenue . . . . .	20
2.3	Marginal Impacts of the Climate Variables . . . . .	22
2.4	Endogenous Switching Regression of Adaptation and Crops Net Revenue . . . . .	25
2.5	Counterfactual Analysis of the Expected Crops Revenue . . . . .	27
2.6	Impacts of Climate in 2100 on Crops Revenue in the Study Area. . . . .	28
2.7	Average Annual Precipitation and Average Annual Temperature across 3 Provinces	31
2.8	Ricardian Analysis of Crops Net Revenue with Traditional Climate variables . . .	31
2.9	Factor Loadings of the Monthly Precipitation and Temperature . . . . .	32
2.10	Ricardian Estimates under Alternative Estimation Methods . . . . .	32
2.11	Test on the Validity of the Selection Instrument . . . . .	34
3.1	Eckel-Grossman Task (EGTask) . . . . .	44
3.2	Summary Statistics . . . . .	45
3.3	Ordered Probit Model of Farmers' Risk Preferences/Perception . . . . .	47
4.1	Summary Statistics of the Outcome Variables . . . . .	68
4.2	Propensity Score Estimates of the Treatment Effect on Farmers' Adaptation . . .	69
4.3	Robustness Tests (Sensitivity Analysis and Endogenous Switching Regression) . .	71
4.4	Description of the Exogenous Variables . . . . .	74
4.5	Description of the Exogenous Variables . . . . .	75
4.6	Standard Difference in Mean and Variance Ratio of the Covariates . . . . .	78
4.7	Summary Statistics of the Estimated P-scores . . . . .	79
5.1	Description of the Instruments . . . . .	85

# List of Figures

2.1	Study Districts in the Central Highlands of Afghanistan. . . . .	13
2.2	Distribution of Farmers Across Study Districts . . . . .	35
2.3	Average Monthly Precipitation (in mm) . . . . .	35
2.4	Average Monthly Temperature (in degree Celsius) . . . . .	35
2.5	Average Annual Temperature in the Study Area . . . . .	36
2.6	Average Annual Precipitation in the Study Area . . . . .	36
3.1	Annual Temperature from 1979 to 2014 in Bamiyan, Ghazni, and Diakundi Provinces	52
3.2	Annual Precipitation from 1979 to 2014 in Bamiyan, Ghazni, and Diakundi Provinces	52
4.1	Pscore Distribution . . . . .	75
4.2	Pscore Cumulative Distribution Before and After Matching . . . . .	77
4.3	Sample Distribution with Respect to <i>Treatment</i> . . . . .	80
4.4	NEPA/UNEP Project Sites . . . . .	80

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# Preface

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This dissertation is a collection of three essays contributing to the field of Environmental and Behavioral Economics. The title of the first essay is "*Climate Sensitivity of Crops Revenue and Adaptation: A Ricardian and Endogenous Switching Analysis of Farms in the Central Highlands of Afghanistan*". The second essay — co-authored by Menusch Khadjavi (PhD) — takes on the issue of extreme weather events and farmers' behavior. The title of the second essay is "*Exposure to Climate Change-related Extreme Weather Events and Risk Preferences: Evidence from Farmers in Afghanistan*". The third essay — co-authored by Menusch Khadjavi (PhD) — titled "*Adaptation to Climate Change in Afghanistan: Evidence on the Impact of External Interventions*", addresses adaptation and the impact of external supports (provided by government/non-governmental organizations) on farmers' adaptation. The third essay is published in the *Journal of Economic Analysis and Policy* and is available online at <https://doi.org/10.1016/j.eap.2019.07.010>. I believe the combination of the three essays makes a significant contribution to the literature on climate change, agriculture, and farmers' behavior in the context of Afghanistan.

# 1 Introduction

*"Many key [climate change-related] risks constitute particular challenges for the least developed countries and vulnerable communities, given their limited ability to cope."*

— IPCC, 5th Assessment Report, Working Group 2 (2014)

Climate change is largely ranked as the greatest challenge the global community faces. Stern (2007) calls climate change *"the greatest market failure the world has ever seen."* (p. viii). Global warming has emerged as one of the most passionate topics in political, economic, science, and development discourse. Considering the extremely complex dynamics, any conclusion about climate change cause(s), impacts, and the way they are unfolded carries a high degree of uncertainty. As Nordhaus and Boyer (2003) state *"attempts to estimate the impacts of climate change continue to be highly speculative."* (p. 98). With more rigorous insights and abundant data in recent years, scientists are convinced that global climate change is happening. There is robust evidence on a 1°C increase in average global temperature since the preindustrial era <sup>1</sup>. However, the proposition that global warming is human-driven has still got some sceptics. For managing the ongoing discussions and consolidating the scientific evidence, the Intergovernmental Panel on Climate Change (IPCC<sup>2</sup>) was established in 1988. So far, the panel has released five assessment reports (AR), and the 6th report is underway <sup>3</sup>.

Apart from other ramifications, the impact of climate change on agriculture has been evident and attracted ample attention among researchers and policymakers in recent decades (Innes and Kane, 1995; Kaiser and Crosson, 1995; Reilly, 1995; Antle, 1995; Mendelsohn et al., 1994; Mendelsohn and Dinar, 2003; Gbetibouo and Hassan, 2005; Molua, 2009; Mendelsohn and Dinar, 2009; Zinyengere et al., 2013; Yongfu et al., 2013; Karimi et al., 2018). Agriculture is proved to be highly sensitive to environmental variation, such as a change in temperature and precipitation (Mendelsohn and Dinar, 2009). Hence, the sector is immediately affected by changes in the climate. Thereupon, a substantial interest lies in understanding the possible effects and the mechanisms through which climate change and other environmental disruptions impact agriculture (Mendelsohn et al., 1994).

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<sup>1</sup> <https://www.ipcc.ch/sr15/chapter/summary-for-policy-makers/>

<sup>2</sup> IPCC is the scientific body which provides an objective, scientific view of climate change, its natural, political and economic impacts and risks, and possible adaptation options.

<sup>3</sup> <https://archive.ipcc.ch/>



Contributing to this line of research, the first essay (of the current dissertation) studies the economic impact of climate change on agriculture. Titled as "*Climate Sensitivity of Crops Revenue and Adaptation: A Ricardian and Endogenous Switching Analysis of Farms in the Central Highlands of Afghanistan*", the first essay uses 34 years<sup>4</sup> of daily weather information and detailed household data (including annual farm revenue, the annual cost of farming, and adaptation) from 1502 farming households to shed light on the sensitivity of crops net revenue to climate factors. By understanding the sign, significance, and the magnitude of the coefficients of the exogenous climate variables in the model, the first essay provides evidence on how changes in those climate factors would affect crops revenue. A Ricardian (first proposed by Mendelsohn et al. (1994)) model is used for investigating the climate–crops revenue relationship. The traditional model is extended by explicitly considering the farmers' adaptation. By employing an endogenous switching model, the essay contributes to the debate on the endogeneity of farmers' adaptation. Past studies have been improved by systematically addressing the multicollinearity of climate factors. The likely impacts of future changes in the climate on crops revenue are analysed by combining the estimated model with future climate scenarios. The rigorous and detailed treatment is presented in Chapter 2.

The impact of climate change and related extreme events on agriculture is not limited to the effects on yield, productivity, and revenue. Recent literature has started addressing the behavioural impacts and investigates individual's (e.g. farmers') behavioural adjustments in response to the realised effects (Adger et al., 2005). However, the question of whether climate change and related extreme events trigger changes in individuals' economic behaviour remains an understudied subject (Dang, 2012). Such studies are especially critical for adaptation, which has emerged as one of the central matters in climate change discourse (see, for instance, (Stern, 2007) or (IPCC, 2014)). Contributing to this literature, the second essay — co-authored by Menuşch Khadjavi — addresses the farmers' risk preferences. Titled as "*Exposure to Climate Change-Related Extreme Weather Events and Risk Preferences: Evidence from Farmers in Afghanistan*", the second essay explores the association of farmers' risk preferences and their exposure to extreme weather events, such as drought, flood, and cold/heatwaves. We use experimental and survey data from a total of 1741 farmers to shed light on the question of whether long-term exposure to extreme events affects farmers' risk preferences. Additionally, we contribute to the growing debate on the endogeneity of risk preferences. The detailed treatment is provided in Chapter 3.

With the world's population is expected to grow rapidly<sup>5</sup>, feeding them depends on agriculture sector to survive the consequences of global warming and thrive under the changing climate and increasing related extreme events. Extreme weather events — including drought, heatwaves, and flood — are threatening food security, decreasing crops yield and quality, and limiting access to food, especially in developing countries (IPCC, 2014). In this regard, designing and practising appropriate response options — that reduce the adverse effects and optimally use the opportunities — has been suggested as a critical research and policy matter (Khanal et al., 2018). Contributing

<sup>4</sup> 1979-2014

<sup>5</sup> <https://www.un.org/en/sections/issues-depth/population/index.html>

to this growing body of literature, the third essay — which is co-authored by Menusch Khadjavi — investigates farmers' adaptation to climate change. Titled "*Adaptation to Climate Change in Afghanistan: Evidence on the Impact of External Interventions*", the third essay explores farmers' perception of- and adaptation to climate change. Using quasi-experimental methods, the third essay further explores the role of external support in farmers' adaptation. Chapter 4 presents the details. The third essay is published in the *Journal of Economic Analysis and Policy*. It is available online at: <https://doi.org/10.1016/j.eap.2019.07.010>.

A notable aspect of the dissertation is its focus on a least developed, highly susceptible, and politically extremely fragile country: Afghanistan. The literature largely agrees that agriculture in the least developed and developing countries, such as Afghanistan, are most vulnerable and least capable to adapt to climate change and related environmental disruptions (such as drought) (Khanal et al., 2019).

Afghanistan, a country which has been in a relentless war and political instability for more than 40 years<sup>6</sup>, has been continuously ranked as one of the most vulnerable countries to the impacts of climate change (Kreft et al., 2016; Aich et al., 2017). Several factors are contributing to bringing Afghanistan to this position. First, with an arid and semi-arid climate (Aich et al., 2017), the country is very exposed to any changes in the climate. Although it is hard (due to data limitation) to establish a causal relation, the outbreak of drought, flood, and landslide has increased in recent decades. Second, the economy of the country largely depends on agriculture. According to the World Bank, even though the sector's contribution to the national GDP is about 20%, it remains the primary source of livelihood for more than 79% of the Afghans (Haque et al., 2018). Thus, climate change can be a real threat<sup>7</sup> to the income, employment, food security, and livelihood of nearly 2/3 of the country's inhabitants. Third, due to more than four decades of war and instability (which continues to date), a robust institutional framework has not been existing. Hence, the governmental and institutional capacity to respond to the impacts of climate change is minimal. Such limitation extends to the household and community levels too as, according to the World Bank, about 55% of the country's population (mostly farmers) live in absolute poverty (Haque et al., 2018).

A distinguished facet of this dissertation is that it uses primary data from a large group of farmers living in one of the most marginalised and least developed areas in Afghanistan. The Central Highlands is one of the country's five climate zones (Aich et al., 2017). There is no major city in the area. Majority of the people are engaged in farming, herding, or both. Agriculture plays a decisive role in people's livelihood. Due to the harsh and mountainous topology, arable land scarce in the whole of the Central Highlands. Evidence suggests that climate in the Central Highlands has changed<sup>8</sup>, like other parts of the country. Various dimensions of the impacts (realised and expected; physical, behavioural), possible mechanisms, farmers' responses, and external interventions are yet to be studied. Having a clear understanding of these matters is vital for designing

<sup>6</sup> <https://www.worldbank.org/en/country/afghanistan/overview>

<sup>7</sup> Underlining that some regions are benefiting from climate change.

<sup>8</sup> A detailed treatment is provided in Section 3.2

policies responding to the consequences of climate change in the area.

Current work is the first that systematically attempts to investigate significant issues related to climate change in the Central Highlands of Afghanistan. By analysing the economic and behavioural impacts and studying the farmers' perception and adaptation, the dissertation provides a unique combination of topics essential to all stakeholders. In addition, it provides a sound analysis of the recent history of climate change in the Central Highlands. Due to the importance of agriculture and climate change for the study area as well as the whole country, the dissertation will make a tremendous contribution in policy development and further research on climate change and related matters in Afghanistan.

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## 2 Climate Sensitivity of Crops Revenue and Adaptation: A Ricardian and Endogenous Switching Analysis of Farms in the Central Highlands of Afghanistan

*This essay is under review in the Journal of Asian Economics*

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### **Abstract**

This chapter provides evidence on the climate sensitivity of crops revenue in the Central Highlands of Afghanistan. A novel dataset of 1502 farmers from 14 districts in 3 central provinces and 34 years of weather information are used to study the impact of seasonal/annual precipitation and temperature on crops revenue per unit of land. Our findings suggest a significant and nonlinear effect of climate factors on crops revenue. The estimates are robust to several specifications. To address the potential endogeneity of adaptation and to compare the climate sensitivity of revenue between the two sub-samples (farmers who adapted and the rest), an endogenous switching regression with known endogenous switching point is exercised. The corresponding estimates confirm that adaptation is indeed endogenous, and there are apparent structural differences between the Ricardian function of the farmers who adapted and the farmers who did not. Also, the estimates of the choice model for adaptation show that climate is a vital driver of the farmer's decision to adapt. The current study is the first analysing the sensitivity of crops revenue to the climate in Afghanistan, providing firsthand evidence for climate change adaptation policy development in the country.

*Keywords:* Climate change; Agriculture; Crops revenue; Ricardian method; Endogenous switching regression; Afghanistan.

## 2.1 Introduction

Agriculture is one of the sectors that's very susceptible to climate change and variability (Seo, 2007; Yongfu et al., 2013). Both laboratory experiments and field experiences affirm that agriculture yields the highest growth and production at specific climatic conditions (Mendelsohn and Dinar, 2009). Hence, any changes in the climate can impact farm yields. Moreover, crops and livestock can be indirectly affected by changes in the climate, for instance through the availability of water, expansion of weeds, and pests' infestations (Molua, 2009; Mendelsohn and Dinar, 2009). Due to global warming, the study of the impact of climate change on agriculture has surged in recent decades (Innes and Kane, 1995; Kaiser and Crosson, 1995; Reilly, 1995; Antle, 1995; Mendelsohn et al., 1994; Mendelsohn and Dinar, 2003; Gbetibouo and Hassan, 2005; Molua, 2009; Mendelsohn and Dinar, 2009; Zinyengere et al., 2013; Yongfu et al., 2013; Karimi et al., 2018). The literature on the impact of climate change in Africa (Maddison et al., 2007), South America (Mendelsohn and Dinar, 2009), and China (Wang et al., 2009) suggests that even with adaptation, farm revenue will decrease as a result of global warming. Understanding the potential impacts on agriculture is particularly relevant for developing and least developed countries, like Afghanistan, which are highly dependent on agriculture for their national income and employment and possess a limited capacity to adapt (Antle, 1995; Mertz et al., 2009; Molua, 2009).

Afghanistan is ranked among the countries most vulnerable to climate change (Kreft et al., 2016; Aich et al., 2017) due to a number of factors, such as country's climate characteristics, the high dependency of its economy on agriculture, and limited adaptive capacity. The country possesses an arid and semi-arid continental climate (Savage et al., 2014), and a recent analysis by Aich et al. (2017) suggests that climate in Afghanistan has changed since the second half of the 20th century. In particular, the average annual temperature has increased by 1.8 °C; and the average precipitation has decreased, although with higher heterogeneity across space and seasons. Meanwhile, the frequency of extreme weather events, such as drought and flood, has increased (check Jawid and Khadjavi (2019) for details on the risk of extreme weather events).

Afghanistan is traditionally an agrarian country. Even though the contribution of agriculture to the national GDP is about 22%, it remains an important sector as a source of livelihoods for the rural poor population (Haque et al., 2018). It is estimated that around 79% of the population is engaged in farming, herding, or both (UNEP, 2004; Baizayee et al., 2014). The vulnerability of agriculture sector in Afghanistan to the changes in the climate is particularly high. Increased soil evaporation, reduced river flow, and less frequent rain during peak cultivation seasons impact agricultural productivity and crop choice availability (Savage et al., 2014).

To minimise the adverse effects of climate change and optimally use the opportunities it may bring, adaptation is imperative (Kurukulasuriya and Shane, 2003). However, for designing appropriate response policies, understanding the current and future impacts is crucial.

To the best of our knowledge, there are only one study (Mendelsohn, 2014) that has touched the issue of the economic impact of climate change on agriculture in Afghanistan. Mendelsohn (2014) uses studies on Chinese agriculture to estimate the potential effects of climate change on

agriculture in the rest of the Asian continent, including Afghanistan. Insights from such studies are crucial in understanding the extent of the problem and designing appropriate mitigation and adaptation strategies. The aggregate nature of such studies, however, makes it very difficult to provide evidence in terms of impact on crops revenue and effective adaptation strategies at local or household levels.

Therefore, the central motivation of this study is to contribute to the literature from the perspective of climate sensitivity of crops revenue and farmers' adaptation to climate change in Afghanistan, using household-level data. Specifically, we investigate the importance of climate for farming by exploring the impact of climatic factors on net crops revenue in the Central Highlands of Afghanistan. A Ricardian approach — first proposed by [Mendelsohn et al. \(1994\)](#) — is employed to estimate the impact of exogenous climate factors (temperature and precipitation) on crops net revenue per acre. The traditional Ricardian model considers the farmers' adaptation as a "black box" ([Seo, 2007](#)). Recent literature, however, proposes to explicitly account for adaptation ([Di Falco et al., 2011](#)). Such an exercise is particularly attractive for understanding the relevance of climate factors to adaptation and investigating the structural differences between the Ricardian models of farmers who adapted and those who did not. Using a switching model, we address the potential endogeneity of farmers' adaptation to climate change and carry out a comparative analysis of climate sensitivity of revenue among the two groups of farmers. Furthermore, the results of the Ricardian analyses and switching model are combined with future climate scenarios to predict the likely effects of future changes in climate on crops revenue.

The analyses are based on primary data collected in the summer (May–July) of 2017 from 1502 farmers across 14 districts in the Central Highlands of Afghanistan. An advanced survey application developed by the World Bank was used to carry out face-to-face interviews. Besides, weather information of 34 years (1979–2014) and soil data complement the analyses.

The results of the Ricardian model yield a significant yet complex impact of climate on crops net revenue. The effect of precipitation in the wet season (November–April) is non-linear. An increase in precipitation during the wet season has a decreasing marginal effect on revenue up to the minimum point after which it starts increasing. The impact of precipitation in the semi-wet season (May, June, September, and October) is estimated to be positive. A substantial increase in precipitation in this season might transform the effect to non-linear with a maximum point. Precipitation in the dry season (July, August) has a linear and negative impact on revenue. Due to high collinearity, the effect of temperature can only be studied on an annual basis. The overall impact of annual temperature on crop revenue is found to be beneficial.

The results of the endogenous switching regression confirm that the farmers' decision to adapt to climate change is indeed endogenous. The estimates further suggest that climate sensitivity of crops revenue is more profound among farmers who adapted to climate change. Moreover, the findings reveal that climate plays a significant role in farmers' decision to adapt.

The remainder of this chapter is organized as follows: Section 2.2 discusses the theory of Ricardian model as well as endogenous switching regression. Study area and survey instruments



are introduced in Section 2.3. Results and discussions are presented in Section 2.4. Section 2.5 provides concluding remarks.

## 2.2 Methodology

### 2.2.1 The Ricardian Model

Our analyses of the impact of climate change on crops revenue in the Central Highlands of Afghanistan are based on the Ricardian approach, which was first proposed by Mendelsohn et al. (1994). In the initial implementation for the farms in the United States, Mendelsohn et al. (1994) have used the land value per hectare as the endogenous variable. In the later adjustments, however, farm net revenue per unit of land was proposed for studies related to developing nations, due to the non-existence of consistent land market in those countries (Mendelsohn and Dinar (2009); Wang et al. (2009)). The Ricardian analysis is a cross-sectional model applied to crops production. The model assumes that farmers try to maximise their income subject to exogenous factors, such as climate and soil. Specifically, the price taker farmers choose the types of crops and the amount of each input for each unit of land that maximises their net revenue as defined in Eq. (2.1)

$$\pi = \sum P_{qi}Q_i(X_i, C, W, S) - \sum X_iP_{xi} \quad (2.1)$$

Where  $\pi$  is the net annual revenue per unit of land (acre),  $P_{qi}$  is the market price for crop  $i$ ,  $Q_i$  is the output of crop  $i$ ,  $X_i$  is a vector of annual inputs (seeds, fertilizer, labor, and pesticides) for each crop  $i$ ,  $P_{xi}$  is the vector of market prices for the yearly inputs,  $C$  is a vector of climate factors,  $W$  is a vector of irrigation systems, and  $S$  is a vector of soil variables.

Net revenue is defined as the difference between gross annual revenue from all types of products (potato, wheat, vegetables, fruits, etc.) and the total annual costs (seeds, fertilizer, pesticide, labor, cost of irrigation, etc.). The total cost does not include the household's labor. All of the output that was consumed by the farmer's household was given a value based on market prices as if it was sold in the market.

If farmers choose those crops that yield the highest revenue and each endogenous input in order to maximise net revenue, the resulting net revenue will be a function of just the exogenous factors:

$$\pi^* = f(P_q, P_x, C, S, W) \quad (2.2)$$

The net revenue function in Eq. (2.2) includes only the most profitable crops with respect to exogenous factors, such as precipitation and temperature. Hence, it is not a response function for every single crop but rather an envelope of all crop types that farmers choose. For instance, in warmer areas such as Jaghori district, farmers choose fruit trees and a variety of vegetables. In a slightly colder region like Malistan district, the same farmers would choose non-fruit trees. In warmer and more water-scarce areas like Diakundi province, these farmers would go for walnut and almond, which are more heat- and drought-tolerant. In a much colder climate in Bamiyan

province, the farmers would cultivate potato because other crops are less profitable. The Ricardian function in Eq. (2.2) captures the locus of maximum profits for each climate type. Eq. (2.2) is estimated across crops/trees and inputs, revealing the net effect of change in the exogenous factors (Wang et al., 2009). Since farmers are assumed to make the most profitable choices, the Ricardian method implicitly captures the adaptation inherent in the market (Mendelsohn et al., 1994).

## 2.2.2 Endogenous Switching Model

As mentioned in Section 2.2.1, the traditional Ricardian model considers adaptation only implicitly as a black box. Recent studies, however, suggest to explicitly include the farmers' adaptation in the model (Di Falco et al., 2011). To do so, a dummy variable — which is 1 if a farmer has adapted at least one agricultural adaptation strategy and 0 otherwise — is defined. Agricultural adaptation includes various soil and water conservation measures, crop diversification and use of improved types of seeds, use of fertilizer, and digging a water well. The most straightforward approach to specify explicit adaptation is to include the adaptation dummy directly into the model. But since adaptation is most likely endogenous, such an exercise might yield biased estimates (Di Falco et al., 2011). Hence, it is suggested to account for the endogeneity of adaptation decision by estimating a simultaneous equations model of climate change adaptation and crops net revenue with endogenous switching by full information maximum likelihood (Lokshin and Sajaia, 2004).

To this end, a two-stage approach, as summarised by Lokshin and Sajaia (2004), is practised. In the first stage, a selection model for climate change adaptation, where a representative farmer chooses to implement adaptation strategies if their net benefit is positive, is implemented. Let  $A^* = Z_i\gamma + \eta_i$  be a latent variable that captures the expected benefits from the adaptation choices. Then a dummy variable  $A_i$ , which is 1 if the farmer  $i$  adapts, is specified as follows:

$$A_i = \begin{cases} 1 & \text{if } A^* \text{ is positive} \\ 0 & \text{Otherwise.} \end{cases} \quad (2.3)$$

$Z$  includes factors that affect the expected benefits of adaptation and hence, the probability of implementing adaptation strategies. Variables such as climate, soil, extreme weather events, and farmer and farm characteristics are included in  $Z$ .

In the second stage, the impact of climate change on crops revenue by the representation of the Ricardian function in Eq. (2.2) for the two groups of farmers (adapters and non-adapters) is modelled.

Under an endogenous switching regression model of crops revenue, the Ricardian functions of the farmers who adapted and those who did not are defined as follows:

$$\pi_{1i}^* = M_{1i}\beta_1 + \epsilon_{1i} \text{ for } A_i = 1 \quad (2.4)$$

$$\pi_{0i}^* = M_{0i}\beta_1 + \epsilon_{0i} \text{ for } A_i = 0 \quad (2.5)$$

Where  $\pi_{1i}^*$  and  $\pi_{0i}^*$  are the crops net revenue (per acre) of the farmers who adapted and the farmers who did not, respectively;  $M$  is a vector of exogenous factors, such as climate and soil. The error terms  $\eta_i$ ,  $\epsilon_{1i}$ ,  $\epsilon_{0i}$  are assumed to have a trivariate normal distribution, with zero mean and covariance matrix  $\Sigma$  with

$$\Sigma = \begin{bmatrix} \sigma_{\eta}^2 & \sigma_{\eta 1}^2 & \sigma_{\eta 0}^2 \\ \sigma_{\eta 1}^2 & \sigma_1^2 & . \\ \sigma_{\eta 0}^2 & . & \sigma_0^2 \end{bmatrix} \quad (2.6)$$

Where  $\sigma_{\eta}^2$  is the variance of the error term in selection Eq. (2.3),  $\sigma_1^2$  and  $\sigma_0^2$  are the variances of the error terms in the Ricardian functions in (2.4) and (2.5);  $\sigma_{\eta 1}^2$  and  $\sigma_{\eta 0}^2$  represent the covariance of  $\eta_i$  and  $\epsilon_{1i}$  and  $\epsilon_{0i}$ , respectively. Since  $\pi_{1i}^*$  and  $\pi_{0i}^*$  are not observed simultaneously, the covariance of  $\epsilon_{1i}$  and  $\epsilon_{0i}$  is not defined. An important implication of this error structure is that because of the error term of the selection equation 2.3, if  $\eta_i$  is correlated with error terms in Ricardian functions in Eq. 2.4 and Eq. 2.5, the expected values of  $\epsilon_{1i}$  and  $\epsilon_{0i}$  conditioned on the sample selection are not zero:

$$E[\epsilon_{1i}|A_i = 1] = \sigma_{\eta 1}^2 \lambda_{1i} \quad \& \quad E[\epsilon_{0i}|A_i = 0] = \sigma_{\eta 0}^2 \lambda_{0i} \quad (2.7)$$

Where  $\lambda_{1i} = \frac{\phi(z_i \alpha)}{\Phi(z_i \alpha)}$  and  $\lambda_{10} = \frac{-\phi(z_i \alpha)}{1 - \Phi(z_i \alpha)}$ . If the estimated covariances  $\sigma_{\eta 1}^2$  and  $\sigma_{\eta 0}^2$  are statistically significant, the decision to adapt and the net revenue are correlated. That is, we find evidence to reject the null hypothesis of the absence of sample selection bias.

## 2.3 Study Area and Data

### 2.3.1 Study Area

The study area for the current research includes 14 districts in three central provinces of Afghanistan. Figure 2.1 depicts the study districts. The Central Highlands of Afghanistan is one of the five climate zones in the country (Aich et al., 2017) and traditionally home to Hazaras, an ethnic minority in Afghanistan. The region is widely characterised by deep valleys, and mountain ranges up to 6400 m above the sea level (Aich et al., 2017). Baba Mountain Range is extended from 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.

The geographical boundaries of the Central Highlands are not clear cut. Until the 1880s, the Central Highlands (Hazarajat) used to be an autonomous region. Until then, it covered a large area extended from north-west of Kabul to the east of Herat; and from Balkh to north of Kandahar. Hazarajat has continuously been shrinking in size since then, and it is suggested that it has lost about 150000 Square Kilometers of its area (Mousavi, 1997).

Even though the post 1880s developments have dramatically affected the way Hazaras used to live since 300 BC (see Mousavi (1997) for the details), agriculture including farming and animal

husbandry has remained the primary employment and source of income for the inhabitants of the region.

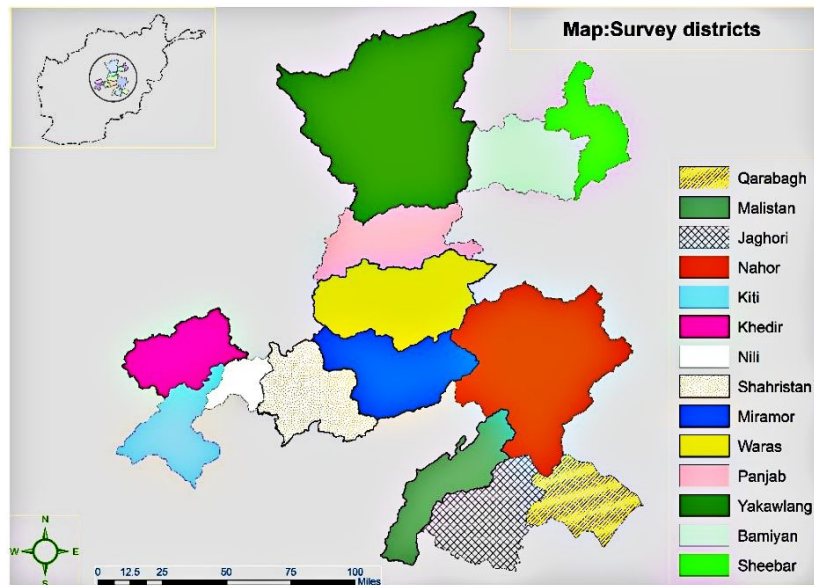


Figure 2.1: Study Districts in the Central Highlands of Afghanistan.

Potato, wheat, and almond are the primary products in the study area. Sheep/goat, chicken, and cow are the primary livestock kept by the households.

There is no major city in the Central Highlands, but throughout the history, Bamiyan center, the centre of Bamiyan province (also known as the Bamiyan valley), represented an important meeting place for travellers, pilgrims, and cultures. Bamiyan valley used to be a major Buddhist centre in Central Asia until the Islamic occupation of the 9th-century (Margottini et al., 2015). Afghanistan's first national park, Band-e-Amir<sup>1</sup>, is located in Bamiyan, and Buddha's joints were standing in Bamiyan valley before they were blown up by Taliban in March 2001<sup>2</sup>.

The Central Highlands possess heterogeneous climate regimes and receive on average about 390 mm of precipitation annually. The amount of rain varies considerably across space (Table 2.7 in Appendix 2.6.1 presents the average amount of rainfall across 3 provinces, also depicted in Figure 2.6 in Appendix 2.6.2) and time (Figure 2.3 in Appendix 2.6.2 depicts the amount of precipitation across 12 months). In some districts like Nili and Kiti, the total amount of rain is around 260 mm while in some districts such as Shibar, Malistan, and Jaghori the total annual rainfall exceeds 500 mm. The average temperature also varies across space and time. The average temperature in the cold season can be as warm as 0 °C in deep valleys in Bamiyan and Diakundi and can be as cold as -7 °C in Nahoor plateau (Figure 2.5 in Appendix 2.6.2 depicts the variation of temperature across space.). The variation of temperature across time is also high. Figure 2.4 in Appendix 2.6.2

<sup>1</sup> [https://en.wikipedia.org/wiki/Band-e\\_Amir\\_National\\_Park](https://en.wikipedia.org/wiki/Band-e_Amir_National_Park)

<sup>2</sup> Visit the media coverage of the incident on the following website: <https://www.telegraph.co.uk/news/worldnews/asia/afghanistan/1326063/After-1700-years-Buddhas-fall-to-Taliban-dynamite.html>

depicts the average monthly temperature.

The climate of the study area, like other parts of the country, has changed during recent decades. An analysis of the weather information from the past 34 (1979 to 2014) years shows that the annual average temperature has increased by about  $1.5^{\circ}\text{C}$  ( $p < 0.05$ ) and the average precipitation has decreased, although with higher heterogeneity across seasons and regions<sup>3</sup>. Climate change has been accompanied by a steady increase in the risk of extreme weather events. Risks of drought, cold/heatwaves, and flood are perceived to be high in the Central Highlands (a detailed discussion on the risks of various extreme weather events is provided in Chapter 4).

### 2.3.2 Data and Survey Instruments

The primary data for the current research was collected directly from the farmers in the Central Highlands of Afghanistan from May to July 2017. A multi-stage systematic random sampling was implemented to choose the subjects. A structured questionnaire<sup>4</sup> and the World Bank's Survey Solution Application<sup>5</sup> were used to conduct face-to-face interviews with the heads of the farming households. In addition to the data on yields of different products, amount of inputs, and local prices, we have collected data on farmers' perception of climate change, climate change adaptation, climate change-related risks, household's characteristics, and farm's GPS coordinates.

Data on the climate of the region were obtained from an online database for the Reanalysis data — The Climate Forecast System Reanalysis (CFSR)<sup>6</sup>. The database provides global high resolution (about 45 Square Kilometers) gridded data on daily precipitation, temperature, wind, and humidity from 1979 to 2014.

To predict the values of climate factors at each sample point (for each farmer), first we have used spatial interpolation techniques (Kriging, Spline, Natural Neighbor, and Inverse Distance Weighting) to predict the values of climate variables for the whole region. All four interpolation techniques yield very similar estimates for climate factors. In the next step, we have matched the climate values, estimated through different interpolation techniques, to each observation in the sample based on their longitudes and latitudes.

The soil data were obtained from an online database of the Food and Agriculture Organization (FAO<sup>7</sup>). To obtain the soil type for each household, the soil raster from FAO was matched with farmers' location based on their GPS coordinates. Table 2.1 presents the summary statistics of the variables.

<sup>3</sup> A detailed summary of climate change in the Central Highlands is provided in Section 3.2 and in Chapter 4.

<sup>4</sup> An English translation of the questionnaire is provided in Section 5.

<sup>5</sup> <https://mysurvey.solutions/>

<sup>6</sup> <https://globalweather.tamu.edu/>

<sup>7</sup> [https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/use/?cid=nrcs142p2\\_054000](https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/use/?cid=nrcs142p2_054000)

## 2.4 Results and Discussions

### 2.4.1 Sample Characteristics

Our sample initially consists of 1502 farmers from 14 districts in Bamiyan (38%), Ghazni (31%), and Diakundi province (31%). The spatial distribution of farmers across the 14 districts is depicted in Figure 2.2 in Appendix 2.6.2.

The women-headed household is very rare (2.7%) in our sample (and possibly in the whole of Afghanistan). Farming is the primary employment for 80% of the farmers in the sample, and almost 37% of them work only on their farms. The average household size is 9 persons, about 45% of whom are working — 4 members work on the farm, and 1 person works off the farm. School attendance is 2.8 students per household, and 3.7 members are literate. About 65% of the respondents spent some time abroad (mainly in Pakistan or Iran). The rate of temporary migration to Pakistan and/or Iran is highest among farmers in Ghazni province with about 74%. 60% of our subjects are literate (with different levels of education). The average age in our sample is 47 years, and they have spent almost half of their living time (22 years) working on their farms.

Table 2.1: Summary Statistics of the Variables.

Variable	Mean (Std. Dev)
<i>Dependent variables</i>	
Crop net revenue	AFN 19263(79827)
Agriculture adaptation <sup>8</sup>	.86(.34)
<i>Inputs</i>	
Seeds	AFN 8713(16898)
Fertilizer	AFN 7992(13374)
Pesticides	AFN 3488(12466)
External labor	AFN 10691(42274)
Other inputs	AFN 875(4628)
<i>Climate factors</i>	
Wet Season Precipitation	55 mm (21)
Semi-wet season precipitation	13.5 mm (7.5)
Dry season precipitation	3 mm (3.5)
Annual precipitation	4.8 mm (2.8)
Winter precipitation	70 mm (25)
Continued on next page	

<sup>8</sup> Defined in Section 2.2.2.

<b>Variable</b>	<b>Mean (Std. Dev)</b>
Spring precipitation	33 mm (17)
Summer precipitation	2.4 mm (2.5)
Fall precipitation	24 mm(10)
Winter temperature	-7°C (3)
Spring temperature	10.4°C (2.3)
Summer temperature	14.4°C (1.7)
Fall temperature	0.19°C (2.8)
<i>Soil type</i>	
Rocky land with Lithic Cryorthents	.82
Rocky land with Lithic Haplocryids	.18
<i>Irrigation</i>	
River	.18
Stream	.41
Karez++	.41
<i>Climate and extreme events</i>	
Risk of drought	3.1 (1.2)
Risk of flash flooding	3.0 (1.1)
Climate change related constraints	.91 (.29)
<i>Farm characteristics</i>	
Flat (dummy)	.40 (.49)
External support (dummy)	.18 (.39)
Distance to the market (in minutes)	41 (43)
Farm size (in acres)	1.5 (.95)
<i>Household head characteristics</i>	
Primary employment	.80 (.40)
Secondary employment	.46(.50)
Literate	.59 (.49)
Risk perception	1.54 (1.39)
Migration background	.65 (.48)
Farming experience (in years)	22 (14)
Continued on next page	

Variable	Mean (Std. Dev)
Household size	9 (3.5)
Age	46.8 (15)
Observations	1435

++ Karez is a chain of underground canals that direct irrigation water from its source to the farmland.

Traditional and non-traditional seasons are defined in Section [2.4.2](#)

Most of the farmers (78%) do not own a car. More than half of them (54%), however, own at least one motorcycle. Since the farmers are mostly poor and the region is predominantly mountainous, motorcycle seems to be the best mean of transportation. Use of the computer is not very common — only 31% have one or more computers at home. Likewise, access to the internet is low to 15% among the subjects. Watching TV (about 62% have at least one TV at home) and use of mobile phones (all most 100%) on the other hand is common. About 70% have access (on average 4.5 hrs. a day) to electricity. Use of solar panels is still not common; only 7% of the households use them to generate electricity.

Due to the particular topology of the region, arable land is minimal. The average farm size per household is 7.2 acres, and 5.3 acres of it is under cultivation. The farm size is largest among farmers in Bamiyan province (9 acres), about 86% of which is under cultivation. The ratio of cultivation area and farm size in Ghazni and Diakundi provinces are 55% and 70% respectively. The average annual net revenue from the farm is about AFN 81829 (about USD 1100). The distribution of farm revenue is very heterogeneous across the three provinces. In Bamiyan, the average annual revenue from the farm is AFN 115609; in Ghazni, the average net revenue is estimated to be AFN 18538; in Diakundi province, this average is about AFN 103664. Therefore, farming plays a greater role in household's livelihood in Bamiyan compared to Diakundi and, in particular, Ghazni province.

Farming is the primary source of income for 87%, 51%, and 78% of the farmers in Bamiyan, Ghazni, and Diakundi, respectively.

Remittances play a more prominent role in farmers' income in Ghazni province as it is the primary source of income for about 20% of them. This number is down to 2% and 3% in Bamiyan and Diakundi provinces.

Three systems of irrigation are prevalent in the area — 19% 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 41% of the households. The remaining 41% channel water from a stream that flows in a nearby valley.

Almost all farmers (98%) have perceived changes in the climate, generally in the form of warming (87%) and/or a decrease in snow/rainfall (91%). Almost 2/3 of the 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). Almost 61% think that the impact of climate change on



their farming has been negative and 30% (mostly living in Bamiyan) believe that their farming business has been booming as a result of climate change. Meanwhile, almost 92% think that their farming business is vulnerable to the future impacts of climate change.

About 62% reported a decrease in their farming production compared to 15 to 20 years ago, and 23% 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).

#### 2.4.2 Multicollinearity of Climate Variables

Literature suggests a quadratic specification of the Ricardian function (Mendelsohn et al., 1994; Wang et al., 2009; Mendelsohn and Dinar, 2009). The standard Ricardian model is given in Eq. (2.8).

$$R = B_0 + B_1C + B_2C^2 + B_3W + B_4S + u \quad (2.8)$$

With  $R$  representing the crop net revenue per acre (as defined in Section 2.2) and  $C$  representing climate factors, such as precipitation and temperature. Following the literature, we have included the seasonal temperature and precipitation and their squares in the model. Four different seasons can be distinguished: winter (January, February, March), spring (April, May, June), summer (July, August, September), and fall (October, November, December). Due to the high correlation of seasonal variables in our case, the regression model that includes these variables and their squares suffers from extremely high multicollinearity (the average VIF is 22932). To reduce the colinearity of climate factors and their squares, we have mean-centered these variables. This exercise has reduced the average VIF to 1603 — a significant improvement but still far from an acceptable value. The estimates of the Ricardian model using traditional climate factors are reported in Table 2.8 in Appendix 2.6.1.

Due to the high multicollinearity of seasonal factors, the OLS estimates are highly unstable and may not be used for predicting the impact of climate on crops revenue. A few past studies (Niggol Seo et al., 2005) have tried to remedy the problem of multicollinearity by dropping factors with high VIF. However, dropping factors may be the easiest solution but not the most efficient one.

In order to systematically address the problem, we have employed Exploratory Factor Analysis (EFA) of the monthly precipitation and temperature to discover the seasonal patterns. All prior consistency and reliability tests satisfy the assumptions necessary for running the EFA (p-value for Bartlett test of sphericity: 0.000; KMO>.80; Scale of reliability coefficient >.93). Based on the results of the EFA of the monthly precipitation, we have identified three seasons: wet (Jan, Feb, Mar, Apr, Nov, Dec), semi-wet (May, June, Sep, Oct), and dry (Jul, Aug). The three factors together explain 98% of the variation in the original precipitation variables.

However, the EFA of the monthly temperature shows that the temperature throughout 12 months varies together. Hence, in the case of temperature, we use the annual average. The only factor

explains 99% of the variation of the original temperature variables. The results of the EFA are reported in Table 2.9 in Appendix 2.6.1.

Based on the outcomes of the EFA, we have redefined the climate factors (as wet, semi-wet, and dry season for precipitation and the annual temperature) and used the new versions in the subsequent econometric analyses. Using the re-defined factors, the VIF has been reduced dramatically (the average VIF, in this case, is down to 55). A couple of more modifications are applied to reduce the VIF to an acceptable level. Firstly, we have mean-centred the variables to reduce the collinearity of them with their squared terms. Furthermore, the squared term of precipitation in the dry season was dropped from the model due to its high VIF. Doing the latter, however, does not pose a considerable analytical challenge since the amount of rainfall in the dry season is minimal (3 mm per month on average). Altogether, we manage to reduce the average VIF to 6, a value within the acceptable range.

### 2.4.3 Ricardian Analysis of the Climate Sensitivity of Crops Net Revenue

Following the discussions in Section 2.2, we estimate three Ricardian models based on equations (2.9), (2.10), and (2.11)

$$R = \beta_0 + \beta_1 WP + \beta_2 SWP + \beta_3 DP + \beta_4 WP^2 + \beta_5 SWP^2 + \beta_6 AT + \beta_7 AT^2 + u \quad (2.9)$$

$$R = \beta_0 + \beta_1 WP + \beta_2 SWP + \beta_3 DP + \beta_4 WP^2 + \beta_5 SWP^2 + \beta_6 AT + \beta_7 AT^2 + \theta E + u \quad (2.10)$$

$$R = \beta_0 + \beta_1 WP + \beta_2 SWP + \beta_3 DP + \beta_4 WP^2 + \beta_5 SWP^2 + \beta_6 AT + \beta_7 AT^2 + \theta E + \gamma X + u \quad (2.11)$$

Where  $R$  is the net crops revenue per acre (as defined in Section 2.2.1);  $WP$ ,  $SWP$ , and  $DP$  represent precipitation in the wet, semi-wet, and dry seasons, respectively;  $AT$  is the annual temperature;  $E$  represents irrigation, adaptation, and extreme weather events;  $X$  includes all other control variables;  $\theta$  and  $\gamma$  represent vectors of coefficients. The empirical implementation of the Ricardian function specified in Eq. (2.9), Eq. (2.10), and Eq. (2.11) are based on three different model results. Based on Eq. (2.9), first the effect of the climate factors (precipitation and temperature) on crops net revenue is examined in Model 1 (column 2 in Table 2.2). Next, other environmental factors, such as the risk of drought, risk of flood, adaptation, external support, and soil are introduced in Model 2 (based on Eq. (2.10)). Results are reported in column 3 of Table 2.2. Lastly, the farm and farmers' characteristics (primary occupation, literacy, migration background, household size, distance to the nearest market, etc.) are added in Model 3 (based on Eq. (2.11)). Results are reported in column 4 of Table 2.2. Such an exercise is common in the literature of the Ricardian method (Seo, 2007). To represent the impact of climate, following the discussions in Section 2.4.2, we have included three precipitation and one temperature variables in the Ricardian model. The effect of all four climate variables are significant (both statistically and economically). A test of joint significance suggests that the combined effect of climate factors is also significant ( $F=35.00$ ;  $p < 0.01$ ). The estimates are robust across the three models. The corresponding results

are presented in Table 2.2.

Table 2.2: Ricardian Analysis of Climate Sensitivity of Crops Net Revenue.

<b>Independent Variables</b>	<b>Model 1</b>	<b>Model 2</b>	<b>Model 3</b>
Wet season precipitation	-633.6*** (124.7)	-597.1*** (120.0)	-631.1*** (124.0)
Semi-wet season precipitation	1627.0*** (369.0)	1563.5*** (358.8)	1620.3*** (374.9)
Dry season precipitation	-2096.0*** (304.3)	-1970.9*** (324.7)	-2089.3*** (327.6)
Wet season precipitation square	5.679* (2.273)	5.958** (2.245)	6.749** (2.423)
Semi-wet season precipitation square	-12.36 (15.54)	-9.788 (16.49)	-2.407 (19.05)
Annual temperature	3273.0*** (509.5)	3265.4*** (518.8)	3083.6*** (525.3)
Annual temperature square	20.21 (136.5)	72.74 (139.7)	87.14 (141.1)
<b>Irrigation-water:Base-category—</b>			
<b>River</b>			
Stream		2343.8 (2424.8)	1248.0 (2540.0)
Karez		5156.3* (2612.7)	3760.0 (2721.9)
Risk of flood		446.8 (632.2)	138.6 (642.0)
Risk of drought		-2815.1*** (648.4)	-2481.9*** (659.3)
External support		2653.9 (1998.4)	2260.9 (1955.0)
Agricultural Adaptation		1887.1 (1948.9)	4029.1* (2019.0)
Soil		-21.04	-8.081

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		(18.70)	(18.06)
Market distance (by car in minutes)			0.890 (25.43)
Main occupation (farming)			-6099.9** (1975.5)
Literate			2743.0* (1255.8)
Household size			326.4 (228.5)
Migration			373.2 (1448.5)
Farming Experience			-28.70 (43.03)
Flat			-2595.6 (1566.6)
Log farm size			-2483.4** (787.3)
Constant	13831.2*** (1995.3)	16970.6*** (4679.2)	19627.2*** (5737.2)
Observations	1415	1415	1415
Adjusted $R^2$	0.132	0.147	0.166
F	37.87	21.16	15.56
Standard errors in parentheses. Climate factors are mean centered. * $p < 0.1$ , ** $p < 0.05$ , *** $p < 0.01$			

The results in Model 3 suggest that control variables such as the risk of drought, adaptation, primary employment, literacy of the household head, and the log of farm size are significantly associated to crops net revenue. Risk of drought, as expected, is negatively associated with revenue. Adaptation and the literacy of the household head increase the revenue, which makes sense. Surprising, however, is the negative sign of primary employment and farm size. A joint analysis of the farm size and primary occupation suggests that farmers whose primary occupation is farming own larger farm size. This observation suggests that per acre productivity of smaller farms is higher, which is confirmed by past studies [Mendelsohn and Dinar \(2009, pp. 100-149\)](#).

Table 2.3: Marginal Impacts of the Climate Variables

<b>Climate Variables</b>	<b>Marginal Impact (Std. Err)</b>
Wet season precipitation	-630 (124)***
Semi-wet season Precipitation	1,620 (374) ***
Dry season Precipitation	-2,089 (324) ***
Annual Precipitation	-123 (75) *
Annual Temperature	3,084 (524) ***

Standard errors in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

The amounts are in Afghani (Afghanistan's national currency).

Most important for the current research are the estimates of climate variables. Referring to Model 3, all four climate variables (three precipitation and one temperature) are significant. At least one squared term (that of wet season precipitation) is also significant implying a non-linear effect. As a result and in order to facilitate the interpretation of the estimated climate coefficients, the marginal effects of these variables. Such an exercise is particularly useful in models involving non-linearity. The marginal impacts can be calculated at any value of interest. Here we have estimated the marginal impacts of all 4 climate variables at their sample mean. The outputs of the marginal impact analyses are reported in Table 2.3.

The impact of precipitation in the wet season is non-linear (with the minimum value attained at around 47 mm) with a negative marginal effect (-630 AFN/mm). The result at first glance is unexpected. The wet season is the main precipitation period in the Central Highlands. The amount of snow/rainfall in this season is crucial for water availability during the rest of the year. Hence, it is expected that more precipitation during the wet season shall be beneficial. An analysis of the climate data suggests that the 34 years average precipitation during the wet season is significantly higher in Ghazni (79 mm) compared to Bamiyan (41 mm) and Diakundi (47 mm). Ghazni was hit by recent droughts (during the 2000s), which have caused the crops revenue to decrease dramatically. In Bamiyan on the other hand, Baba Mountain Range houses tens of glaciers and sustains snow all year round — both of which are decisive to supporting water resources in the province. This support from the Baba Mountains coupled with further warming has caused the farming business to flourish in Bamiyan. Because of the non-linear effect, however, a notable increase in the amount of precipitation — that takes the mean above 47 mm per month — would cause the marginal impact to be increasing in most of the areas, including in Ghazni.

More precipitation in the semi-wet season is useful (1620 AFN/mm). Since the quadratic term of precipitation in this season is not significant, the impact can be regarded as linear. Although most of the precipitation in the Central Highlands happens during the wet season, the complementary rainfall during the semi-wet season, especially in spring, is significant for enriching water resources. Because of the snow in the winter and early spring, the soil has its maximum capac-

ity to absorb water in mid and late spring. Hence, rainfall in this time is absorbed and enhances underground water reserves. Furthermore, spring is usually the start of the cultivation period for which further rain is mostly useful. It should be noted, however, that a significant increase in precipitation during the semi-wet season — that makes the quadratic term significant — would cause the marginal effect to decrease in some areas. The reason is that exceeding rainfall, on the one hand, would exceed the holding capacity of the land and would cause floods and landslides, and on the other hand, would alter proper cultivation and productivity.

Precipitation in the dry season is negatively associated with the revenue (-2089 AFN/mm). Similar to precipitation in the semi-wet season, the quadratic term of the precipitation in the dry season is insignificant — in fact, it was dropped from the model due to its high collinearity. During this season, the soil is parched and has its minimum capacity to absorb the rainwater. Hence a moderate rainfall could quickly turn into flash flooding, damaging the farms and products, killing the livestock, and destroying farmers' property.

A higher annual temperature is beneficial. A 1°C increase in average annual temperature would increase the net crops revenue (per acre) by AFN 3084. The quadratic term of the annual temperature is not significant; hence, the impact can be regarded as linear. The positive and significant (both statistically and economically) warming effect on revenue is due to the cold climate of the region. [Mendelsohn \(2014\)](#) reports a similar result for the whole of Afghanistan.

We also address some additional concerns related to our econometric method. The results are reported in [Table 2.10](#) in [Appendix 2.6.1](#). Although in the primary analyses using OLS, we have discarded the observations whose studentized residuals were larger than 2 (in absolute value), the sensitivity of OLS can still prone the estimates to be influenced by the outliers. Robust regression, on the other hand, is not sensitive to the outlying values and hence provides estimates that are more robust in this regard. Thus, we re-estimate the Ricardian model using a robust regression.

Another issue that can undermine the OLS estimates is the measurement error in one or more explanatory variables. It is possible that one or more climate variables (in the Ricardian models) are observed with error — the true values are the sum of observed values and an error. In this case, the OLS estimates would be biased. Error-in-variables regression assumes that independent variables are measured with error and the model is estimated under this assumption. By doing so, the model provides robust estimates of the climate variables and other independent variables that are assumed to be observed with error. Hence, the model is re-estimated using an error-in-variables regression.

In studies involving crops revenue, likely, the revenue within the same region is not independent. This occurs, for instance, if, because of climate, soil, and spillover effects, the farmers grow the same crop types. In such cases, the OLS assumption of independent residuals is violated. To address this, the model is re-estimated, assuming that residuals are dependent at the district level.

The corresponding results are reported in [Table 2.10](#) in [Appendix 2.6.1](#). The estimates are very similar to those of the OLS presented in [Table 2.2](#). Hence the OLS estimates of the Ricardian model are robust.

#### 2.4.4 Endogeneity of Farmers' Adaptation

Referring to the discussions in Section 2.2.2, it is suggested to include (agricultural) adaptation<sup>9</sup> in the Ricardian model explicitly. In our initial analysis (the results are reported in Table 2.2), we have included agricultural adaptation, defined in Section 2.2.2, as a dummy variable. Since adaptation is potentially endogenous, OLS might yield biased and inconsistent estimates. Furthermore, OLS estimates do not explicitly account for potential structural differences between the Ricardian function of households who adapted<sup>10</sup> and the Ricardian function of farmers who did not. To address these concerns, an endogenous switching regression is practised. To this end, a simultaneous equations model of adaptation and revenue, with known endogenous switching point, is estimated by full information maximum likelihood (the detailed treatment is provided in Lokshin and Sajaia (2004)).

For the model to be identified, there should be at least one variable in the selection model that does not appear in the revenue models (Abdulai and Huffman, 2014). Such instruments should directly affect the decision to adapt but not the crops revenue among the farmers who have not adapted.

In our case, we have included as selection instruments a dummy variable which is 1 if the household head is literate and 0 otherwise; a categorical variable of farmers' risk perception; and TV ownership (a dummy variable as an indicator of access to information).

The literacy of household head would directly affect their decision to adaptation. For instance, more educated farmers would have more knowledge of adaptation options and would better implement them.

Likewise, knowing different types of adjustment strategies would impact farmers' decision. Having TV at home and watching programs related to agriculture and adaptation would help farmers learn more about climate change and adaptation.

Since adaptation is a decision under uncertainty, the farmers' risk preferences would directly affect adaptation decisions. For instance, cultivating a new product directly depends on the farmers' degree of risk aversion.

These variables, however, do not directly affect the farm revenue. The validity of these instruments is formally tested: the instruments are collectively statistically significant drivers of the farmers' decision to adapt (Model 1:  $\chi^2=8.12$ ;  $p=0.04$ ) but not of the crops net revenue (Model 2:  $F=1.67$ ;  $p=0.17$ ). Such an exercise is proposed by Di Falco et al. (2011). Table 2.11 in Appendix 2.6.1 reports the results of the corresponding validation tests.

Table 2.4 reports the estimates of the endogenous switching regression for the determinants of adaptation and two Ricardian models for adapters and non-adapters. The three models, Model 4, Model 5A, and Model 5B, respectively, estimate the factors affecting the farmer's decision to adapt; the Ricardian model of crops revenue of the farmers who adapted; and the Ricardian model of crops revenue of the farmers who did not adapt. The set of explanatory variables of the

<sup>9</sup> Chapter 4 provides a concise summary of farmers' adaptation at the study area.

<sup>10</sup> The ratio of the non-adapters is higher in Ghazni (.21) compared to Bamiyan (.07) and Diakundi (.14).

Ricardian functions includes climate factors, risk of extreme weather events, and external support (similar to Model 2 in Table 2.2).

Table 2.4: Endogenous Switching Regression of Adaptation and Crops Net Revenue

Independent Variables	Model-4- (Adapt. 0/1)	Model-5A (Adapt.=1)	Model-5B-(Adapt.=0)
Wet season precipitation	-.04*** (.007)	-840.8*** (129.0)	613.8 (386.0)
Semi-wet season precipitation	.08*** (.022)	2072*** (407)	-1237 (1087)
Dry season precipitation	.014 (.02)	-1363 *** (464.0)	-2289*** (720.6)
Wet season precipitation square	.0004*** (.0001)	-.516 (2.73)	6.07 (6.667)
Semi-wet-season-precipitation-square	.0014 (.002)	28.6 (18.49)	-57.4 (51.51)
Annual temperature	.05 (.03)	3138.4*** (549.1)	2244.7 (1641)
Annual temperature square	-.007 (.008)	183.9 (161.4)	-660.11 (527)
Irrigation	.002 (.067)	1853.8 (1289)	910 (3305)
Risk of flood	.01 (.042)	644 (756)	396 (151)
Risk of drought	-.04 (.034)	-2777.1*** (716.8)	118.6 (1646.8)
External support	.24 * (.13)	3691.1 * (2081)	1441.1 (8957)
Soil	.16 (.17)	-7160 *** (2577)	-15046*** (7036)
TV ownership	-.03		

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	(.04)		
Risk perception	.04***		
	(.03)		
Literate	-.08		
	(.07)		
Constant	1.23***	12961***	-315115***
	(.25)	(4203)	(11022)
Observations	1415	1217	198
rho0	-.93 (.03)		
rho1	.87 (.03)		

LR test of indep. eqns. ( $\rho_1 = \rho_0 = 0$ ):  $\chi^2(2) = 100$  Prob >  $\chi^2 = 0.0000$

Standard errors in parentheses. Climate factors are mean centered. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Control variables in Model 4, the selection model, are mostly insignificant. Most important for us in the current study, however, is to investigate the role of climate in farmers' adaptation to climate change. The estimates generally confirm the importance of climate in farmers' decision to adapt, which is consistent with past studies of the impact of climate on farmers' adaptation (see, for example, [Mendelsohn and Dinar \(2009, pp. 151-172\)](#)). More precipitation in the wet season decreases the likelihood of adaptation. The wet season is the primary season of snow/rainfall in the region. The amount of precipitation in this season determines the water availability in the rest of the year. Hence, more precipitation in the wet season implies less water scarcity in the rest of the year, which can decrease the need for adapting various water preservation measures. The coefficient of the precipitation in the semi-wet season is positive and significant. The complementary rainfall in the semi-wet season, especially in spring, is crucial for cultivation and supporting water resources. More precipitation in this season can increase the possibility of cultivating different products and possibly more of the farmland. Precipitation in the dry season is negatively associated with adaptation. In other words, farmers living in areas with more precipitation in the dry season are less likely to adapt. An analysis of the weather information suggests that Ghazni receives the highest amount and Bamiyan receives the least amount of precipitation in the dry season. As discussed in Section 2.4.1, agriculture plays a minor role in farmers' income and employment in Ghazni but a decisive role in those of farmers in Bamiyan. Hence, a reason that might explain the negative (and significant) coefficient of precipitation in the dry season is the importance of farming in general. For those whose income and employment are less dependent on agriculture, adaptation might have only secondary importance. Temperature is positively associated with the likelihood of adaptation. Warming can further lengthen the cultivation period and provides the chance to cultivate a variety of new products, which previously were not possible to try due to

an extremely cold climate (for instance in Bamiyan). Warming on the other side can increase the chance of adaptation in more water-scarce regions, by pushing the farmers to, for example, dig water well or employ additional water preservation measures.

The results of the two Ricardian models (Model 5A and Model 5B) suggest significant structural differences between the Ricardian functions of adapters and non-adapters. In particular, the climate sensitivity of crops revenue among farmers who have adapted is much higher and profound compared to the farmers who did not adapt. In addition, a counterfactual analysis of the expected crops revenue, based on the estimates of the endogenous switching model, suggests a notable impact of adaptation. Table 2.5 reports the corresponding results.

Table 2.5: Counterfactual Analysis of the Expected Crops Revenue

<b>Farmers Category</b>	<b>Expected Net Revenue</b>	<b>Counterfactual Expected Net Revenue</b>
Adaptation=1	AFN 17788	AFN -46727
Adaptation=0	AFN -24505	AFN 12608

The estimates in Table 2.5 suggest that the farmers who have adapted would have been facing significant losses had they not been adapting. On the other hand, the expected revenue of the farmers who did not adapt would have been almost three times higher had they adapted.

Comparing the estimates of the endogenous switching model to those of the OLS model (presented in Table 2.2) yield a significant difference of the estimates. Except for semi-wet season precipitation, the estimates of all other climate factors in Model 5B (non-adapters) are insignificant. While under endogenous switching, the estimate of semi-wet season precipitation is negative (AFN -2576), the OLS estimate (reported in column 3 of Table 2.2) is positive (AFN 1563). In case of the farmers who have adapted, although the sign and significance of the estimates in Model 5A are similar to those of the OLS model (Model 2), the magnitude of the effects differs. For instance, the estimated coefficient of the dry season precipitation in Model 5A is AFN -3610, but the corresponding OLS estimate in Model 2 is AFN -1970.

Moreover, the estimates for both coefficients of correlation  $\rho_{1,2}$  are significantly different from zero ( $p < 0.01$ ), implying that the null hypothesis of no sample selectivity bias is rejected. In other words, farmers' decision to adapt to climate change is indeed endogenous.

#### 2.4.5 Climate Simulations

A vital contribution of the Ricardian literature is to use the estimated coefficients (reported in Table 2.2) for predicting the likely impacts of future climate changes on crops revenue under various scenarios. Traditionally, the marginal effects of annual precipitation and annual temperature are combined with the estimates of future climate scenarios to predict the likely impacts of future climate changes on revenue. In our case, apart from that exercise, we have used the estimates of the endogenous switching regression to estimate the likely impacts of future changes in the climate

among farmers who have adapted and those who did not adapt. It should be emphasised, however, that such an exercise examines the effect of changes in the climate on revenue. The impact of other factors that are likely to change over time, including prices, technology, different adaptation options, and policies are not explored Mendelsohn and Dinar (2009, p.114).

In this study, we combine the estimates of the Ricardian model (Model 1 in Table 2.2) with two future climate scenarios — the Parallel Climate Model (PCM) (Washington et al., 2000) and the Canadian Climate Centre (CCC) (Flato et al., 2000) — in order to predict the likely impact of climate change on crops net revenue in the year 2100. The PCM is mild and wet, and the CCC is hot and dry. The PCM predicts a 2.5°C increase in average temperature and about 8% increase in average annual precipitation by 2100. The CCC predicts hotter (4.1°C of warming) and drier (about 2% decrease in precipitation) climate for the same time horizon.

Table 2.6 reports the results of climate simulations. The aggregate impact of climate in 2100 under both PCM and CCC is positive and significant. Disaggregating the result reveals that the positive effect of climate change is mainly due to warming. The reason might be the cold climate of the region. More warming would further lengthen the cultivation season and provides the opportunity to cultivate/plant other products (a variety of vegetables, saffron, and fruits, for instance). It has to be emphasized though that water availability and water resources management are crucial for further warming to be beneficial. Moreover, the estimates of the climate simulation confirm the findings of the endogenous switching regression regarding climate sensitivity of crops revenue of farmers who adapted versus those who did not. The impact of future climate changes (under both PCM and CCC) would be significantly positive (mainly due to warming) among farmers who have adapted. The aggregate impact of annual precipitation would slightly decrease the crops revenue (-150 to -165 AFG/mm). The effect of 1-degree warming would notably increase crops revenue (3722 to 4257 AFG/°C). The impact of future climate (under both PCM and CCC) among farmers who did not adapt would be negative. The effect of annual precipitation would be relatively small (-333 to -360 AFG/mm). The temperature would cause much more harm (-5681 to -11563 AFG/°C) to the crops revenue of the farmers who did not adapt.

Table 2.6: Impacts of Climate in 2100 on Crops Revenue in the Study Area.

<b>Baseline</b>		<b>Climate Scenario: PCM</b>		
—	—	Precipitation	Temperature	Aggregate
All-farms	19267	-193*(81)	3372 *** (604)	3233*** (621)
Adapt=1	20434	-165*(91)	3888*** (629)	3722*** (646)
Adapt=0	11956	-333(221)	-5349*** (2289)	-5681*** (2388)
<b>Baseline</b>		<b>Climate Scenario: CCC</b>		
—	—	Precipitation	Temperature	Aggregate
All farms	19267	-131*(76)	3443*** (994)	3312*** (991)

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Adapt=1	20434	-150*(85)	4257***(1023)	4106***(1023)
Adapt=0	11956	-360*(209)	-11563***(3928)	-12013***(4047)

Standard errors in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Amounts in Afghani

## 2.5 Conclusion

This chapter provides evidence on the sensitivity of crops revenue to climate change in Afghanistan. It uses primary household level data of 1502 farmers from 14 districts in three central provinces of Afghanistan (Bamiyan, Ghazni, and Diakundi) and information on daily temperature and precipitation from 1979 to 2014. We employ a Ricardian model to investigate the effect of the average annual/seasonal precipitation and temperature on the net crops revenue. Exploratory factor analysis is exercised to address the multicollinearity of climate factors.

Furthermore, an endogenous switching regression was exercised to examine and address the endogeneity of farmers' adaptation and investigate the structural differences between the Ricardian function of the farmers who adapted and that of those who did not adapt. The marginal impact analysis was practised to explore the marginal effects of climate factors on crops revenue. Such an exercise is especially useful for models involving non-linear terms. Lastly, we have combined the estimates of the Ricardian model and endogenous switching regression with two future climate scenarios to study the impact of future changes in the climate on crops revenue in the whole sample as well as in the sub-samples of farmers who adapted and those who did not.

Our analyses confirm the significant effect of climate on crops revenue. The OLS estimates are robust to a number of specifications. Robust regression, error-in-variables regression, and regression with clustered data yield similar results. The impact of seasonal/annual precipitation and temperature is found to be a mix of linear and nonlinear. Hence, farming in the Central Highlands is sensitive to the changes in the climate. The results are consistent with past studies (such as the findings reported in [Mendelsohn and Dinar \(2009\)](#)).

Our findings suggest that precipitation in the wet season has a negative marginal effect up to a certain amount (about 47 mm per month), after which it turns positive. Precipitation in the semi-wet season is generally beneficial. Rainfall in the dry season can cause flash flooding and, hence, is negatively associated with crops revenue. Warming is found to be significantly beneficial. The quadratic term of annual temperature is insignificant; therefore, its effect can be regarded as linear. Due to the cold climate of the region, warming would further lengthen the cultivation period and provide the opportunity to try various new products. It should be emphasised, however, that warming is only beneficial if the issues related to water availability and adaptation are systematically addressed. A combination of warming, water availability, and to some extent adaptation, for instance, has already caused the farming business to boom and expand in most parts of Bamiyan. But in drier areas, like Ghazni, further warming has not been that beneficial since water scarcity and drought pose significant constraints there.

In addition to studying the climate sensitivity of crops revenue among all farmers in the sample, we have explored farmers' adaptation – an important related matter. The traditional Ricardian model considers adaptation only implicitly. Recent studies, however, suggest viewing the adaptation explicitly in the model; doing so singles out the effect of all adaptation measures that farmers have been adapting. Since the decision to adapt is most likely endogenous, we have exercised endogenous switching regression with known endogenous switching point. The estimates of the endogenous switching regression confirm that the decision to adapt is indeed endogenous and that there is a significant structural difference between the Ricardian models of the adapters and non-adapters, which implies that climate sensitivity (and hence climate impact) of crops revenue is different across the two groups. The revenue of the farmers in the first group is found to be much more climate-sensitive. Moreover, the estimates of the selection model suggest that climate plays a decisive role in farmers' adaptation.

Combining the results of the Ricardian analysis, the endogenous switching regression, and two future climate scenarios (PCM and CCC), we provide evidence on the likely impact of future changes in the climate on crops revenue in the Central Highlands of Afghanistan. Under both scenarios, farmers who adapted would benefit from future changes in the climate. The impact of future climate changes on the revenue of the farmers who did not adapt would be negative.

The current study is the first analyzing the sensitivity of crops revenue to climate change in Afghanistan. Understanding the mechanism of the effects is crucial in analysing the possible impacts of future changes in the climate on agriculture. Such knowledge is key to designing adaptation policies — a vital issue in climate change discourse. For instance, understanding the mechanisms through which the effects of climate are unfolded helps the policymakers and researchers to identify the vulnerable regions, communities, and species, and design the appropriate response policies.

The study, however, has some limitations. First, we cover only one climate zone in Afghanistan. To have a full picture of the impact, future studies shall consider the remaining four climate zones in the country. Second, our study uses only one-year data on crops revenue. Due to data limitation in Afghanistan, we cannot check the robustness of our estimations against relevant annual-specific factors, such as extreme weather. Furthermore, some shortcomings of the Ricardian method — such as not counting for the effect of input and output prices, not counting for the cost of transitioning from one farming method to another (cost of adaptation) — continue to exist here ([Mendelsohn and Dinar \(2009, pp. 57–59\)](#) provides a list of the criticisms).

## 2.6 Appendices

### 2.6.1 Appendix A: Additional Tables

Table 2.7: Average Annual Precipitation and Average Annual Temperature across 3 Provinces

Province	Precipitation	Temperature
	Mean(Std.Dev)	Mean(Std.Dev)
Bamiyan	300 (77)	2 (2)
Ghazni	570 (108)	5.5 (2.1)
Diakundi	321 (115)	7.4 (1.4)

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

Table 2.8: Ricardian Analysis of Corps Net Revenue with Traditional Climate Variables

Climate Variables	Estimated Coeff.
Winter Temperature	-11820.0 (10574.7)
Spring Temperature	-3088.8 (13815.7)
Summer Temperature	-35960.8**(12632.8)
Winter Temperature	35238.9 (21975.8)
Winter Temperature squared	537.0(781.6)
Spring Temperature squared	-6012.7*** (1704.0)
Summer Temperature squared	11049.0** (3902.7)
Fall Temperature squared	2119.8 (1432.9)
Winter Precipitation	798.0 (958.0)
Spring Precipitation	-1713.1 1316.2)
Summer Precipitation	-3752.3 (3040.9)
Fall Precipitation	268.5 (3444.9)
Winter Precipitation squared	-11.16(7.356)
Spring Precipitation squared	17.96(11.01)
Summer Precipitation squared	375.5(308.8)
Fall Precipitation squared	25.60(53.29)
_cons	7670.9(4229.3)
<i>N</i>	1415
adj. <i>R</i> <sup>2</sup>	0.154

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Climate variables are mean-centered. The mean VIF is 1,603

Standard errors in parentheses.\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

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Table 2.9: Factor Loadings of the Monthly Precipitation and Temperature

<b>Precip.</b>	<b>Factor 1</b>	<b>Factor 2</b>	<b>Factor 3</b>	<b>Temp.</b>	<b>Factor 1</b>
Jan	.95	—	—	Jan	.98
Feb	.94	—	—	Feb	.97
Mar	.91	—	—	Mar	.99
Apr	.52	—	—	Apr	.99
May	—	.84	—	May	.98
Jun	—	.89	—	Jun	.98
Jul	—	—	.76	Jul	.98
Aug	—	—	.80	Aug	.98
Sep	—	1.02	—	Sep	.99
Oct	—	.66	—	Oct	.99
Nov	.79	—	—	Nov	.99
Dec	.92	—	—	Dec	.98

The loadings less than .5 for the monthly precipitation are not displayed.

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Table 2.10: Ricardian Estimates under Alternative Estimation Methods

<b>Exog. Variables</b>	<b>OLS</b>	<b>Robust- Reg.</b>	<b>Error-in- Var-Reg.</b>	<b>Clustered-Reg.</b>
Wet Season Precip.	-631.1*** (124.0)	-422.2*** (57.68)	-631.1*** (104.9)	-631.1** (187.7)
Semi-Wet-Season-Precip.	1620.3*** (374.9)	1073.8*** (188.2)	1620.3*** (342.2)	1620.3* (707.7)
Dry Season Precip.	-2089.3*** (327.6)	-1410.5*** (205.7)	-2089.3*** (374.1)	-2089.3** (678.6)
Wet Season Precip. squared	6.749** (2.423)	3.238* (1.365)	6.749** (2.482)	6.749 (3.729)
Semi-Wet-Season-Precip.- squared	-2.407 (19.05)	9.853 (8.258)	-2.407 (15.02)	-2.407 (25.32)
Annual T.	3083.6***	2430.9***	3083.6***	3083.6*

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	(525.3)	(298.0)	(541.9)	(1245.4)
Annual T. squared	87.14	30.82	87.14	87.14
	(141.1)	(69.26)	(126.0)	(160.0)
Irrigation water:stream	1248.0	-908.6	1248.0	1248.0
	(2540.0)	(1164.2)	(2117.1)	(2848.6)
Irrigation water: Karez/well	3760.0	-205.6	3760.0	3760.0
	(2721.9)	(1249.5)	(2272.1)	(2500.1)
Risk of flood	138.6	241.6	138.6	138.6
	(642.0)	(337.0)	(612.9)	(679.0)
Risk of drought	-2481.9***	-486.5	-2481.9***	-2481.9*
	(659.3)	(326.3)	(593.3)	(1083.8)
External Support	2260.9	1091.9	2260.9	2260.9
	(1955.0)	(949.3)	(1726.2)	(1178.7)
Agri-Adapt	4029.1*	4151.9***	4029.1*	4029.1
	(2019.0)	(1073.4)	(1952.0)	(2530.7)
Soil	-8.081	-14.50	-8.081	-8.081
	(18.06)	(9.393)	(17.08)	(39.13)
Market distance	0.890	-21.86*	0.890	0.890
	(25.43)	(8.479)	(15.42)	(27.25)
Main OCC-Farming	-6099.9**	-2189.0*	-6099.9***	-6099.9
	(1975.5)	(965.9)	(1756.5)	(3354.8)
Literate	2743.0*	1098.3	2743.0	2743.0*
	(1255.8)	(769.6)	(1399.5)	(1176.1)
HHsize	326.4	164.5	326.4	326.4*
	(228.5)	(100.6)	(182.9)	(119.6)
Migration	373.2	843.0	373.2	373.2
	(1448.5)	(764.9)	(1391.0)	(1734.5)
Farming Experience	-28.70	-35.95	-28.70	-28.70
	(43.03)	(27.10)	(49.29)	(42.01)
Flat	-2595.6	-3034.5***	-2595.6	-2595.6
	(1566.6)	(803.7)	(1461.4)	(2847.9)

Continued on next page



log Farm Size	-2483.4** (787.3)	-2448.6*** (380.2)	-2483.4*** (691.4)	-2483.4 (1231.2)
Constant	19627.2*** (5737.2)	13340.6*** (2591.2)	19627.2*** (4712.1)	19627.2 (11301.6)
Observations	1415	1415	1415	1415
Adjusted $R^2$	0.166	0.218		0.166
F	15.56	18.94	13.83	.

Standard errors in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Robust-Reg.: Robust Regression.

Error-in-Var-Reg.: Error in Variable Regression. Clustered-Reg.: Clustered Regression

Table 2.11: Test on the Validity of the Selection Instrument

Variable	Model-A: Adaptation- 0/1	Model S: Crops Net Revenue
Risk Perception	.17 (.06) ***	-201 (1170)
Literate	-.15 (.17)	6690 (3492)*
TV	-.12 (.15)	-1797 (3174)
Wald test of joint significance	8.8***	F-stat=1.48
Observations	1312	190

Standard errors in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

### 2.6.2 Appendix B: Additional Figures

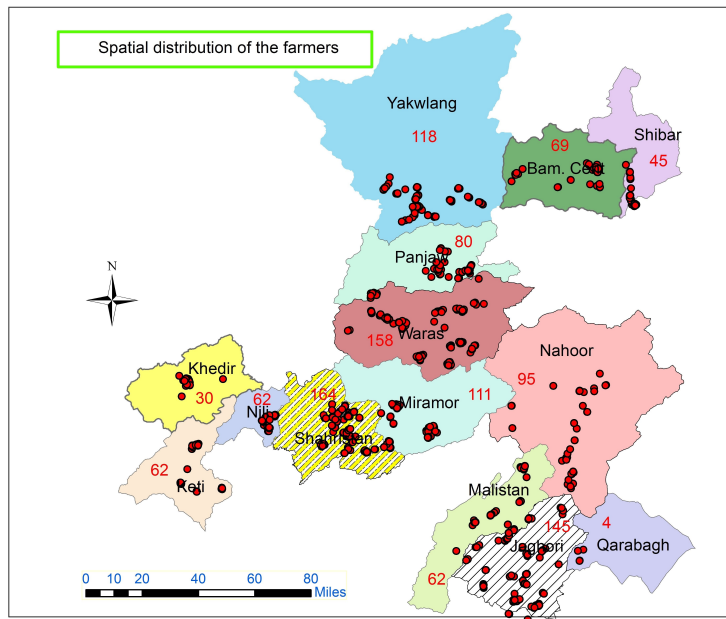


Figure 2.2: Distribution of Farmers Across Study Districts

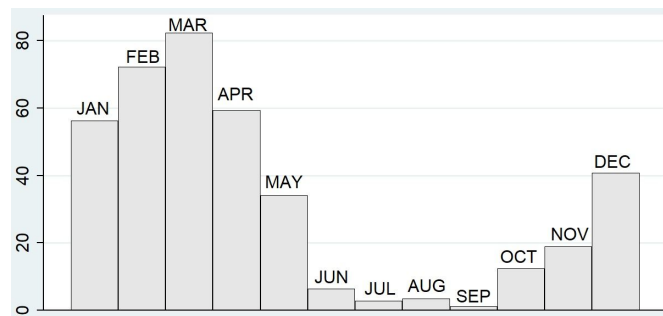


Figure 2.3: Average Monthly Precipitation (in mm)

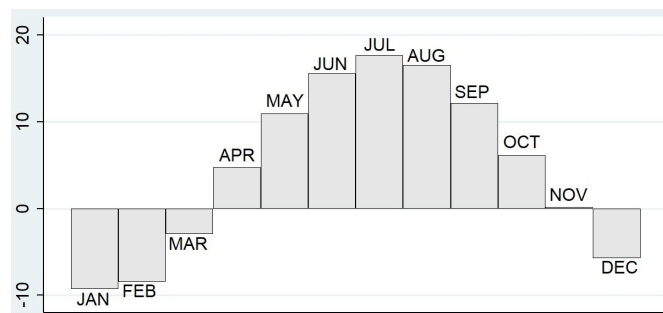


Figure 2.4: Average Monthly Temperature (in degree Celsius)

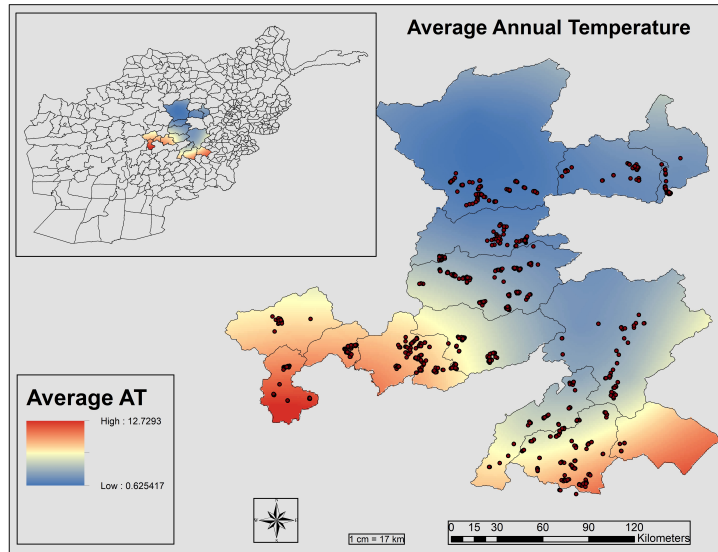


Figure 2.5: Average Annual Temperature in the Study Area

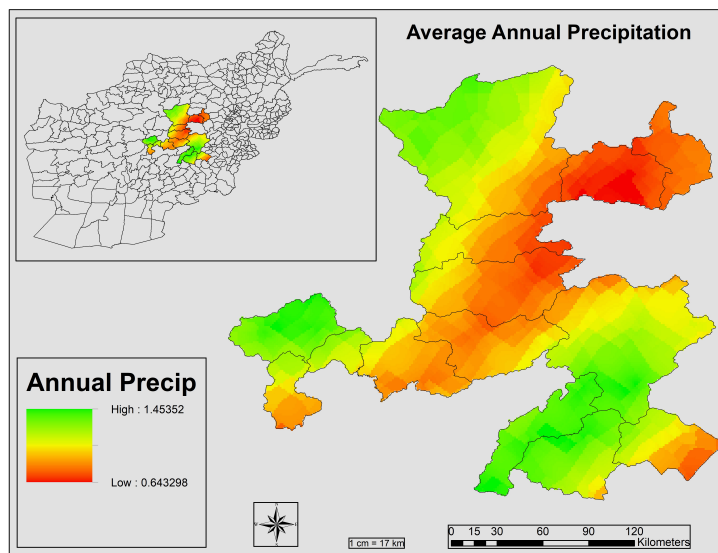


Figure 2.6: Average Annual Precipitation in the Study Area

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# 3 Exposure to Climate Change-Related Extreme Weather Events and Risk Preferences: Evidence from Farmers in Afghanistan

## Abstract

This chapter explores the endogeneity of risk preferences to climate change-related extremes among farmers in the Central Highlands of Afghanistan. To this end, we have collected and analysed experiment and survey data from 1741 farmers in 3 central provinces of Afghanistan. Our findings show that exposure to extreme weather events correlates positively with farmers' willingness to take risks. While our data does not allow for the establishment of a definite causal relationship, we can rule out alternative explanations. That is, our results are unlikely explained by either sorting or endogenous adaptation to climate change due to the high immobility and poverty levels of Afghan farmers. Our study opens a new dimension in the literature on the endogeneity of preferences addressing long-term exposure to extreme weather events. Such studies are particularly valuable for adaptation — an essential policy and research issue in the climate change discourse <sup>1</sup>.

*Keywords:* Risk preferences; Climate change; Extreme weather events; Exposure; Adaptation; Afghanistan.

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<sup>1</sup> This paper is co-authored by Menusch Khadjavi (PhD)

### 3.1 Introduction

In recent decades, changes in climate has impacted natural and human systems on all continents and across oceans. With continuing climate change, the likelihood of climate-related extremes, such as drought, floods, as well as cold and heat waves, has increased. Impacts of such extreme events reveal significant vulnerability and exposure of ecosystems and everyday human life to current climate variability. Although the evidence of climate change impacts is most robust and comprehensive for natural systems, many effects on humans (livelihood, health, well-being and economic prosperity) are attributed to climate change (IPCC, 2014).

To reduce the vulnerability of human systems to the impacts of climate change and related extreme events, adaptation is crucial, especially in developing countries (Smit and Wandel, 2006; Dixon et al., 2014; IPCC, 2014; Jianjun et al., 2015). For designing and implementing adaptation plans, understanding the (current and future) impacts is essential. A large body of research is devoted to studying the physical and ecological implications of climate change and related extreme events (e.g. (Edwards and Richardson, 2004; Kelly and Goulden, 2008; Mertz et al., 2009; IPCC, 2014). Some studies address individuals' behavioural adjustments in response to the realised impacts (Adger et al., 2005). However, the question of whether the effects of climate change and related extreme events trigger changes in individuals' economic behaviour and risk preferences remains an understudied subject (Dang, 2012). Investigating such an association is particularly relevant to the adaptation process, as adaptation is a decision under uncertainty and related to individuals degree of risk aversion.

Among other sectors, agriculture is very susceptible to the impacts of climate change and extreme events (Kurukulasuriya and Rosenthal, 2014; Yongfu et al., 2013). Due to the limited adaptive capacity, farmers in developing countries are more vulnerable to climate change-related impacts (Parry et al., 2004; Bandara and Cai, 2014; Kahsay and Hansen, 2016; Khanal et al., 2018). In such a setting, farmers' adaptation is key to their livelihood, food security, employment, and development (Khanal et al., 2019). Hence, understanding the factors that are associated with farmers' adaptation is a crucial research and policy question.

Therefore, the main intention of this study is examining the possible association between farmers' exposure to climate-change-related extreme weather events and their economic behavior, specifically, risk preferences. To this end, we are combining climate, survey, and experimental data of farmers in the Central Highlands of Afghanistan (Bamiyan, Ghazni, and Diakundi provinces). First, we gathered detailed information on weather and climate of the region, containing daily weather records from 1979 to 2014. Next, we conducted a survey collecting information on household and community characteristics, climate change, extreme weather events, and related risks, covering 1502 farmers. Finally, we did a lab-in-the-field experiment to elicit farmers' risk preferences in an incentive-compatible fashion, with 239 participants.

Our results suggest a strong association between farmers' risk preferences and their (perceived) exposure to extreme weather events. We find that the farmers who have experienced a higher intensity of extreme events are less risk-averse. Therefore, we speculate that farmers' risk aversion



has been affected by their long term exposure to extreme weather events, such as drought, flood, and cold/heatwaves.

The literature on the endogeneity of the risk preferences is rich. [Nguyen \(2011\)](#) has discussed the impact of the working environment on preferences. People like [Callen et al. \(2014\)](#) and [Voors et al. \(2012\)](#) have explored the endogeneity of risk preferences to exposure to violent conflict. Related to extreme events and natural disasters, the literature discusses the impact of flooding ([Page et al., 2014](#)), earthquake ([Hanaoka et al., 2018](#)), or both ([Cameron and Shah, 2015](#)) on individuals risk preferences. Our study contributes to this literature by flagging the importance of climate change for economic preferences by exploring the problem from a different perspective in the sense that not only experiencing short-term high-intensity shocks affect behaviour (see, for instance, [Callen et al. \(2014\)](#); [Page et al. \(2014\)](#); [Imas \(2016\)](#)) but also long-term exposure to extreme events (with relatively lower intensity) might affect preferences.

The rest of the chapter is organised as follows. Section 3.2 provides an overview of climate change and extreme events in the study area. Section 3.3 discusses the methods. Results are presented in Section 3.4. Section 3.5 presents the discussions. Section 3.6 concludes.

## 3.2 Climate Change and Extreme Weather Events in the Study Area

The Central Highlands is one of the five climatic zones in Afghanistan. Deep valleys and mountain range up to 6,400 m above the sea level widely characterise the region. Baba mountain range is extended from north-east to the south-west of the area providing the source for many of the country's major rivers, such as Helmand, Kabul, Harirood, and Baghlan ([Aich et al., 2017](#)). The climate in the Central Highlands has changed (like other parts of the country) since the second half of the 20th century ([Savage et al., 2014](#)).

An analysis of the weather data shows that the temperature over the study area has increased by about 1.5 °C. Figure 3.1 in Appendix 3.7.2 depicts the changes in average temperature in Bamiyan, Ghazni, and Diakundi provinces from 1979 to 2014.

The amount of average precipitation has decreased in most parts of the Central Highlands. Figure 3.2 in Appendix 3.7.2 shows the changes in average annual precipitation in Bamiyan, Ghazni, and Diakundi provinces from 1979 to 2014.

No literature exists on the early history of extreme weather events in the area. But what is being remembered by old farmers is a severe drought around 1930, causing huge losses in the farm's product which left a notable number of people (the exact number is not known) starving. In recent decades, for which the weather data are available<sup>2</sup>, a severe drought unfolded around the year 2000/1. Our data suggest that the year 2000/1 drought followed by a continual drop in the amount of precipitation in the preceding years. Hence, drought continues to be a significant challenge in most parts of the study area.

<sup>2</sup> The weather data were obtained from the following website: <https://globalweather.tamu.edu/>

In addition to drought — the main extreme weather event in the area — the risk of flood is also reported to be high. Floods damage farms and products, kill livestock, and destroy farmers' property. No literature, however, exists studying the history of flooding in the area.

Due to climate change, the intensity and frequency of cold/heatwaves have increased (Ali and Erenstein, 2017). Considering the extreme nature of these events, they can cause considerable losses in the farm's production. A cold wave in spring when most of the products blossom, for instance, can freeze the pre-mature seeds. In the same way, a heat spell in the summer, when water scarcity is at its peak, can damage products. To the best of our knowledge, there is no study investigating the risk of cold/heatwaves and their associated losses in the area.

Climate change, including the year 2000/1 drought (depicted in Figure 3.2), has been happening uniformly across all three provinces under study. But the consequences in different locations have been mainly depending on the topology (mountain ranges, river, altitude, etc.) of those areas. As a result, some farmers (like those in Ghazni province) face losses due to climate change while other farmers (like the majority of those in Bamiyan province) mostly benefit.

### 3.3 Research Design and Data

The data for our analyses were collected from 1742 farmers. These farmers took part in our survey and lab-in-the-field experiment to study the association between risk preferences and exposure to extreme events. The subjects were sampled from across 14 districts in three central provinces (Bamiyan, Ghazni, and Diakundi) of Afghanistan (study districts are depicted in Figure 2.1). We conducted the field experiment in July 2017 in two districts, selected from 14 districts surveyed earlier in May-June 2017. Nili (centre of Diakundi province) and Bamiyan centre (centre of Bamiyan province) were chosen to represent areas where the risk of extreme events is very high and very low, respectively. The earlier survey in May-June 2017 includes variables on the local risk of drought, flood, cold/heatwaves, and change in the climate, their consequences, and a range of household, farm, and community characteristics. In order to gauge the farmers' overall willingness to take risk, a variable (Risk Perception), taking values from 0 (not willing to take any risks) to 4 (highly willing to take risks) was included in the survey. The summary statistics of these variables are reported in Table 3.2, Section 3.4.1.

During the field experiment later in July 2017, we randomly selected 239 farmers from 20 communities in Bamiyan centre and Nili districts, inviting them to participate in our experiment. From these farmers, 61 of them (mostly living in Nili) experienced the high intensity of extreme events, and 178 of them (mostly residing in Bamiyan centre) experienced no or very low intensity of extreme events. To elicit their risk preferences, we have employed a well-established method proposed by Binswanger as well as Eckel and Grossman (Binswanger-Mkhize, 1981; Eckel and Grossman, 2002; Charness et al., 2013).

The farmers were presented with 6 lottery choices and were asked to choose the one they prefer. Each option, listed in Table 3.1, involves a 50% chance of receiving the low payoff and a

50% chance of the high payoff. Before asking the farmers to make a choice, a research assistant explained the method in a simple language to ensure understanding<sup>3</sup>.

Table 3.1: Eckel-Grossman Task (EGTask).

<b>Choice- 50/50- Gamble</b>	<b>Low-Payoff</b>	<b>High-Payoff</b>	<b>Expected- Return</b>	<b>Std-Dev.</b>	<b>CRRA-Range</b>
Gamble 1	150	150	150	0	$r > 1.25$
Gamble 2	120	190	155	35	$.99 < r < 1.25$
Gamble 3	100	220	160	60	$70 < r < .99$
Gamble 4	80	260	170	90	$.49 < r < 70$
Gamble 5	60	300	180	120	$r \approx 0$
Gamble 6	10	350	180	170	$r < 0$

All payoff amounts are in Afghani (Afghanistan's national currency). 1 USD ~ 74 AFN, in July 2017

Following [Eckel and Grossman \(2002\)](#), Gamble 1 involved a guaranteed payoff of AFN 150<sup>4</sup>. For Gambles 1 to 5, the expected payoff increases linearly with risk (given by the standard deviation). Gamble 6 has the same expected payoff as Gamble 5 but with higher standard deviation. The gambles are designed so that the risk-averse farmers would choose those with lower risk (Gambles 1-4). Risk-neutral farmers would choose Gamble 5, and risk-seeking farmers would choose Gamble 6. Under the assumption of constant relative risk aversion (CRRA), the farmers' utility function can be represented by a power function of the form  $u(x) = x^{(1-r)}$ , with  $r$  corresponding to the coefficient of relative risk aversion and  $x$  corresponding to wealth. Farmers with  $r > 0$  can be classified as risk-averse,  $r < 0$  as risk-seeking, and  $r = 0$  as risk-neutral.

The key variable of interest in our study is the (self-reported) measure of the intensity of the extreme weather events (drought, flood, and cold/heatwaves). We have used the risk of three main extreme events (drought, flood, and cold/heatwaves) to define our exposure (dummy) variable.

## 3.4 Results

### 3.4.1 Descriptive Statistics

In order to examine differences in descriptive statistics between farmers who are exposed to climate-change extremes and those farmers who are not, we define a dummy variable (exposure) which equals 1 if the average risk of such events is high to very high and 0 otherwise. To construct the exposure dummy, we have used the mean of three categorical variables measuring farmers

<sup>3</sup> A detailed summary of the experimental procedure is provided in Appendix 3.7.1.

<sup>4</sup> AFN 150 is equivalent to the hourly wage of a farmworker at the study area.

perception on the risk of drought, flood, and cold/heatwaves. Table 3.2 provides a summary of the variables of interest by exposure, including the p-values of corresponding two-tailed t-tests.

The two variables measuring farmers' risk-taking behavior (EGTask and Risk Perception) show that the farmers in our sample are in general risk-averse. The mean of the variables EGTask and Risk Perception are higher among exposed farmers showing more exposed farmers to be less risk-averse ( $p < 0.01$ ). Furthermore, households' on-farm employment is higher among less exposed farmers. The difference is, however, only significant for experimental data. The number of farmers who sell a part of their farm product in the market is higher among less exposed farmers ( $p < 0.05$ ). The change in farm production (as a result of climate change) is positive among less exposed farmers ( $p < 0.01$ ). In the same way, the overall impact of climate change is less negative among less exposed farmers ( $p < 0.01$ ). A similar result is observed on the degree of farm's vulnerability to the effects of climate change (and related extremes) in the sense that the less exposed farmers reported that their farms are less vulnerable ( $p < 0.01$ ).

Table 3.2: Summary Statistics and Test of Means

Variables	Experiment		Survey	
	Mean(SD)	Exposure 0 (1)	Mean(SD)	Exposure 0 (1)
Exposure[high=1]	.26(.44)	—	.76(.40)	—
EGTask	3.94(1.5)	3.75(4.58)***	—	—
Risk Perception[0-4]	—	—	1.54(1.4)	1.30(1.60)***
Risk of drought [0-4]	2.28(1.8)	1.71(3.95)***	3.09(1.19)	1.71(3.75)***
Risk of flood [0-4]	1.60(1.2)	1.15(2.93)***	2.94(1.11)	1.83(3.22)***
Risk of cold/heatwaves [0-4]	2.25(.93)	1.96(3.08)***	2.85(1.22)	1.29(2.91)***
Gender[male=1]	.94(.23)	.97(.87)***	.97(.16)	.97(.97)
Literate[yes=1]	.58(.49)	.56(.57)	.58(.49)	.66(.56)***
Farming experience	24.3(15)	26(20)***	22(14)	22(21.8)
Stayed abroad [yes=1]	.50(.50)	.46(.64)	.65(.45)	.66(.65)
Works only on farm[yes=1]	.51(.50)	.57(.36)***	.37(.47)	.30(.38)***
Main-cause-of-CC[God's-will=1]	.41(.79)	.44(.31)	.62(.93)	.62(.63)
Main-source-of-income[farming=1]	.79(.41)	.83(.67)**	.71(.45)	.67(.72)***
On form employment	3.2(2)	3.4(2.7)**	2.5(5.4)	2.9(2.4)
Access to electricity (in hrs)	6.3(3.3)	6.7(5)***	4.9(5.8)	5.3(4.7)

Continued on next page

Sale farm's product[yes=1]	.69(.46)	.85(.25)***	.21(.41)	.26(.20)**
Change-in-farm-production- because-of-CC[-1,0,+1]	.31(.93)	.56(-.42)***	-.40(.83)	-.17(-.45)***
Overall-impact-of-CC[- 1,0,+1]	.05(.98)	.28(- .64)***	-.34(.88)	-.08(-.40)***
Form-vulnerability-to- CC[0,1,2]	.88(.84)	.69(1.46)***	1.36(.61)	1.12(1.41)***
Agri-adaptation[yes=1]	.78(.42)	.88(.47)***	.85(.35)	.82(.86)*
External support[yes=1]	.39(.49)	.36(.48)	.18(.35)	.23(.16)***
Capital index	.26(.33)	.25(.29)	.32(.38)	.39(.30)***
District[Nili=1]	.29(.45)	.13(.75)***	—	—
N(0/1)	239 (178/61)		1502 (1192/310)	

p-value < 0.01 \*\*, p-value < 0.05 \*. CC stands for Climate Change.

Section 5 provides a detailed description of the variables.

### 3.4.2 Exposure to Climate Change-Related Extremes and Risk Preferences

In the previous sub-section, we have seen a considerable heterogeneity in farmers risk preferences/perception with respect to their exposure to extreme events. Farmers spend a considerable amount of time (mostly their whole life) working on and being engaged with their farms. Thus, a significant interaction between farmers' occupation-related events and their beliefs and attitudes appears likely.

Using a unique dataset of farmers, we analyze the association between exposure to extreme events and farmers' risk-taking behavior. Exogenous climate-change-related extremes (such as drought, flood, as well as cold/heatwaves) can affect farmers' preferences through various mechanisms. In general, causality is difficult to establish — mobility, selective migration, violence, and relevance of climate change and its related extremes present natural confounds — our results (presented in Table 3.2) suggests that the farmers' risk preferences are strongly associated with their exposure to extreme events ( $p < 0.01$ ). Notably, farmers who have been facing the higher intensity of extreme events (such as drought) are less risk-averse. The observation holds true for both survey data as well as experimental evidence. To control for the effects of other factors, we run ordered Probit regression<sup>5</sup> of both risk preferences and risk perception for experimental and survey data, including the relevant personal, farm, community, and regional characteristics. Factors such as gender, experience (age), migration background, employment, religious belief (represented by

<sup>5</sup> Ordered Probit model is chosen due to the ordinal, with more than two outcomes, nature of the dependent variables — EGTASK and Risk Perception.

the leading cause of climate change), market engagement (represented by selling products), prior losses/gains (represented by change in farm production), external support, and regional fixed effects (described by province) are included in the Probit models. The results are reported in Table 3.3.

Table 3.3: Exposure to Climate Change-Related Extremes and Farmers' Risk Preferences.

Variables	Experiment		Survey	
	IA	IB	IIA	IIB
Dependent Variables: EGTask in models IA and IB. Risk Perception in models IIA and IIB				
Exposure[high=1]	.52(.13)***	0.34(.16)**	.19(.06)***	.24***(.06)
Gender[male=1]	—	0.46(.26)*	—	-.2(.19)
Farming experience	—	0.005(.005)	—	.001(.002)
Stayed abroad[yes=1]	—	-0.202(.16)	—	.07(.06)
Works-only-on-the-farm[yes=1]	—	-0.242(.2)	—	.17***(.06)
Main-cause-of-CC[God's will=1]	—	-0.237(.2)	—	-.2***(.06)
Main-source-of-income[farming=1]	—	0.0385(.2)	—	.22***(.07)
On-farm-employment	—	.0206 (.04)	—	.001(.008)
Access-to-electricity	—	.00815(.02)	—	-.003(.005)
Sale-farm's-product	—	.281 (.4)	—	-.14***(.07)
Farm-production[decreased==1]	—	0.14 (.19)	—	.16**(.07)
Overall-impact-of-CC[negative==1]	—	-.1(.25)	—	.05(.1)
Farm-vulnerability[not vulnerable=1]	—	-.03(.2)	—	-.009(.1)
Agri-Adaptation[yes=1]	—	0.187 (.3)	—	.10(.09)
External-support[yes=1]	—	0.0156 (.14)	—	.22***(.07)
District[Nili=1]	—	0.657 (.4)	—	—
Province	—	—	—	.11***(.04)
N		239		1502

p-value < 0.01 \*\*\*, p-value<0.05 \*\*, p-value<0.1 \*. Province: Bamiyan(1), Ghazni(2), Daikudni(3)

The estimates of control factors are mostly insignificant, especially in the experimental model (IB). However, certain variables are significant in Model IIB. Farmers who are engaged only in farming seem to be less risk-averse (.17,  $p < .01$ ). Similarly, farmers whose main source of income is farming seem to be less risk-averse (.22,  $p < .01$ ). This could be because of their intensive engagement with extreme weather events. Farmers who are selling agriculture products are also more risk-averse (-.2,  $p < .01$ ). The negative correlation results from the fact that farmers who sell farm products are living in less exposed areas, hence, less affected by extreme weather events. The same line of arguments explains the positive correlation of the variable Province. Farmers living in more exposed provinces (Ghazni and Daikundi) are less risk-averse. The estimate of the Main Cause of Climate Change is negative. Those who think that the main cause of climate change is God's will are more risk-averse (-.2,  $p < .01$ ).

Most important to the current study is the estimates of the exposure dummy. The results in IA, IB (experimental models), IIA and IIB (survey models) suggest a significant association between farmers' risk preferences/perception and their exposure to extreme weather events. In particular, more exposed farmers are less risk-averse.

### 3.5 Discussion of Possible Mechanisms

Our findings, presented in Table 3.3, suggest that there is a significant association between farmers' risk preferences/perception and their exposure to climate-change-related extremes. Past studies explored the possible endogeneity of risk preferences to working environment (Nguyen, 2011) and experienced events (Voors et al., 2012; Callen et al., 2014; Page et al., 2014; Imas, 2016). Our results, presented in Table 3.3, indicate that not only shocks affect preferences, but also long-term exposure to extreme weather events (with relatively lower intensity) is associated to individuals risk preferences.

If the observed association is not just a simple correlation (because of a common cause), each variable (risk preferences and exposure) can cause the other one. The first scenario is that the risk preferences have caused the farmers to choose their degree of exposure. Under this scenario, it is possible that more risk-averse farmers have chosen to live and work in the areas with a lower risk of extreme events. Or, only more risk-seeking farmers in highly exposed areas have chosen to stay, and the rest have migrated to the big cities — due to a significant decrease in agriculture production in recent years, such internal migration has been happening. The design of our research addresses the first mechanism. Selective migration within the area is controlled for, as almost all of our subjects live and farm in the villages where they have been born and raised. Hence, risk preferences do not play any role in farmers' choice of the living/working environment. For migration to the big cities, although we cannot directly control for such an effect, the fact that immigration to big cities, searching for new job opportunities, and setting a new life involves a high degree of uncertainty, the chance that only more risk-averse farmers systematically would have chosen to move to the big cities is unlikely.



The second scenario is that long-term exposure to extreme weather events affects risk preferences. In this setup, the change in risk preferences could be caused by continual exposure to extreme events. In this case, risk preferences are endogenous to exposure to extreme events.

Psychological evidence suggests that individuals' preferences can undergo some form of adaptation (Dang, 2012). For instance, (Nguyen, 2011) argues that risk preferences are shaped and adapted over time by the working environment. The longer one works in the same environment the more her/his reference of risk is adapted to it. The preference, in turn, plays a crucial role in determining how much risk one is willing to take.

Adaptation seems a compelling explanation for the endogeneity of farmers' risk preferences to their exposure to climate change-related extremes. Farmers' long-term exposure to extreme events might have caused their preferences to adapt to a harsher and riskier environment. Specifically, the farmers — who repeatedly and for years have been making decisions in the face (relatively) higher average risk of extreme events — might have developed a higher tolerance for accepting risks.

A second possible explanation is the effect of background risk. In areas where the farmers are more exposed, background risk of this sort is higher, and one might expect to observe different risk-taking behaviour than those living in less exposed areas (Cameron and Shah, 2015). Hanaoka et al. (2018), for instance, observe that people who are exposed to higher intensities of Japan's 2011 Earthquake become more risk-tolerant. A key argument on the effect of background risk is that the people living in areas with high background risk are less concerned about additional small independent risk (Cameron and Shah, 2015).

It may be the case for the Afghan farmers in our study as well. If we consider the climate-change-related extremes as the background risk, it is evident that more exposed farmers are facing higher background risk. Farmers who live in areas with higher background risk may be less concerned about additional small independent risk. As a result, they might have systematically chosen riskier gambles/option in our experiment and survey.

The significant association between farmers' risk preferences and their exposure to extreme events might have several other explanations. The association might have resulted from a common cause (missing variable in our models). Factors such as violent conflict over land and water could have affected preferences and correlated to extreme weather events. Exposed farmers might have systematically been facing various shocks in the past (such as financial losses/gains, violence, loss of family members, etc.) which could have affected their risk preferences. Another concern is the construction of the exposure dummy which is based on subjective measures. While we regard our study as a worthwhile contribution to the literature, more research is necessary to investigate such potentially confounding factors.



### 3.6 Conclusion

The literature on the endogeneity of risk preferences has surged in recent years. Studies have investigated the problem from various angles. The effect of prior losses and gains on current risk-taking has been investigated both in the lab (Weber and Camerer, 1998; Haigh and List, 2005; Weber and Zuchel, 2005) as well as in the field (Odean, 1998; Locke and Mann, 2005). Several studies investigate the effect of short-run natural disasters on risk preferences (Page et al., 2014; Cameron and Shah, 2015; Hanaoka et al., 2018; Cassar et al., 2017). Similarly, the endogeneity of risk preferences has been studied in the context of long-run effects such as occupation (Nguyen, 2011), the environment (Bchir and Willinger, 2013), and exposure to conflict (Voors et al., 2012; Callen et al., 2014).

In this paper, we contribute to this literature by investigating the association of risk preferences to the long-term exposure to climate-change-related extremes. We study the problem among farmers in the Central Highlands of Afghanistan by using both survey and experimental data. The farmers in our sample are on average risk-averse. Our analyses suggest that more exposed farmers (those who are living in high-risk areas) are less risk-averse. A primary explanation for our finding may be the adaptation of the risk preferences as a result of repeated and long-term exposure to the events that are relevant for farmers' income and employment. The result holds for both experimental as well as survey data.

Furthermore and in the light that risk-taking determines important household and individual decisions (such as investment, saving, and employment), our results have important policy implications for rural economic development. In particular, with climate change happening, adaptation has become a key policy issue. Since adaptation is primarily a decision under uncertainty, farmers' degree of risk tolerance plays a central role in exercising various adjustments (both physical and behavioural) in response to climate change. Hence, policy makers in adaptation sector shall consider the heterogeneity of farmers' risk preferences with respect to their exposure to extreme events. Such a consideration, for instance, would include the introduction of a new type of seed. Whether a farmer would practice it highly depends on his/her degree of risk aversion.

Considering the cross-sectional nature of our data, we cannot establish a causal relation and alternative explanations, such as the existence of missing factors and self-selection, are possible. Our study, however, opens a new dimension in the literature on the endogeneity of the risk preferences in the sense that behavior might be affected by long-term exposure to extreme weather events related to climate change. As the impacts of climate change become more distinct, further research and especially large panel datasets are needed to fill remaining gaps in the literature.

## 3.7 Appendices

### 3.7.1 Appendix A: Field Experiment

In the following, we explain how we conducted the lab-in-the-field experiment with farmers in Afghanistan. Note that due to literacy problems, our field research team needed to explain the risk task verbally. We followed the steps below:

1. First, we explained to the farmers in very general terms that we conduct a scientific study on the impact of climate change on agriculture in the region. We emphasised that the study is being authorised and supported by the Ministry of Higher Education, Islamic Republic of Afghanistan and the office of Ayatullah Fayaz (an influential religious leader) in Kabul.
2. Second, the farmers were told that participation in the study is entirely voluntary and that they can stop cooperation at any time during the study.
3. Third, each farmer was walked through the following steps for the EGTask. A research assistant was explaining the EGTask in a straightforward and plain local language. The details included: (a) the number of choices, (b) the amount of money in each choice, (c) we used two non-transparent bottles, with two different messages in them, from which the participant could choose one, (d) how the amount that one wins depends his/her choice; and (e) the possibility of winning smaller amount or larger amount (in each choice) by choosing one of the two randomized bottles.
4. The same research assistant was making sure that the farmer understood the task by asking him/her to explain back the task briefly. If there was a problem with understanding (this happened with some older farmers), the research assistant was re-explaining the tasks.
5. After making sure that the farmer understood the task, the farmer was asked to choose one of the six possible choices in the EGTask.
6. After the farmer chose her/his preferred choice, she/he was asked to select one of the two bottles. In one of the bottles, there was a piece of paper with "Smaller Amount" written on it; and in the other bottle, there was another piece of paper with "Larger Amount" written on it. Important: We did not use a coin or a die, as the act of tossing a coin or rolling a die would have created negative feelings of gambling among our study participants.
7. The farmer was given time to choose a bottle. After selecting the bottle, the farmer her/himself was asked to open it and check the piece of paper in it. If the farmer was able to read, he was being asked to read the piece of paper and was paid accordingly (in Afghan currency) — else the research assistant was reading the piece of paper and was paying the farmer accordingly.
8. The research assistant was making sure that the farmer counts the money before continuing with the questionnaire.

### 3.7.2 Appendix B: Figures

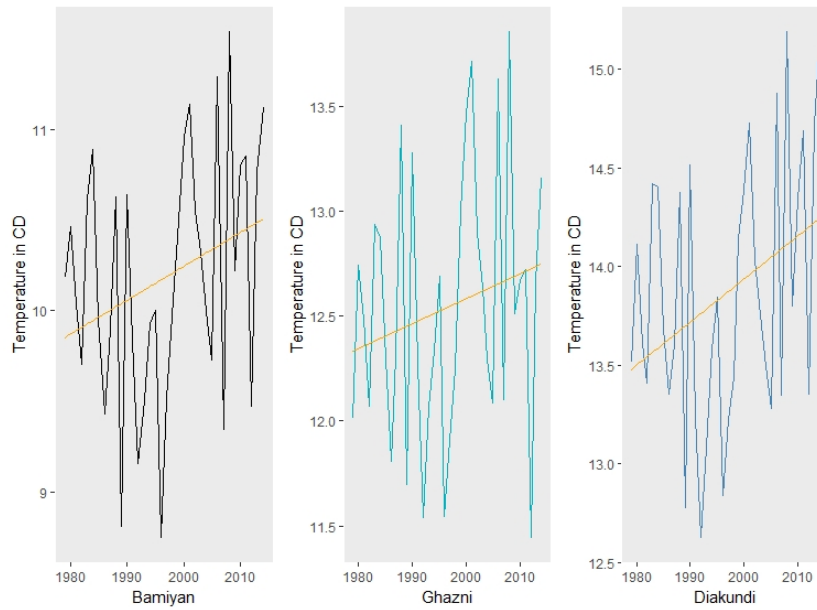


Figure 3.1: Annual Temperature from 1979 to 2014 in Bamiyan, Ghazni, and Diakundi Provinces

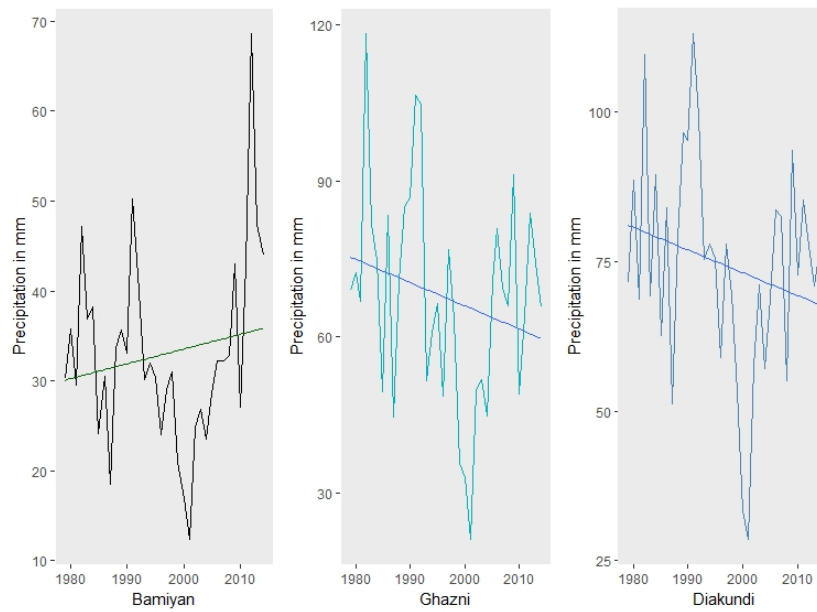


Figure 3.2: Annual Precipitation from 1979 to 2014 in Bamiyan, Ghazni, and Diakundi Provinces

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

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### Abstract

Climate change is a significant obstacle for farmers in the least developed countries like Afghanistan and adaptation support is exceptionally scarce. This chapter provides a summary of farmers adaptation to climate change and studies 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' self-reported priorities, we provide a list of policy recommendations for adaptation to climate change in farming communities in Afghanistan.

*Keywords:* Climate change; Adaptation; Project evaluation; Quasi-experiment method; Governmental/non-governmental Organizations; Afghanistan.

## 4.1 Introduction

The literature agrees that global climate change has been accompanied by a steady increase in the number and severity of climate-related extreme events, such as drought and flood (Jayatilleke S. and Yiyong, 2014). Climate change and related extreme events have caused impacts on both natural and human systems (IPCC, 2014; Islam et al., 2016).

Farmers, mostly in the 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 effects of climate change, limited resources for adaptation is a significant contributor to the high vulnerability of farmers in these countries (Khanal et al., 2019). The literature confirms the crucial need of enhancing farmers' adaptive capacity 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, 2004; Baizayee et al., 2014). Furthermore, there has been a consistent policy position that agriculture will be central to Afghanistan's growth and development (Pain and 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 (Adger et al., 2003). 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., 2014).

In such circumstances, external support provided by the governmental (GO), non-governmental (NGO), and community-based (CBO) organizations for enhancing farmers' adaptive capacity, is vital. Evidence confirms the critical role of extension services<sup>1</sup> and community-based organizations in supporting farmers to adapt to climate change (Hassan and Nhemachena, 2008; Deressa et al., 2011; Khanal et al., 2019).

In the post-2001 era<sup>2</sup>, rural development has been a significant focus of the new government in Kabul, its international partners, and NGOs. Agriculture, as a critical developmental sector, has been at the heart of all initiatives, interventions, and projects that have been carried out by GOs/NGOs in rural areas<sup>3</sup> (Savage et al., 2014; Pain and Shah, 2009). Such support has been, and continues to be, decisive for rural development, poverty reduction, and dealing with consequences

<sup>1</sup> Extension services are an important source of information on agronomic practices as well as on climate. FAO provides a detailed summary of extension and extension services. <http://www.fao.org/3/t0060e/T0060E03.htm>

<sup>2</sup> In late 2001, the Taliban regime was overthrown and a new west-backed government was formed in the country.

<sup>3</sup> For more information from the United Nations Development Programme, see <http://www.af.undp.org/content/afghanistan/en/home/projects/CCAP-Afghanistan.html>



of climate change and extreme weather events. Hence, understanding the impact of these interventions is vital for further policy development and implementation. Despite this fact, to date, the effect of the support provided by these organizations (GOs/NGOs) for farmers' adaptation to climate change has not been documented in the scientific literature<sup>4</sup>. 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) on farmers' 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 to estimate the effect of external support provided by different GOs/NGOs on their 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 adapt<sup>5</sup> to the impacts of 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, extension services, concreting water 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 1434 farmers across 14 districts in the Central Highlands of Afghanistan. An advanced survey application developed by the World Bank was used to carry out 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 and Abdulai, 2010; Ali and Erenstein, 2017; Antle 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 it 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 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 neighbour (NN), and inverse probability weighting (IPW)

<sup>4</sup> We do not rule out the existence of the project-based evaluation reports.

<sup>5</sup> 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.

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. Economic and financial; knowledge, awareness, and limited use of technology; and government and institutional constraints are the main adaptation obstacles reported by the farmers. Although some positive impacts of warming have been reported, the majority of farmers believe that their farming business is vulnerable to the current and expected consequences 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 effect of the interventions on outcomes such as access to irrigation water and the use of improved types of seeds are found to be significant and robust. The treatment impact on the risk of the 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, drought-, pest-, and disease-resistance seeds, crops, and trees; and investment in irrigation and water resources management are recommended.

The remainder of this chapter is organized as follows: A summary of climate change and related issues in Afghanistan is provided in Section 4.2. Section 4.3 discusses the methods. The study area and the instruments are introduced in Section 4.4. Results and discussions are presented in Section 4.5. Section 4.6 presents the policy recommendations and concludes the paper.

## 4.2 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., 2014). The country has an extreme continental arid climate that is characterized by desert, steppe, and highland temperature regimes (Shroder, 2016). Afghanistan is divided into five climate regions (Aich et al., 2017): (1) The Hindukush Region; (2) Northern Plains; (3) Central Highlands; (4) Eastern Slopes; and (5) Southern Plateau.

A recent analysis by Aich et al. (2017) suggests a significant change in the climate of the coun-

try 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. \(2014\)](#) reported a 0.6 degree Celsius increase in average annual temperature and 0.2 mm decrease in average monthly precipitation since 1960. The reason for such a large deviation between the two findings is the use of available data from neighbouring countries in [Savage et al. \(2014\)](#). [Aich et al. \(2017\)](#), on the other hand, used reanalysis data and validated the results using the observed data by (few) meteorological centers across the country. Projections suggest that by 2100 the average temperature over Afghanistan would increase by 5–8.4 degrees Celsius and the country would have generally a drier condition. Average annual precipitation would decrease by 22–31% ([Aich et al., 2017](#)).

Afghanistan's National Adaptation Program of Action for Climate Change (NAPA<sup>6</sup>) lists drought, flood, warming, heat/cold waves, thunder, and the Monsoon 120 day wind as the main climatic hazards which are exacerbated by climate change ([UNEP, 2009](#)).

With climate change happening, understanding the vulnerability of various sectors and the implications of these changes for development, stability, and food security have 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, 2009](#); [Savage et al., 2014](#)). Food security among rural households is another primary 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 ([UNEP, 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 ([UNEP, 2016](#)). However, several 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<sup>7</sup>; a range of initiatives and projects by the Ministry of Agriculture, Irrigation and Livestock<sup>8</sup>; and various climate change-related projects by World Food Program<sup>9</sup>, Action Aid<sup>10</sup>, and Agha Khan Foundation<sup>11</sup>.

<sup>6</sup> <https://unfccc.int/resource/docs/napa/afg01.pdf>

<sup>7</sup> <http://www.projects.worldbank.org/P117103/national-solidarity-program-iii?lang=en>

<sup>8</sup> <http://www.af.undp.org/content/afghanistan/en/home.html> and <http://mail.gov.af/en/page/3253/3254>

<sup>9</sup> <http://www1.wfp.org/countries/afghanistan>

<sup>10</sup> <https://actonaid.org/>

<sup>11</sup> <https://www.akdn.org/where-we-work/central-asia/afghanistan/akdn-activities-afghanistan>

NAPA has prioritized the sectors that have to be supported under various adaptation interventions. Water management is the sector that needs to be addressed immediately. Persistent drought has been threatening water resources which are crucial to agriculture production. Community-based watershed management is one particular sector which is being prioritized by NAPA (UNEP, 2009).

The first climate change adaptation project executed by NEPA and UNEP was piloted in Bamiyan, Diakundi, Balkh, Badakhshan, and Kabul provinces (project locations are depicted in Figure 4.4 in Appendix 4.7.4). 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 what NAPA has prioritized (UNEP, 2009; Baizayee et al., 2014). The project intended to meet its objectives by reducing climate change vulnerability in the selected project sites through local institutional capacity building and concrete interventions to improve water use efficiency, and increasing knowledge and awareness of climate change adaptation and best practices at the national, provincial, and community levels.

The intervention was implemented from May 2013 to May 2017 (Baizayee et al., 2014).

## 4.3 Methodology

To analyse the impact of a treatment on certain outcomes of interest, several 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 modelling, the pipeline approach, and propensity score are available to estimate the impacts of treatment on specific 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 1174 comparison farmers from the same area — which makes propensity score an appropriate method for estimating the treatment effects. To test the reliability of the results, we utilize some other methods, such as the doubly robust estimator and endogenous switching regression.

### 4.3.1 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 these factors simultaneously affect 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 and 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 outcome — 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

$$ATT = E[Y(1)|T = 1] - E[Y(0)|T = 1] \quad (4.1)$$

The first term in Eq. (4.1) 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

$$E[Y(0)|\mathbf{x}, T] = E[Y(0)|\mathbf{x}] \quad (4.2)$$

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)

$$pscore = P(T = 1|\mathbf{x} = x) \quad (4.3)$$

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 Eq. (4.2), we should rule out the cases for which the pscore 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 pscore, as defined in Eq. (4.3), can be used instead (Rosenbaum and Rubin, 1983). Then, matching estimators will compare farmers in the treated group to those in the control group that is closest to them regarding the estimated pscore values. An important issue related to the estimation of the pscore is the selection of the covariates to be included in the pscore model. Since pscores are used to reduce confounding, the variables that are related to both treatment and outcomes should be included

in the pscore model (Garrido 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 pscore model (Caliendo and Kopeinig, 2008).

To match using pscore, a number of different methods are available, such as nearest neighbour, calliper 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 of all farmers in the control group to construct the counterfactual. In kernel matching, a weighted mean of all farmers in the control group is used to estimate the counterfactual for each treated farmer. Non-treated farmers with similar pcores get higher weights. There are several kernel-based matching methods (Frölich, 2004), but we use the kernel ridge regression, which Huber et al. (2013) suggest having superior finite sample properties. Since we are using the Epanechnikov kernel, according to a rule of thumb of (Seifert and Gasser, 2000), we have set the ridge parameter to  $\frac{5}{16} = .3125$  (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 pcores as the weights.

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

Another primary 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 to run a sensitivity analysis in order to gauge the robustness of the estimates against 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 and 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 and Gangl, 2004).



### 4.3.2 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 pscore 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 and Huffman, 2014; 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 2.2.2 provides the theoretical background of the method).

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

## 4.4 Study area and Data

### 4.4.1 Study Area

The study area includes 14 districts in 3 central provinces of Afghanistan. Figure 2.1 in Section 2.3.1 depicts the study districts. The Central Highlands of Afghanistan is one of the five climate zones in the country (Aich et al., 2017) and traditionally home to Hazaras, an ethnic minority in Afghanistan. The region is widely characterized by deep valleys and mountain ranges up to 6400 m above the sea level (Aich et al., 2017). 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 region<sup>12</sup>. 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 possess heterogeneous climate regimes and receives on average about 390 mm of precipitation annually. The amount of rainfall varies considerably across space (Table 2.6.1 in Appendix 2.6 presents the average amount of rainfall across 3 provinces) and time (Figure 2.3 in Appendix 2.6.2 depicts the amount of precipitation across 12 months). In some districts such as Nili and Kiti, total rainfall is around 260 mm while in some districts such as Shibar, Malistan, and Jaghori it exceeds 500 mm. 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

<sup>12</sup> Sample characteristics are presented in Section 4.5.1.

also high. Figure 2.4 in Appendix 2.6.2 depicts the average monthly temperature.

#### 4.4.2 Data and Survey Instruments

The primary data for our study were collected from farmers in the Central Highlands of Afghanistan from May to July 2017. Our sample consists of 1434 farmers (260 of whom received adaptation-related external support and 1174 who had not received such as support). A multi-stage systematic random sampling was implemented to choose the subjects. At the first stage, from each of 14 districts, certain number of Community Development Councils<sup>13</sup> (CDCs) were selected randomly and according to the population of the districts. At the second stage, from each chosen CDC, a certain number of households, according to the size of the CDC, were chosen for the interview. A structured questionnaire<sup>14</sup> 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 5.1 in Appendix 5.

### 4.5 Results and Discussions

#### 4.5.1 Sample Characteristics

Our sample consists of 1434 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 Section 4.5.3 provides details on received external support.). The spatial distribution of treated and non-treated farmers is depicted in Figure 4.3 in Appendix 4.7.4.

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 nine persons with nearly 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 are literate with different education levels. 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 motorcycle. Because the farmers are mostly poor and the region is predominantly mountainous, motorcycle seems to be a preferred mean of transportation. Use of the computer is not very common — only 27% have one or more computers at home. Likewise, the use of

<sup>13</sup> More information on CDC: <https://www.eldis.org/document/A48625>

<sup>14</sup> The English translation of the questionnaire is provided in Section 5.



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 about 5 h. 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 are under cultivation. The average annual net revenue per acre is estimated to be around AFN 69000 (about USD 900).

Agriculture remains the primary source of income for 76% of farmers and almost 24% of them 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.

#### 4.5.2 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 (1979-2014)<sup>15</sup> years shows that the annual average temperature has increased by about 1.5 degrees 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 compared to 25 to 30 years ago — 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 [Kebede and Gizachew \(2017\)](#). 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% said 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 a 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 4.1 reports these variables summary statistics

<sup>15</sup> Data were obtained from <https://globalweather.tamu.edu/>

### 4.5.3 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 to climate change 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 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 employments 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 have 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 Report<sup>16</sup>, 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 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<sup>17</sup>. 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%), giving improved types of seeds (13%), providing extra fertilizer (9%), providing irrigation related services (5%), and providing different kinds of fruit trees (6%).

### 4.5.4 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 4.5.3) and 0 otherwise. For ease of estimation, 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)

<sup>16</sup> WGII-Chapter 16

<sup>17</sup> We do not have any information on which type of support was provided by either organizations — however, usually the projects have been implemented in a close cooperation. For instance NEPA and UNEP adaptation project.

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) contains 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 4.1.

Before applying the kernel ridge estimator, we have tested the covariate balance and the overlap of the estimated pscores. The corresponding discussions are presented in Appendix 4.7.2. The results confirm both satisfactory covariate balance and sufficient pscore overlap among treated and non-treated farmers.

Table 4.1: Summary Statistics of the Outcome Variables

<b>Variables (Category)</b>	<b>Mean (T=0)</b>	<b>Diff in Means</b>
Risk of drought (I)	3.159284	.4323614***
Risk of flood (I)	2.526405	.2610208**
Risk of cold/heat waves (I)	2.574106	-.0258944
Risk of crop failure (I)	3.006814	.2375835***
Risk of disease/pest (I)	2.934412	.0805661
Farming constraint: water scarcity (II)	.6942078	.2442078***
Adpt: shift to other jobs (III)	.4011925	-.0141921
Adpt: more work on the farm (III)	.6729131	-.0078561
Adpt: use of improved seeds (III)	.3006814	-.2531647***
Economic/financial constraint (IV)	.8688245	.1342091***
Government/institutional constraint (IV)	.6908007	.1292622***
Knowledge, awareness, and tech use constraint (IV)	.471891	-.0819552*
Human resources constraint (IV)	.6039182	.0346875
Environment (physical/bio) constraint (IV)	.4284497	-.0023195
<i>N</i>	1434	

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

With the two assumptions satisfied, we have applied the kernel ridge regression estimator to all outcome variables, summarized in Table 4.1.

The kernel estimates of the average treatment effects (ATT) of the provided support by GOs/NGOs among treated farmers are reported in column 2 of Table 4.2.

Table 4.2: Propensity Score Estimates of the Treatment Effect on Farmers' Adaptation

Outcome (Category)	ATT(KM)	ATT(DR)	ATT(NNM)	ATT(IPW)
Risk of drought (I)	.11(.10)	-.13(.09)	-.22(.11)**	-.13(.09)
Risk of flood (I)	-.27(.12)**	-.23(.10)**	-.34(.13)**	-.24(.12)**
Risk of cold/heat waves(I)	.05(.11)	.08(.09)	-.03(.13)	.07(.09)
Risk of crop failure (I)	-.03(.09)	-.04(.07)	-.15(.1)	-.05(.07)
Risk of disease/pest (I)	-.07(.09)		-.19(.1)*	-.04(.07)
Farming-constraint:water-scarcity (II)	-.11(.04)***	-.14(.03)***	-.09(.04)**	-.14(.03)***
Adpt: shift to other jobs (III)	.01(.04)	-.002(.03)	-.5(.05)	-.002(.04)
Adpt:more work on the farm (III)	.01(.04)	.01(.03)	.07(.04)	.02(.03)
Adpt:use of improved seeds (III)	.09(.04)**	.10(.03)***	.10(.04)***	.10(.04)***
Economic/financial-constraint (IV)	-.10(.04)**	-.09(.03)***	-.09(.04)***	-.09(.03)***
Government/institutional-constraint (IV)	-.12(.04)**	-.12(.03)***	-.18(.04)***	-.14(.03)***
Knowledge, awareness, and tech use constraint (IV)	.02(.04)	.01(.03)	.06(.05)	.01(.04)
Human resources constraint (IV)	-.07(.04)	-.06(.03)*	-.02(.05)	-.06(.04)
Environment (physical/bio) constraint (IV)	-.03(.05)	-.02(.04)	.003(.05)	-.03(.04)
<i>N</i>	1,434			

Standard errors in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . KM:Kernel Matching.  
DR:Doubly Robust. NNM:Nearest Neighbor Matching. IPW:Inverse Probability Weighting.

Category I contains the main climate change-related hazards, such as drought, flood, and pest. Evidence suggests that the risk of extreme events has increased as a result of climate change (Jayatilleke S. and Yiyong, 2014). Agriculture in Afghanistan is mainly affected by extreme events, such as flood and drought (Savage et al., 2014). Therefore, increasing farmers' resilience to these events should be a central issue in adaptation interventions (Baizayee et al., 2014). The KM estimates, presented in column 2 of Table 4.2, 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 smaller among 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 are 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 critical adaptation strategy, can increase the resilience of farming communities to the impacts of climate change (Biswas and Tortajada, 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. The KM estimates, presented in column 2 of Table 4.2, 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, behavioural, and ecological adjustments in order for the 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 (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. The KM estimates, presented in column 2 of Table 4.2, suggest that the number of farmers implementing this measure is higher among the treated subjects. Specifically, the use of improved types of seeds, that are more drought- and pest-tolerant with a 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 employment) is found to be insignificant.

The kernel estimates (column 2 of Table 4.2) of treatment effects on outcomes in Category IV are also mixed. Results in this category represent adaptation constraints. The IPCC's Fifth Assessment Report<sup>18</sup> summarizes all types of constraints to adaptation, including economic and financial, knowledge, awareness and technology. In the least developed countries, such as Afghanistan, where the poverty rate and is very high, and the literacy rate is 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 KM estimations (presented in col-

<sup>18</sup> The following website provides more information: [https://www.ipcc.ch/site/assets/uploads/2018/02/WGIAR5-Chap16\\_FINAL.pdf](https://www.ipcc.ch/site/assets/uploads/2018/02/WGIAR5-Chap16_FINAL.pdf)

umn 2 of Table 4.2), 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% lower among treated farmers. Similarly, government and institutional constraints are 13% lower 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 estimates (reported in column 2 of Table 4.2), we have estimated the ATTs using Doubly Robust (DR), Nearest Neighbor matching (NNM), and Inverse Probability Weighting (IPW) estimators. The results are reported in columns 3 to 5 of Table 4.2. The estimates of these estimators are very similar (in terms of the sign, significance, and up to a large extent, the magnitude) to those of the kernel matching reported in column 2. Hence, our kernel estimates are robust under different estimation method.

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 significant and robust treatment effects.

The results of the sensitivity analysis (reported in column 2 of Table 4.3) suggest that the treatment effect on some outcomes, such as the Risk of flood and Economic/financial constraints, are sensitive to the existence of unobserved heterogeneity. For instance, in the case of Risk of flooding, 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 ATT is undermined. The remaining significant estimates (Use of improved seeds, Availability of irrigation water, Government/Institutional constraints) are not sensitive to the existence of unobserved factors.

The results of sensitivity analysis, presented in column 2 of Table 4.3, reveals that unobserved factors undermine the propensity score-based estimates. Following the discussions in Section 4.3.2, Endogenous Switching Regression (ESR) is exercised to provide further robustness in terms of unobserved factors. To this end, we practice an 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 ESR are reported in column 3 of Table 4.3.

Table 4.3: Robustness Tests (Sensitivity Analysis and Endogenous Switching Regression)

<b>Outcome (Category)</b>	<b>Sensitivity Analysis(Tau)</b>	<b>Endogenous Switching</b>
Risk of flood (I)	.45(45%)	—
Farming constraint: water scarcity (II)	1.00(100%)	.44(.23)*
Adpt: use of improved seeds (III)	.65(65%)	-.44(.19)**
Economic/financial constraint (IV)	.20(20%)	—

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Government/institutional constraint (IV)	.90(90%)	.07(.17)
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Standard errors in endogenous switching model are reported in parentheses.

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

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The results of the ESR model indicate the presence of a significant treatment effect on the availability of irrigation water and use of improved seeds. Specifically, the probability that treated farmers face irrigation water constraint is 44 percentage point lower than the farmers in the comparison group. Likewise, the likelihood of using improved types of seeds is 44 percentage point higher among treated farmers. The endogenous switching estimate of the treatment effect on Government/Institutional constraints is not significant.

Altogether, our estimations suggest the 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.

## 4.6 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 1434 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 the 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 neighbour matching, and the inverse probability weighting techniques yield similar estimates of the treatment effect. The treatment estimates of the 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. The corresponding outcomes suggest

a robust impact of external adaptation support on farmers' access to irrigation water and the 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 critical. 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 some 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, helping 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 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 the 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.



## 4.7 Appendices

### 4.7.1 Appendix A.1: Pscore and Outcome Models

As outlined in Section 4.3.1, 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 Eq. (4.3) (in Section 4.3.1) — includes variables such as occupation, age, literacy, migration background, and farming experience of the household head, farm size, distance to the market, household size, irrigation, soil fertility, change in temperature and precipitation, and province.

$$P(T = 1|\mathbf{x} = x) = F(\mathbf{X}) \quad (4.4)$$

where the vector of exogenous variables  $\mathbf{x} = \mathbf{x}(x_1, x_2, \dots, x_{14})$  are defined in Table 4.4.

Table 4.4: Description of the Exogenous Variables

Variable	Description
$x_1$	Primary occupation
$x_2$	Secondary occupation
$x_3$	Irrigation type
$x_4$	Household size
$x_5$	Change in temperature
$x_6$	Change in precipitation
$x_7$	log(Market distance)
$x_8$	Stayed abroad
$x_9$	log(Farm size)
$x_{10}$	Literacy
$x_{11}$	log(household size)
$x_{12}$	log(farming experience)
$x_{13}$	Province
$x_{14}$	Soil fertility

The distribution of the pscore among treated and non-treated farmers is depicted in Figure 4.1.

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 Eq. (4.5) — using the pscores, estimated using the model in Eq. (4.4), as weights is performed. In the outcome model, Eq. (4.5), in addition to the variables included in the pscore

model, we have included the variables that affect the outcomes with some interaction terms — as suggested by Wooldridge (2010, p. 930).

$$y = \mathbf{G}(\mathbf{x}) \quad (4.5)$$

where the vector of exogenous variables  $\mathbf{x} = \mathbf{x}(x_1, x_2, \dots, x_{25})$  are defined in Table 4.5.

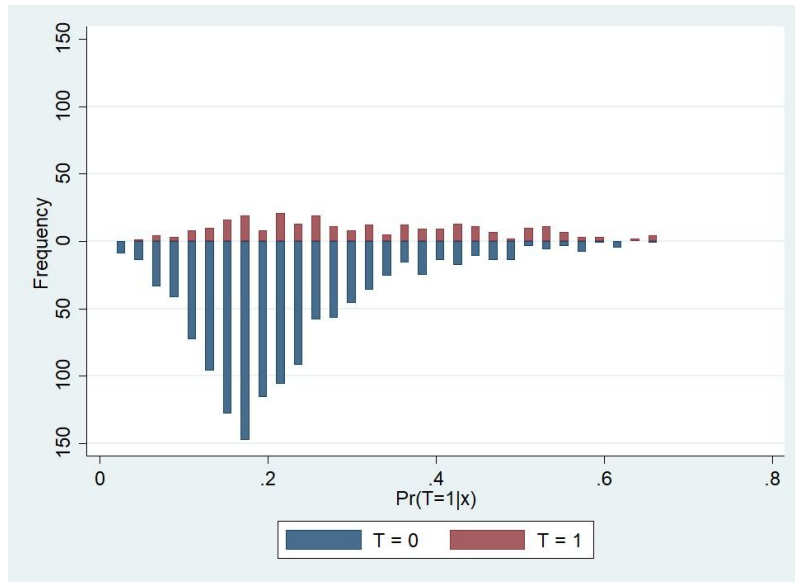


Figure 4.1: Pscore Distribution

Table 4.5: Description of the Exogenous Variables

Variable	Description
$x_1$	Primary occupation
$x_2$	Secondary occupation
$x_3$	Irrigation type
$x_4$	Household size
$x_5$	Gender
$x_6$	Change in temperature
$x_7$	Change in precipitation
$x_8$	log(Market distance)
$x_9$	Stayed abroad
$x_{10}$	log(Farm size)
$x_{11}$	log(household size)

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Variable	Description
$x_{12}$	log(farming experience)
$x_{13}$	Province
$x_{14}$	Cause of climate change
$x_{15}$	Soil fertility
$x_{16}$	Stayed Abroad
$x_{17}$	Literacy
$x_{18}$	Literate members
$x_{19}$	TV ownership
$x_{20}$	Primary Occ*log(farm size)
$x_{21}$	Literate members*log(farm size)
$x_{22}$	Primary Occ*log(market distance)
$x_{23}$	Literacy*Secondary Occ
$x_{24}$	Literate members*log(market distance)
$x_{25}$	Cause of CC*Literate members

#### 4.7.2 Appendix A.2: Pscore and Covariates Balance

Following the discussions in Section 4.3.1, to estimate the ATT using the propensity scores, the condition in Eq. (4.2) 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, given the observed covariates. The summary statistics of the pscores, reported in Table 4.7 in Appendix 4.7.3, and pscore distribution, depicted in Figures 4.1 and 4.2, confirm a sufficient scores overlap.

Unlike overlap assumption, the condition in Eq. (4.2) is not directly testable. However, it has a testable implication that can be invoked in practice. The condition in Eq. (4.2) 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.

$$SD = \frac{\overline{X_T} - \overline{X_C}}{\sqrt{\frac{S_T^2 + S_C^2}{2}}} \quad (4.6)$$

$$SB = |SD| \cdot 100\% \quad (4.7)$$

$$VR = \frac{S_T^2}{S_C^2} \quad (4.8)$$

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. 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 estimators. The results, reported in [Table 4.6](#) in [Appendix 4.7.3](#), confirm a satisfactory balance of the covariates under both kernel matching and doubly robust estimators.

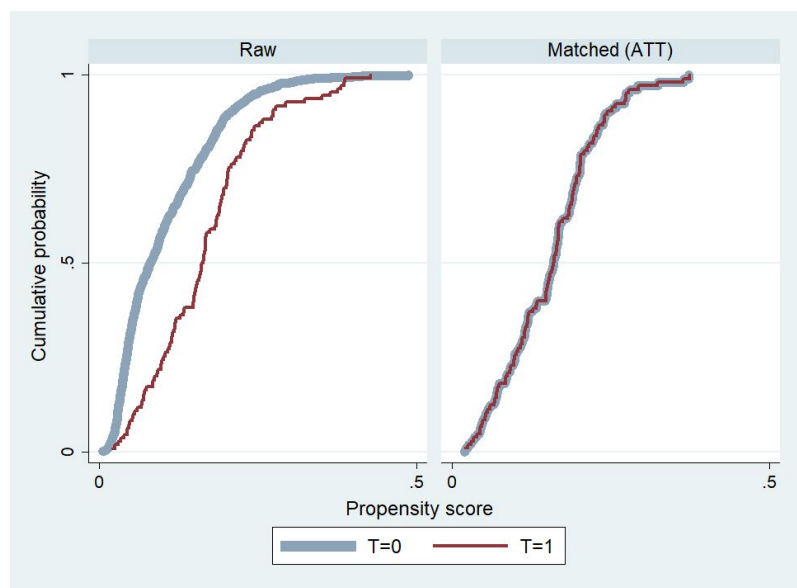


Figure 4.2: Pscore Cumulative Distribution Before and After Matching

## 4.7.3 Appendix B: Additional Tables

Table 4.6: Standard Difference in Mean and Variance Ratio of the Covariates.

Covariate	Standard Difference in Means		Variance Ratio	
	KM	DR	KM	DR
Primary- Occupation[farming=1]	-.04	-.03	1.05	.97
Secondary- Occupation[farming=1]	-.03	-.01	1.00	1.00
Irrigation: Stream	.05	.02	1.05	1.00
Irrigation: Karez	.0009	-.02	1.00	.98
Temperature:increased	-.02	.004	.92	.98
Temperature:decreased	-.009	-.002	.95	.98
Temperature:no idea	-.01	-.0007	.90	.99
Precipitation:decreased	.02	.001	.95	.99
Precipitation:increased	-.04	-.02	.87	.94
Precipitation:no idea	.02	.007	1.1	1.05
Province:Ghazni	-.005	.0006	.97	1.00
Province:Diakundi	-.009	-.01	.99	.99
Household size	.003	-.005	1.01	1.00
Log(Market distance)	.03	-.003	1.01	.98
Log(Household size)	.004	-.003	.97	.97
Log(Farm size)	.02	-.004	.69	.69
Age	.02	-.006	.84	.87
Log(Farming experience)	.005	-.007	.79	.82
Soil fertility[yes=1]	.01	.02	1.00	1.00
Stayed abroad[yes=1]	.01	-.006	.99	1.00
Literate[yes=1]	-.003	-.03	1.00	1.02

KM:stands for "Kernel Matching". DR: stands for "Doubly Robust"

Table 4.7: Summary Statistics of the Estimated Pcores

<b>pscore</b>	<b>Min.</b>	<b>Max.</b>	<b>Mean</b>	<b>Mean(0)</b>	<b>Mean(1)</b>
	.015	.67	.24(.12)	.12(.11)	.31(.14)
Observations				1,222	261

Standard errors are reported in parenthesis.

### 4.7.4 Appendix C: Additional Figures

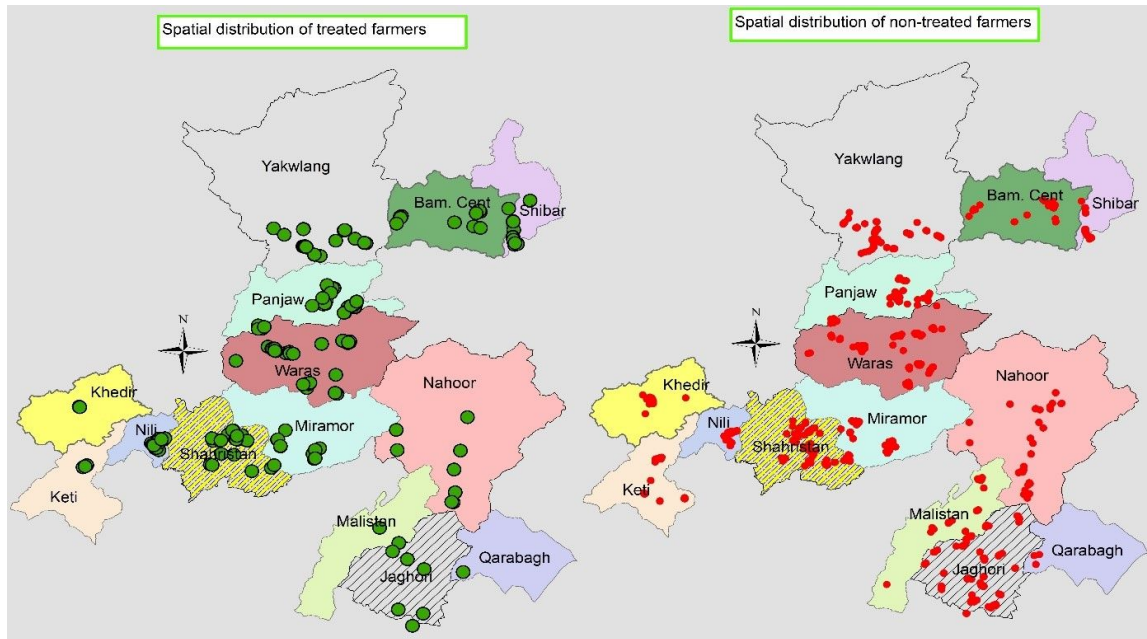


Figure 4.3: Sample Distribution with Respect to *Treatment*

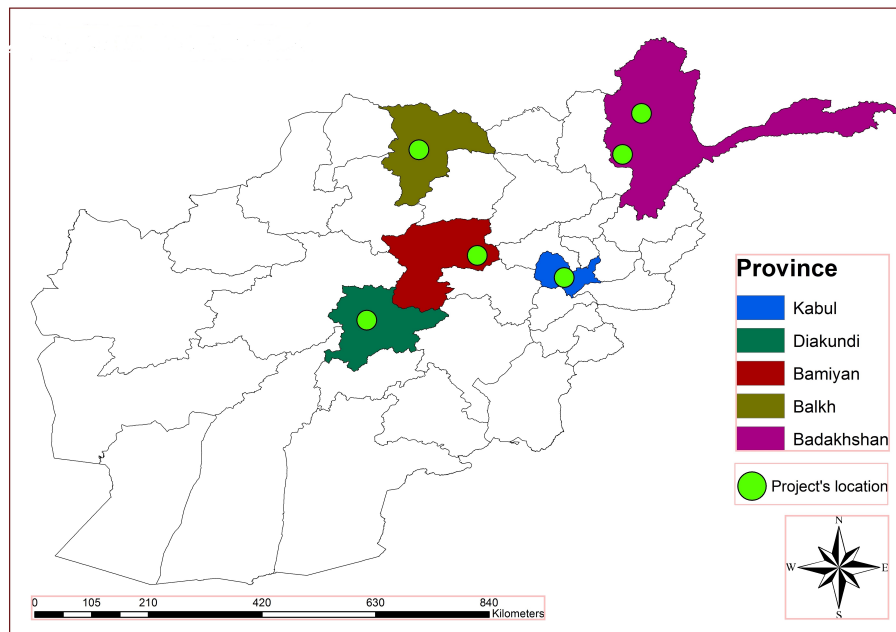


Figure 4.4: NEPA/UNEP Project Sites

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## 5 Instruments Description and Questionnaire

### 5.1 Instrument Description and Summary Statistics

Table 5.1: Description of the Instruments.

Variable	Description	Mean(SD)
<i>Personal/household characteristics</i>		
Province	Province[1:Bamiyan, 2:Gahzni,3:Diakudni]	36%, 33%, 30%
Gender	Gender of the household head[male=1]	.97
Primary source of income	Primary source of income[farming=1]	.71
Primary occupation	The primary occupation is farming [yes=1]	.79
Secondary occupation	The secondary occupation is farming [yes=1]	.46
Literate	Household head can at least read and write [yes=1]	.59
Stayed abroad	Household head spent sometime abroad [yes=1]	.65
Farming experience	The number of years the household engaged in farming: continues	22(14)
Age	Age of the household head: continues	47(14)
Place of birth	The farmer was born and grown up in the same village[yes=1]	.99
Risk perception	General risk perception of the household head: categorical (0:accepts no risk to 4:accepts high risks)	1.54(1.4)
Household size	The number of family members	9(3.5)
No of literate members	The number of family members who are literate	3.7(2.6)
TV	TV ownership[yes=1]	.67
Electricity	Hours with access to electricity:continues	4.5(5.8)
<i>Climate change, extreme weather events, adaptation</i>		

Continued on next page

<b>Variable</b>	<b>Description</b>	<b>Mean(SD)</b>
Perceived climate change	Farmer has perceived climate change[yes=1]	.95
Change in temperature	Average temperature changed[0:no change, 1:increased, 2:decreased, 3:no idea]	1.1(.43)
Change in precipitation	Average amount of precipitation changed[0:no change, 1:decreased, 2:increased, 3:no idea]	1.1(.37)
Main cause of climate change	The main cause of climate change[0:God's will, 1:human, 2:nature, 3:others]	.67(.92)
Overall impact of climate change	Overall impact of climate change on agriculture[+1:positive, 0:none, -1:negative]	-.33(.88)
Change in farm production	Change in farm production as a result of climate change[+1:increased, 0:no change, -1:decreased]	-.39(.83)
Farm vulnerability	Farm vulnerability to climate change[0:not vulnerable, 1:vulnerable, 2: very vulnerable]	1.4(.61)
Risk of drought	Perceived risk of drought: Categorical (1 no risk to 4 very high risk)	3.1(1.2)
Risk of flood	Perceived risk of flood: Categorical (1 no risk to 4 very high risk)	2.5(1.4)
Risk of cold/heatwaves	Perceived risk of cold/heat: Categorical (1 no risk to 4 very high risk)	2.6(1.2)
Risk of crop failure	Perceived risk of crop failure: Categorical (1 no risk to 4 very high risk)	2.9(1)
Risk of disease/pest	Perceived risk of disease: Categorical (1 no risk to 4 very high risk)	2.9(1)
Farming constraint: water scarcity	The availability of irrigation water is a constraint to farming [yes=1]	.65
Adaptation:Shift to other employment	The farmer has partly or entirely shifted to other employment as a result of impact of climate change on their farm [yes=1]	.41
Adaptation:more work on the farm	The farmer spends more time working on his farm compared to 15-to 20 years ago [yes=1]	.66

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<b>Variable</b>	<b>Description</b>	<b>Mean(SD)</b>
Adaptation:use of improved seeds	Farmer uses improved types of seeds [yes=1]	.33
Economic/financial constraint	Farmer's poverty constraints adaptation [yes=1]	.85
Government/institutional constraint	Limited external support constraints adaptation [yes=1]	.67
Knowledge, awareness, use of tech	Limited knowledge and use of tech constraints adaptation[yes=1]	.48
External support	The farmer received at least one type of adaptation related support from GOs/NGOs[yes=1]	.18
Climate change related constraints	Perceived climate change-related constraints for farming: dummy [yes=1]	.43
<i>Farm characteristics</i>		
Market distance	Distance to the nearest market in minutes: continues	40(43)
Farm size	Farm size in acre: continues	6.9(9.9)
Flat	The farmland is flat [yes=1]	.40
Sell farm's product	Sale a part of the farm products[yes=1]	.21
Soil type I	Rocky land with Lithic Cryorthents	.82
Soil type II	Rocky land with Lithic Haplocryids	.18
Soil fertility	The soil is fertile [yes=1]	.70
Irrigation types	[0:river, 1:stream, 2: karez]	1.22(.73)
Crop net revenue	The difference of total annual income from all crops and total annual expenses (in AFN): continues	19263(79827)
Seeds	The amount of money spent annually for varieties of seeds (in AFN): continues	8713(16898)
Fertilizer	The amount of money spent annually for fertilizer (in AFN): continues	7992(13374)
Pesticides	The amount of money spent annually for different types pesticides (in AFN):continues	3488(12466)

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<b>Variable</b>	<b>Description</b>	<b>Mean(SD)</b>
External labor	The amount of money spent annually for external labor (in AFN): continues	1069(4628)
Other inputs	The amount of money spent annually for any other type of inputs (water pump etc.) (in AFN):continues	875(4628)
<i>Climate factors<sup>1</sup></i>		
Wet Season Precipitation	The total precipitation in November, December, January, February, March, and April (in mm):continues	55(21)
Semi-wet season precipitation	The total precipitation in May, Jun, September, and October (in mm): continues	13.5(7.5)
Dry season precipitation	The total precipitation in July and August (in mm): continues	3(3.5)
Winter temperature	The average temperature in the traditional winter season (°C): January, February, and March: continues	-7(3)
Spring temperature	The average temperature in the traditional spring season: April, May, and Jun (°C): continues	10.4(2.3)
Summer temperature	The average temperature in the traditional summer season: July, August, and September (°C): continues	14.4(1.7)
Fall temperature	The average temperature in the traditional fall season (°C): October, November, and December: continues	.19(2.8)

<sup>1</sup> Climate data were obtained from an online database <https://globalweather.tamu.edu/>

# 5.2 Questionnaire (English translation)

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## SURVEY IDENTIFICATION INFORMATION QUESTIONNAIRE DESCRIPTION

### SECTION 1-GENERAL INFORMATION

No sub-sections, No rosters, Questions: 14.

### SECTION 2-HEAD OF THE HH AND HH MEMBERS

Sub-sections: 3, No rosters, Questions: 32.

### SECTION 3-FARM'S INCOME (LAST 12 MONTHS)

Sub-sections: 5, No rosters, Questions: 36.

### SECTION 4-CLIMATE CHANGE PERCEPTION

Sub-sections: 3, No rosters, Questions: 7.

### SECTION 5-ADAPTATION TO CLIMATE CHANGE

Sub-sections: 4, No rosters, Questions: 9.

### SECTION 6-CLIMATE CHANGE RISK

No sub-sections, No rosters, Questions: 10.

## LEGEND



# SECTION 1-GENERAL INFORMATION

Date and time of the interview	DATE SCOPE: IDENTIFYING Datt .....
Province	SINGLE-SELECT Province 01 <input type="radio"/> Bamiyan 02 <input type="radio"/> Diakundi 03 <input type="radio"/> Ghazni
District	SINGLE-SELECT District 01 <input type="radio"/> Jaghori 02 <input type="radio"/> Malistan 03 <input type="radio"/> Nahoor 04 <input type="radio"/> Qarabagh 05 <input type="radio"/> Miramor 06 <input type="radio"/> Shahristan 07 <input type="radio"/> Nili 08 <input type="radio"/> Bamyán Center 09 <input type="radio"/> Sheebar 10 <input type="radio"/> Yakawlang 11 <input type="radio"/> Waras 12 <input type="radio"/> Panjab 13 <input type="radio"/> Kiti 14 <input type="radio"/> Khedir
CDC ID	TEXT CDC .....
HH ID	TEXT HH .....
How is the weather condition at the time of the interview?	SINGLE-SELECT wcondition 01 <input type="radio"/> Sunny 02 <input type="radio"/> Cloudy 03 <input type="radio"/> Rainy
GPS-location of the HH	GPS GPS ----- N ----- W ----- A
Does a river pass through the village?	SINGLE-SELECT River 01 <input type="radio"/> Yes 00 <input type="radio"/> No
Does the village have access to telecommunication?	SINGLE-SELECT Telecomun 01 <input type="radio"/> Yes 00 <input type="radio"/> No
Is the agriculture land in the village flat?	SINGLE-SELECT Flat 01 <input type="radio"/> Yes 00 <input type="radio"/> No

Does the village have access to a road?	SINGLE-SELECT 01 <input type="radio"/> Yes 00 <input type="radio"/> No	Road
Has the respondent accepted to participate in the survey?	SINGLE-SELECT 01 <input type="radio"/> Yes 00 <input type="radio"/> No	Response
EGTask.	NUMERIC: INTEGER -----	
Why the respondent did not participate in the survey? E Response==0	SINGLE-SELECT 01 <input type="radio"/> Was not at home 02 <input type="radio"/> Has migrated completely 03 <input type="radio"/> Was at home but refused to participate 04 <input type="radio"/> Others	Nonresponse

## SECTION 2-HEAD OF THE HH AND HH MEMBERS

### SECTION 2-HEAD OF THE HH AND HH MEMBERS HOUSEHOLD HEAD

Gender	SINGLE-SELECT 01 <input type="radio"/> Male 00 <input type="radio"/> Female	Gender
Marital Status	SINGLE-SELECT 01 <input type="radio"/> Married 00 <input type="radio"/> Single	MaritalS
Age	NUMERIC: INTEGER -----	Age
Place of Birth	SINGLE-SELECT 01 <input type="radio"/> مرکز بامیان Bamiyan center 02 <input type="radio"/> شیبیر Shebar 03 <input type="radio"/> یکاو لنگ Yakwang 04 <input type="radio"/> ورس Waras 05 <input type="radio"/> پنجاب Panjab 06 <input type="radio"/> نیلی Nili 07 <input type="radio"/> شهرستان Shahristan 08 <input type="radio"/> میرامور Miramor 09 <input type="radio"/> جاغوری Jaghori 10 <input type="radio"/> مالستان Malistan 11 <input type="radio"/> ناهور Nahoor 12 <input type="radio"/> قره باغ Qarabagh 13 <input type="radio"/> کیتی Kiti 14 <input type="radio"/> خدیبر Khedir	BirthP

Main occupation	SINGLE-SELECT: COMBO BOX 01 <input type="radio"/> Farmer 02 <input type="radio"/> Teacher 03 <input type="radio"/> Shopkeeper 04 <input type="radio"/> Carpenter 05 <input type="radio"/> Tailor 06 <input type="radio"/> NGO E 07 <input type="radio"/> Govrt E 08 <input type="radio"/> Self E 09 <input type="radio"/> Work at home 10 <input type="radio"/> Others	MainO
Second occupation	SINGLE-SELECT: COMBO BOX 01 <input type="radio"/> Farmer 02 <input type="radio"/> Teacher 03 <input type="radio"/> Shopkeeper 04 <input type="radio"/> Carpenter 05 <input type="radio"/> Tailor 06 <input type="radio"/> NGO E 07 <input type="radio"/> Govrt E 08 <input type="radio"/> Self E 09 <input type="radio"/> Work at home 10 <input type="radio"/> Others	SecondO
Have you ever lived or worked at a foriegn country?	SINGLE-SELECT 01 <input type="radio"/> Yes 00 <input type="radio"/> No	MigranE
Education level	SINGLE-SELECT: COMBO BOX 01 <input type="radio"/> Illiterate 02 <input type="radio"/> Can R&W 03 <input type="radio"/> Primary 04 <input type="radio"/> Secondary 05 <input type="radio"/> High 06 <input type="radio"/> Others	Education
How many years of experience do you have in farming?	NUMERIC: INTEGER -----	Experience

SECTION 2-HEAD OF THE HH AND HH MEMBERS  
HOUSEHOLD MEMBERS

HH size	NUMERIC: INTEGER -----	HHSize
How many of the household members participate in agricultural activities?	NUMERIC: INTEGER -----	Agriculture
How many the household members are engaged in non-farming activities?	NUMERIC: INTEGER -----	Nonfarm
How many male members does the household have?	NUMERIC: INTEGER -----	MaleM
How many female members of the househol take part in farming and production (knitting) activities?	NUMERIC: INTEGER -----	FemaleA

How important is the participation of the female members in the household's livelihood, income, and farm production?	SINGLE-SELECT 00 <input type="radio"/> Not important 01 <input type="radio"/> Somehow important 03 <input type="radio"/> Very important	Importanceoffemale
Number of household members going to school/university?	NUMERIC: INTEGER -----	student
Number household members who are literate?	NUMERIC: INTEGER -----	Literate
Number of household members migrated abroad?	NUMERIC: INTEGER -----	Migrant_Int
Number of household members migrated within the country?	NUMERIC: INTEGER -----	domesticmigra

SECTION 2-HEAD OF THE HH AND HH MEMBERS  
HOUSEHOLD CAPITAL

Car	NUMERIC: INTEGER -----	Car
Motorcycle	NUMERIC: INTEGER -----	MotorB
Computer/laptops	NUMERIC: INTEGER -----	Computer
TV	NUMERIC: INTEGER -----	TV
Mobile	NUMERIC: INTEGER -----	Mobile
Power generator	SINGLE-SELECT 01 <input type="radio"/> Yes 00 <input type="radio"/> No	Generator
Access to the internet	SINGLE-SELECT 01 <input type="radio"/> Yes 00 <input type="radio"/> No	InternetA
Tractor	SINGLE-SELECT 01 <input type="radio"/> Yes 00 <input type="radio"/> No	Tractor
Permanent access to electricity	SINGLE-SELECT 01 <input type="radio"/> Yes 00 <input type="radio"/> No	AccessE1
How many hours a day (in 24 hours), the household has access to electricity?	NUMERIC: INTEGER -----	HrseactE

E AccessE1==1

Do you use solar power for your farming activities?	SINGLE-SELECT 01 <input type="radio"/> Yes 00 <input type="radio"/> No	solarP
How large is your farm land?	NUMERIC: INTEGER -----	farmland
What is the main source of income for the household?	SINGLE-SELECT 01 <input type="radio"/> Farming (including livestock) 02 <input type="radio"/> Non-farm activities 03 <input type="radio"/> Remittances	IncomSo

## SECTION 3-FARM'S INCOME (LAST 12 MONTHS)

### SECTION 3-FARMS INCOME (LAST 12 MONTHS) GENERAL QUESTIONS

The distance to the nearest market, in minutes, by car?	LIST -----	MarketD
The farming (including livestock) products are used for:	SINGLE-SELECT 01 <input type="radio"/> Sale 00 <input type="radio"/> Own household consumption 02 <input type="radio"/> Both	usefarming
How important is farming for the household income and livelihood?	SINGLE-SELECT 00 <input type="radio"/> Not important 01 <input type="radio"/> Somehow important 02 <input type="radio"/> Very important	importancefa
How large is the cultivation area (an approximate number)?	NUMERIC: INTEGER -----	Cultia

### SECTION 3-FARMS INCOME (LAST 12 MONTHS) FARM'S PRODUCTION

Wheat	NUMERIC: INTEGER -----	wheat
Maize and barley	NUMERIC: INTEGER -----	Maize
Legume (bean, pea, lentil, mung bean)	NUMERIC: INTEGER -----	Legume
Wood/fuel	NUMERIC: INTEGER -----	Fwood
Timber	NUMERIC: INTEGER -----	Timber

Potato, turnip, and carrot	NUMERIC: INTEGER	Potato
-----		
Vegetable (tomato, onion, peper...)	NUMERIC: INTEGER	Vegetable
-----		
Almond/walnut	NUMERIC: INTEGER	Almond
-----		
Alfalfa, clover, fodder	NUMERIC: INTEGER	Alfalfa
-----		
Fruit (apple, grapes, apricot, berry)	NUMERIC: INTEGER	Fruit
-----		
Dry apricot, dry berry, and apricot kernel	NUMERIC: INTEGER	Apricotkernel
-----		
All other farm production (value in AFN)	NUMERIC: INTEGER	others
-----		

SECTION 3-FARMS INCOME (LAST 12 MONTHS)  
LIVESTOCK

Dairy cattle	NUMERIC: INTEGER	Mcow
-----		
Ox	NUMERIC: INTEGER	Ox
-----		
Horse	NUMERIC: INTEGER	Horse
-----		
Sheep and goat	NUMERIC: INTEGER	Sheep
-----		
Donkey	NUMERIC: INTEGER	Donkey
-----		
Cock and hen	NUMERIC: INTEGER	cockHen
-----		
Daily production of milk:	NUMERIC: INTEGER	Milk
-----		
Daily production of eggs:	NUMERIC: INTEGER	Eggs
-----		
Annual production of meat:	NUMERIC: INTEGER	Meat
-----		
Annual producion of skin, wool:	NUMERIC: INTEGER	Skin
-----		

Carpet in m <sup>2</sup> :	NUMERIC: INTEGER	Carpet
	-----	

SECTION 3-FARMS INCOME (LAST 12 MONTHS)  
**FARMING EXPENSES**

Cost of all kind of seeds, in AFN, used during last 12 months	NUMERIC: INTEGER	Seed
	-----	
Cost of fertilizer used during last 12 months	NUMERIC: INTEGER	Fertilizer
	-----	
Costs of any kind of pesticides	NUMERIC: INTEGER	Pesticide
	-----	
Costs of extra fodder that is bought for the livestock	NUMERIC: INTEGER	Fodder
	-----	
Paid for any kind of external labor	NUMERIC: INTEGER	Elabor
	-----	
Costs associated with the use of waterpump	NUMERIC: INTEGER	Waterpump
	-----	

SECTION 3-FARMS INCOME (LAST 12 MONTHS)  
**CHANGE IN FARM'S INCOME**

During last 15 to 20 years, in your opinion, the farm's income has increased, decreased, or no change is observed?	SINGLE-SELECT	FarmIncome
	00 <input type="radio"/> No change is observed 01 <input type="radio"/> Decreased 02 <input type="radio"/> Increased	
What are the main constrains to your farming?	MULTI-SELECT	FarmingConstraint
	01 <input type="checkbox"/> Insufficient capital 02 <input type="checkbox"/> Soil low fertility 03 <input type="checkbox"/> Small farmland 04 <input type="checkbox"/> Pest and disease 05 <input type="checkbox"/> Engagement in non-farm activities 06 <input type="checkbox"/> Drought 07 <input type="checkbox"/> Cold/hot waves 08 <input type="checkbox"/> Land degradation 09 <input type="checkbox"/> Improper climate	
Irrigation type	SINGLE-SELECT	Irrigation
	01 <input type="radio"/> River 02 <input type="radio"/> Stream 03 <input type="radio"/> Canal (Karez) 04 <input type="radio"/> Well	

**SECTION 4-CLIMATE CHANGE PERCEPTION**

SECTION 4-CLIMATE CHANGE PERCEPTION  
**GENERAL QUESTIONS**

In the last 20 years or so, have you observed any changes in the climate of your village/region?	SINGLE-SELECT 01 <input type="radio"/> Yes 00 <input type="radio"/> No	CC
During last 20 years or so, have you observed any changes in the frequency and intensity of drought, wind, and flood in your village/region?	MULTI-SELECT: YES/NO 01 <input type="checkbox"/> / <input type="checkbox"/> Drought 02 <input type="checkbox"/> / <input type="checkbox"/> Flood 03 <input type="checkbox"/> / <input type="checkbox"/> Wind	DroughFW
In your opinion, how the changes in climate has affected your farming, livestock husbandary, and the livelihood?	SINGLE-SELECT 01 <input type="radio"/> Positive and beneficial -01 <input type="radio"/> Negative and harmful 00 <input type="radio"/> No effect 09 <input type="radio"/> Have no idea	CCImpact
In your opinion, what is main cause of climate change?	SINGLE-SELECT 01 <input type="radio"/> Natural factors 02 <input type="radio"/> Human actions 03 <input type="radio"/> God's will 05 <input type="radio"/> Others	CCcause
How much vulnerable is your farming to climate change?	SINGLE-SELECT 00 <input type="radio"/> Not vulnerable 02 <input type="radio"/> Vulnerable 03 <input type="radio"/> Highly vulnerable	vu1nerabty

SECTION 4-CLIMATE CHANGE PERCEPTION  
CHANGES IN T

During last 20 years, have you observed any changes in overall temperature?	SINGLE-SELECT 01 <input type="radio"/> Yes 00 <input type="radio"/> No	ChangeinT
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SECTION 4-CLIMATE CHANGE PERCEPTION  
CHANGES IN P

During last 20 years, have you observed any changes in overall precipitation?	SINGLE-SELECT 01 <input type="radio"/> Yes 00 <input type="radio"/> No	ChangeinP
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## SECTION 5-ADAPTATION TO CLIMATE CHANGE

SECTION 5-ADAPTATION TO CLIMATE CHANGE  
GENERAL QUESTIONS

Have you used any adaptation strategy in response to climate change?	SINGLE-SELECT 01 <input type="radio"/> Yes 00 <input type="radio"/> No	AdapCC
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<p>Which of the following adaptation measures have you adopted in response to climate change?</p> <p>F AdapCC==1</p>	<p>MULTI-SELECT <span style="float: right;">AdapStrategy</span></p> <p>01 <input type="checkbox"/> Shift to non-farm activities</p> <p>02 <input type="checkbox"/> More work on the farm</p> <p>03 <input type="checkbox"/> More land and soil conservation measures</p> <p>04 <input type="checkbox"/> Use of improved seeds</p> <p>05 <input type="checkbox"/> Use more fertilizer</p> <p>06 <input type="checkbox"/> Participate in adaptation trainings</p> <p>07 <input type="checkbox"/> Shift to more livestock husbandry</p>
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SECTION 5-ADAPTATION TO CLIMATE CHANGE  
GOVT/NGO SUPPPORT

<p>Have you received any assistance related to your farming activities from the Government or NGOs?</p>	<p>SINGLE-SELECT <span style="float: right;">GtNgoS</span></p> <p>01 <input type="radio"/> Yes</p> <p>00 <input type="radio"/> No</p>
<p>Which of the followings measures you have received from the government or NGOs?</p> <p>E GtNgoS==1</p>	<p>MULTI-SELECT: YES/NO <span style="float: right;">GvtNGOSU</span></p> <p>01 <input type="checkbox"/> / <input type="checkbox"/> Extension services</p> <p>02 <input type="checkbox"/> / <input type="checkbox"/> Improved seeds</p> <p>03 <input type="checkbox"/> / <input type="checkbox"/> Fertilizer</p> <p>04 <input type="checkbox"/> / <input type="checkbox"/> Storage</p> <p>05 <input type="checkbox"/> / <input type="checkbox"/> Dam</p> <p>06 <input type="checkbox"/> / <input type="checkbox"/> New trees</p> <p>07 <input type="checkbox"/> / <input type="checkbox"/> Others</p>

SECTION 5-ADAPTATION TO CLIMATE CHANGE  
UNEP

<p>Have benefited from UNEP or Mountain Partner projects?</p>	<p>SINGLE-SELECT <span style="float: right;">UNEP</span></p> <p>01 <input type="radio"/> Yes</p> <p>00 <input type="radio"/> No</p>
<p>Which of the following services have you received from UNEP or Mountain Partners projects?</p> <p>E UNEP==1</p>	<p>MULTI-SELECT: YES/NO <span style="float: right;">UNEPS</span></p> <p>01 <input type="checkbox"/> / <input type="checkbox"/> Water related services</p> <p>02 <input type="checkbox"/> / <input type="checkbox"/> Improved seeds</p> <p>03 <input type="checkbox"/> / <input type="checkbox"/> Forest and tree related services</p> <p>04 <input type="checkbox"/> / <input type="checkbox"/> Early warning system</p> <p>05 <input type="checkbox"/> / <input type="checkbox"/> Training</p> <p>06 <input type="checkbox"/> / <input type="checkbox"/> Management of natural resources</p>
<p>How you rank the UNEP projects?</p> <p>E UNEP==1</p>	<p>SINGLE-SELECT <span style="float: right;">rankUNEP</span></p> <p>00 <input type="radio"/> Not effective and not beneficial</p> <p>02 <input type="radio"/> Effective and beneficial</p> <p>03 <input type="radio"/> Very effective and beneficial</p>

SECTION 5-ADAPTATION TO CLIMATE CHANGE  
ADAPTATION CONSTRAINT

<p>Which of the followings constraints you face in your adaptation to climate change?</p>	<p>MULTI-SELECT <span style="float: right;">Adapconst</span></p> <p>01 <input type="checkbox"/> Economic/financial</p> <p>02 <input type="checkbox"/> Knowledge, awareness, and use of tech</p> <p>03 <input type="checkbox"/> Human capital</p> <p>04 <input type="checkbox"/> Government/institutional</p> <p>05 <input type="checkbox"/> Environmental</p>
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From the followings, choose the most important three services which you need from the government/NGOs in order to adapt to climate change:

- MULTI-SELECT Policy
- 01  Extension services
  - 02  Improved seeds
  - 03  New farming techniques
  - 04  New types of products
  - 05  Water well
  - 06  Storage
  - 07  Land. soil and water conservation
  - 08  Farming equipment

## SECTION 6-CLIMATE CHANGE RISK

<p>In general, how much are you willing to take risks?</p>	<p>SINGLE-SELECT <span style="float: right;">Riska</span></p> <ul style="list-style-type: none"> <li>01 <input type="radio"/> Not willing at all</li> <li>02 <input type="radio"/> Not willing</li> <li>03 <input type="radio"/> Moderately willing</li> <li>04 <input type="radio"/> Willing</li> <li>05 <input type="radio"/> Highly willing</li> </ul>
<p>How serious is the risk of drought for your farming activities?</p>	<p>SINGLE-SELECT <span style="float: right;">Drrisk</span></p> <ul style="list-style-type: none"> <li>01 <input type="radio"/> Not serious at all</li> <li>02 <input type="radio"/> Not serious</li> <li>03 <input type="radio"/> Somehow serious</li> <li>04 <input type="radio"/> Serious</li> <li>05 <input type="radio"/> Very serious</li> </ul>
<p>How serious is the risk of pest and diseases for your farming activities?</p>	<p>SINGLE-SELECT <span style="float: right;">pdir</span></p> <ul style="list-style-type: none"> <li>01 <input type="radio"/> Not serious at all</li> <li>02 <input type="radio"/> Not serious</li> <li>03 <input type="radio"/> Moderately serious</li> <li>04 <input type="radio"/> Serious</li> <li>05 <input type="radio"/> Very serious</li> </ul>
<p>How serious is the risk of cold/heatwaves for your farming activities?</p>	<p>SINGLE-SELECT <span style="float: right;">hotcw</span></p> <ul style="list-style-type: none"> <li>01 <input type="radio"/> Not serious at all</li> <li>02 <input type="radio"/> Not serious</li> <li>03 <input type="radio"/> Moderately serious</li> <li>04 <input type="radio"/> Serious</li> <li>05 <input type="radio"/> Very serious</li> </ul>
<p>How serious is the risk of untimely rains for your farming activities?</p>	<p>SINGLE-SELECT <span style="float: right;">untir</span></p> <ul style="list-style-type: none"> <li>01 <input type="radio"/> Not serious at all</li> <li>02 <input type="radio"/> Not serious</li> <li>03 <input type="radio"/> Moderately serious</li> <li>04 <input type="radio"/> Serious</li> <li>05 <input type="radio"/> Very serious</li> </ul>
<p>How serious is the risk of crop damage for your farming activities?</p>	<p>SINGLE-SELECT <span style="float: right;">CropDa</span></p> <ul style="list-style-type: none"> <li>01 <input type="radio"/> Not serious at all</li> <li>02 <input type="radio"/> Not serious</li> <li>03 <input type="radio"/> Moderately serious</li> <li>04 <input type="radio"/> Serious</li> <li>05 <input type="radio"/> Very serious</li> </ul>

<p>How serious is the risk of flood for your farming activities?</p>	<p>SINGLE-SELECT <span style="float: right;">f1windR</span></p> <p>01 <input type="radio"/> Not serious at all  02 <input type="radio"/> Not serious  03 <input type="radio"/> Moderately serious  04 <input type="radio"/> Serious  05 <input type="radio"/> Very serious</p>
<p>How serious is the risk of avalanche for your farming activities?</p>	<p>SINGLE-SELECT <span style="float: right;">AvalancheR</span></p> <p>01 <input type="radio"/> Not serious at all  02 <input type="radio"/> Not serious  03 <input type="radio"/> Moderately serious  04 <input type="radio"/> Serious  05 <input type="radio"/> Very serious</p>
<p>How serious is the risk of landslide for your farming activities?</p>	<p>SINGLE-SELECT <span style="float: right;">Landslide</span></p> <p>01 <input type="radio"/> Not serious at all  02 <input type="radio"/> Not serious  03 <input type="radio"/> Moderately serious  04 <input type="radio"/> Serious  05 <input type="radio"/> Very serious</p>
<p>How serious is the risk of climate change for your farming activities?</p>	<p>SINGLE-SELECT <span style="float: right;">CCRisk</span></p> <p>01 <input type="radio"/> Not serious at all  02 <input type="radio"/> Not serious  03 <input type="radio"/> Moderately serious  04 <input type="radio"/> Serious  05 <input type="radio"/> Very serious</p>

# Affirmation

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I hereby affirm that the current doctoral dissertation consists of three articles. The first essay is a single-authored paper worked out entirely by myself. As the main author, I have made a significant contribution to writing Essay 2 and Essay 3. I have specially marked all of the quotes I have used from other authors as well as those passages in my work that are extremely close to the thoughts presented by other authors and listed the sources in accordance with the regulations I have been given.

Kiel, January 10, 2020

Asadullah Jawid