Zentrum für Entwicklungsforschung

Climate Volatility and Change in Central Asia: Economic Impacts and Adaptation

Inaugural – Dissertation

zur

Erlangung des Grades
Doktor der Agrarwissenschaften
(Dr.agr.)

der
Hohen Landwirtschaftlichen Fakultät

der
Rheinischen Friedrich-Wilhelms-Universität
zu Bonn

vorgelegt am 25.09.2012

von

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Tag der mündlichen Prüfung: 09. Januar 2013

Erscheinungsjahr: 2013

Diese Dissertation ist auf dem Hochschulschriftenserver der ULB Bonn http://hss.ulb.uni-bonn.de/diss_online/ elektronisch publiziert.

Climate Volatility and Change in Central Asia: Economic Impacts and Adaptation

Abstract

Central Asia is projected to experience a significant climate change, combined with increased weather volatility. Agriculture is a key economic sector and a major source of livelihoods for Central Asia's predominantly rural population, especially for the poor. Agricultural production, being sensitive to weather shocks and climate volatility, may suffer from climate change if no adaptive actions are taken. Taking these into account, the present study seeks to estimate the potential economic impacts of climate change on Central Asia's agriculture and rural livelihoods, as well as to identify factors catalyzing or constraining adaptation to climate change.

Weather shocks could potentially affect the supply of agricultural commodities and their prices. In this thesis, the effects of weather shocks on agricultural commodity prices in Central Asia are studied at the provincial scale using monthly data for the period of 2000-2010. The study analyses the idiosyncratic components of the variables using feasible generalized least squares (FGLS) panel regression in the presence of cross-sectional dependence and serial autocorrelation. The analysis indicates that negative shocks, involving lower than usual temperatures and precipitation amounts, could lead to higher wheat prices in the region. Lower availability of irrigation water may encourage irrigation-dependent countries in the region to aggressively raise wheat stocks to face expected supply shortfalls, thus leading to higher regional wheat prices. This effect could be further aggravated by negative impacts of lower irrigation water availability on wheat yields.

The estimates of the aggregate impacts of climate change on Central Asian agriculture range between +1.21% to -1.43% of net crop production revenues by 2040. The absolute monetary impact is not negligible, ranging from + 180 mln USD annually in the optimistic scenario, to – 210 mln USD annually in the pessimistic scenario relative to 2010 levels, where optimistic and pessimistic scenarios are defined to correspond to B1 (lowest future emission trajectory) and A1FI (highest future emission trajectory) scenarios by IPCC (2007), respectively. As a key conclusion, agricultural producers operating in inherently stressed environments, such as in Central Asia, may have relatively more experience to dynamically adapt to erratic and changing environments.

The analysis of the nationally representative household surveys using quantile regressions with and without instrumentalizing for endogeneity between consumption and production decisions within the framework of agricultural household model confirms that poorer households are more vulnerable to the impacts of weather and climate shocks with every 1% decrease in the level of their farming profits being likely to lead to 0.52% decrease in their food expenses. A similar decrease for the richest 10% of households would translate to only 0.39% decrease in food consumption. The models also show that the profit effect of potato prices seems to be quite important especially for the poorest farmers.

Many farmers in Central Asia are already engaged in ex post adaptation to the changing climate; however, further Government support is needed for pro-active ex ante actions. A vital mechanism for achieving this purpose is through increasing farmers' resilience and adaptive capacities to withstand current and future shocks, both expected and uncertain. The analysis shows that key policy actions to achieve this in the region are through: i) increasing awareness of agricultural producers about climate change impacts and adaptation technologies; and ii) improving rural financial intermediation. The key general message of the adaptation analysis in this study is that most institutional and technological options suggested as measures to adapt to climate change in the region are strongly needed for regional development even with perfect climate change mitigation.

Klimaschwankungen und -veränderung in Zentralasien: Wirtschaftliche Auswirkungen und Anpassungsmöglichkeiten

Zusammenfassung

Zentralasien wird den Vorhersagen zufolge signifikante Klimaveränderungen gekoppelt mit erhöhten Klimaschwankungen erleben. Die Landwirtschaft ist ein wichtiger Wirtschaftszweig und eine wichtige Lebensgrundlage für die überwiegend ländliche Bevölkerung Zentralasiens, vor allem für die Armen. Die landwirtschaftliche Produktion, die anfällig für Wetterextreme und Klimaschwankungen ist, kann durch den Klimawandel beeinträchtigt werden, z.T. mit gravierenden Folgen für die Lebensgrundlage im ländlichen Raum in vielen Teilen der Region, wenn keine adaptive Maßnahmen ergriffen werden. Dies berücksichtigend versucht die vorliegende Studie, die möglichen wirtschaftlichen Auswirkungen des Klimawandels auf die Landwirtschaft und ländliche Lebensgrundlage Zentralasiens zu bewerten sowie die Faktoren, die die Anpassung an den Klimawandel katalysieren oder einschränken, zu identifizieren.

Wetterextreme könnten potenziell die Versorgung mit landwirtschaftlichen Rohstoffen und deren Preise beeinträchtigen. In dieser Arbeit werden die Auswirkungen von Wetterextremen auf landwirtschaftliche Rohstoffpreise in Zentralasien auf Provinzebene mit monatlichen Daten für den Zeitraum von 2000-2010 untersucht. Die Studie verwendet eine innovative Schätzmethode, bei der die idiosynkratischen Komponenten der Variablen mit Verallgemeinerte Kleinste-Quadrate-Modelle (FGLS) Panelregression bei Querschnittsabhängigkeit und serieller Autokorrelation analysiert werden. Die Analyse zeigt, negative Extreme, die niedrigere Temperaturen und Niederschlagsmengen als üblich bedeuten, könnten günstige Bedingungen für höhere Weizenpreise in der Region hervorrufen. Eine geringere Verfügbarkeit von Bewässerungwasser kann die Länder in der Region, die vom Bewässerungswasser abhängig sind, dazu animiere, die Weizenbestände aggressiv zu erhöhen, um die zu erwartenden Engpässen abzupuffern, was zu höheren regionalen Weizenpreisen führen würde. Dieser Effekt könnte zusätzlich verschärft werden durch die negativen Auswirkungen geringerer Wasserverfügbarkeit auf die Weizenerträge.

Die Schätzungen der aggregierten Auswirkungen des Klimawandels auf die zentralasiatische Landwirtschaft schwanken von +1,21% bis -1,43% des Nettoumsatzes für Getreideproduktion im Jahr 2040. Die absoluten monetären Auswirkungen sind nicht unerheblich, sie können von +180 Millionen USD jährlich im optimistischen Szenario bis hin zu -210 Millionen USD jährlich im pessimistischen Szenario gegenüber dem Niveau von 2010 variieren, entsprechend den optimistischen und pessimistischen Szenarien B1 (niedrigste zukünftige Emissionskurve) bzw. A1FI (höchste zukünftige Emissionskurve) des IPCC (2007). Als zentrales Ergebnis ist festzustellen, dass die landwirtschaftlichen Produzenten, die in derart inhärent unsicheren Umgebungen operieren, erfahrener sind, sich dynamisch an eine unregelmäßige und sich verändernde Umwelt anzupassen.

Die Analyse von national repräsentative Haushaltsbefragungen unter Verwendung von Quantilregressionen mit und ohne Instrumentalisierung für Endogenität zwischen Konsum- und Produktionsentscheidungen im Rahmen des landwirtschaftlichen Haushalts-Modells bestätigt, dass ärmere Haushalte anfälliger sind für die Auswirkungen von Wetter- und Klimaextrema. Ein 1%er Rückgang des Niveaus ihrer landwirtschaftlichen Gewinne führt möglicherweise zu einem Rückgang von 0,52% der Verpflegungskosten, während ein ähnlicher Rückgang für die reichsten 10% der Haushalte nur zu einem Rückgang von 0,39% der Nahrungsaufnahme führen würde. Die Modelle zeigen auch, die Gewinnwirkung der Kartoffelpreise scheint vor allem für die ärmsten Bauern wichtig zu sein.

Viele Bauern in Zentralasien sind bereits mit der ex-post-Anpassung an den Klimawandel beschäftigt; weitere Unterstützung seitens der Regierung ist jedoch für pro-aktive ex-ante-Maßnahmen. Ein wichtiger Mechanismus für die Erreichung dieses Ziels ist die Erhöhung der Widerstandsfähigkeit der Landwirte und deren Anpassungsfähigkeit an aktuelle und zukünftige, sowohl vorhersehbare als auch ungewisse Extrema. Die Analyse zeigt die folgenden wichtigsten politischen Maßnahmen auf, um dieses in der Region zu erreichen: i) das Bewusstsein der landwirtschaftlichen Produzenten hinsichtlich der Auswirkungen des Klimawandels und Anpassungtechnologien zu erhöhen; und ii) die Verbesserung der ländlichen Kredit- und Versicherungsvermittlung. Die Schlüsselbotschaft der Anpassungsanalyse dieser Studie ist, dass die meisten institutionellen und technologischen Möglichkeiten, die als Maßnahmen zur Anpassung an den Klimawandel in der Region vorgeschlagen werden, dringend erforderlich sind für regionale Entwicklung auch bei vollständiger Verringerung des Klimawandels.

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List of Abbreviations

ADB	Asian Development Bank
AEZ	Agro-ecological zones
CCCM	Canada Climate Change Model
CPI	Consumer Price Index
CSIRO	Commonwealth Scientific and Industrial Research Organization
FAO	United Nations Food and Agriculture Organization
FOB	Free on Board
GDP	Gross Domestic Product
GFDL	Geophysical Fluid Dynamics Laboratory
GIEWS	Global Information and Early Warning System
GIS	Geographic Information System
ICARDA	International Center for Agricultural Research in the Dry Areas
IFPRI	International Food Policy Research Institute
IPCC	The Intergovernmental Panel on Climate Change
MIROC	Medium Resolution General Circulation
NASA	United States National Aeronautics and Space Agency
NOAA	National Oceanic and Atmospheric Administration
OECD	Organization for Economic Co-operation and Development
SIC-ICWC	Scientific-Information Center of the Interstate Coordination Water Commission of the Central Asia
UNDP	United Nations Development Program
UNPF	United Nations Population Fund
USD	United States Dollars
USDA	United States Department of Agriculture

Acknowledgements

I owe my deepest gratitude and appreciation for many people and organizations for helping me in completing this PhD research.

I would like to thank the IPSWaT program of the German Federal Ministry of Education and Research (BMBF) for funding my PhD studies. I am extremely thankful to Prof. Dr. Joachim von Braun for his inspiring academic guidance, advice and support at various stages of my study. His insightful comments and suggestions on my work greatly helped me to improve it. I am highly indebted to Dr. Daniel Tsegai for his thorough reviews of my thesis chapters and excellent tutoring of my work throughout the PhD period. I am very grateful to Prof. Dr. Thomas Heckelei for his interest in my work and useful suggestions during our very first meeting. I would like to thank Dr. Matthias Kalkuhl for his review and suggestions on Chapter 3 of my thesis.

This research has been greatly aided and supported by the project on the "Impacts of Climate Change and Drought in Central Asia and People's Republic of China", funded by the Asian Development Bank and jointly conducted by ICARDA and IFPRI. I would like to thank the donor and my project colleagues and friends both at ICARDA and IFPRI who provided their advice and support for my work. I am especially grateful to Drs. Aden Aw-Hassan, Aziz Nurbekov, Mohamed Ahmed, Ihtiyor Bobojonov, Ephraim Nkonya, Kato Edward, Tulkun Yuldashev, Mariya Glazirina, Rolf Sommer and Eddy de Pauw.

I am also immensely thankful to several other ICARDA colleagues who greatly encouraged and helped me in directing myself to PhD studies. I am highly grateful to Drs. Christopher Martius, Kamil Shideed, Zakir Khalikulov, Raj Gupta and Josef Turok. I would like to thank Dr. Kirsten Kienzler for her friendly advice and also for translating the abstract of my thesis into German. I would also like to thank all my colleagues and friends at ICARDA Tashkent office, especially Muzaffar Aliev, Farhod Hamraev, Tamara Yugay and Sherzod Qosimov for their help during my field research. Similarly, my field research has been greatly aided by my colleagues from the Central Asian countries, such as Dr. Malik Bekenov, Dr. Altynbek Moldashev, late Academician Rasulmat Husanov, Mr. Javlon Nurbekov, and many others.

My sincere thanks go Dr. Gunther Manske, Dr. Guido Luechters, Mr. Volker Merx, Mrs. Rosemarie Zabel, all friends and colleagues at ZEF, especially my batchmates, for helping in my research and making my PhD life more interesting and pleasant.

My greatest gratitude goes to my wife, Nodira, and daughters, Noila and Lola, as well as my parents, who were a great moral support and inspiration in my work.

Chapter 1

1. Introduction

1.1. Background information and socioeconomic context

The five countries of Central Asia – Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan and Uzbekistan - are located in arid, semiarid and sub-humid regions between 35°-55° of latitude and 46°-87° of longitude. The region occupies 4.0 mln km^2, an area roughly similar to that of the European Union, and borders with China in the east, Russia in the north and the west, Afghanistan and Iran in the south. Its western part is also bounded by the Caspian Sea (Figure 1.1).

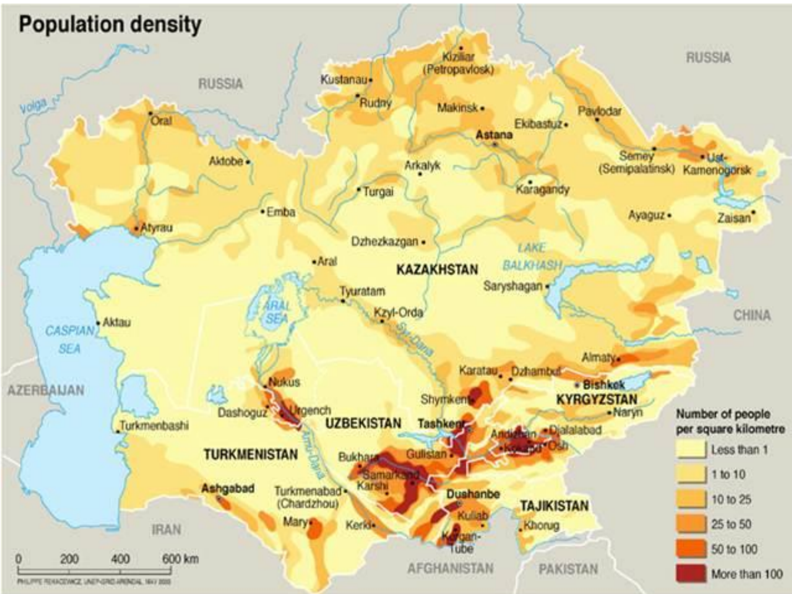


Figure 1.1. Population density in Central Asia

Source: Philippe Rekacewicz, UNEP/GRID-Arendal, http://www.grida.no/graphicslib/detail/population-density-central-asia_30dd

After the collapse of the former Soviet Union in 1991, the newly independent countries of Central Asia have started wide-scale reforms aimed at transition from centrally planned command system towards more market-oriented economies. Numerous institutional and policy reforms were conducted, adopting either rapid and liberal or gradual and conservative approaches. After the passage of two decades, consequently, economic, social, policy and institutional contexts in each of these countries have become quite heterogeneous (Table 1.1). Presently, the population of the region is close to 62 mln people. The population growth rates have been declining over the last decade. The United Nations Population Fund (UNFPA) expects the region's population to reach 79.9 million people by 2050 (Christmann *et al*. 2009). Although the population growth projections are not very high, however, the population pressure is already stressing considerably the arable land and water resources in most of the region; except in Kazakhstan, where per capita arable land endowments are second largest in the world, after Australia (World Bank 2010). The total life expectancy at birth is at about 67-68 years, equal to global average, but full 10 years lower than in high income countries - members of the Organization for Economic Co-operation and Development (OECD). Mean years of schooling is at about 10 years, basically equal to OECD averages (Barro and Lee 2012). A "decade of loss" after the fall of the Soviet Union and till 2001 was characterized by negative Gross Domestic Product (GDP) growth rates, ranging from catastrophic - 8.4% per annum in Tajikistan (no doubt, also influenced by the civil war in the country between 1992-1997) and – 0.1% per year in Uzbekistan. Between 2001-2011, the economies of the region have, in contrast, recorded strong GDP growth rates on average ranging between 4.1% to 13.1%. Among the key reasons for this growth were high commodity prices in the global markets, generally sound macroeconomic policies and increased amount of remittances from migrant laborers, chiefly employed in the booming Russian economy. In addition, higher earnings from exports also allowed commodity-rich countries of the region to considerably ramp up public investment into infrastructure and construction. Although all of the countries of the region had significant GDP growth rates during the last decade, a more dynamic growth in the energy-exporting countries - Kazakhstan and, to a lesser extent, Turkmenistan - has led to increasing divergences in the GDP per capita regionally, but also within the countries between oil-rich provinces and poorer agriculture-dominated ones. For example, in Kazakhstan, provincial GDP per capita of the oil-rich Atyrau province was 37,247 USD in 2010, while that of the agricultural Southern Kazakhstan province only 3,202 USD, i.e. less than one tenth of the former.

At the regional level, out of the five countries, Kazakhstan is in the World Bank's upper middle income country category, Turkmenistan, Uzbekistan and Kyrgyzstan in the lower middle income category, and Tajikistan is in low income country category.

Table 1.1. Selected development indicators for Central Asian countries

Development indicators	Kaz	Kyrg	Taj	Turkm	Uzb
Population, mln in 2010	16.3	5.3	7.0	5.1	28.1
Rural population (% of total), 2009	42	64	74	51	63
Population growth rate, average 2006-2010 (% of total)	1.5	0.8	1.6	1.3	1.4
Life expectancy at birth, total (years), 2010	68	67	67	65	68
Mean years of schooling (adults aged 25 years and above), 2010	10.34	9.25	9.78	9.88	9.95
Human Development Index value, 2010	0.714	0.598	0.580	0.669	0.617
Human Development Rank, 2010	66	109	112	87	102
Global Science Publications Rank, 2012	91	141	145	186	80
Global Hunger Index, 2010	< 5	< 5	15.8	6.3	7.1
GDP per capita (current USD, 2010)	8 764	860	797	4 071	1 384
GDP growth (%)					
average 1991-2000	-3.4	-3.4	-8.4	-2.1	-0.1
average 2001-2010	8.3	4.1	8.4	13.1	7.0
Agriculture, value added (% of GDP), 2008/2009	6	29	22	12	20
Agricultural value added per worker, in USD for 2008/2009	2033	1041	542	2930	2584
Employment in agriculture (% of total), 2004-2008	29.5	34.5	66.5	48.1	29.1
Arable land, ha per person	1.4	0.2	0.1	0.4	0.2
Crop production index (1999-2001=1), 2009	1.50	1.08	1.48	1.28	1.45
Food production index (1999-2001=1), 2010	1.45	1.03	1.62	1.37	1.55

Sources: ADB, 2009a; Global Hunger Index 2010, IFPRI (von Grebmer et al. 2010); UNDP, 2010. Human Development Report 2010, at http://hdr.undp.org/en/statistics/hdi/ accessed on Aug. 04, 2010; World Development Indicators at www.data.worldbank.org accessed on August 04, 2011; SCImago Journal & Country Rank, http://www.scimagojr.com.

Agriculture is an important sector for the region. Even in richer Kazakhstan, where the share of agriculture in the GDP is only about 6%, it employs almost 30% of the labor force. In the rest of the region, the share of agriculture in GDP is as high as 30% in Kyrgyzstan, and in employment as high as 66.5% in Tajikistan. However, these statistics are to a certain degree biased by the important role played by the capital and a few bigger regional cities within each country both in terms of population and share in the GDP. Once we account for them, the importance of agriculture for the livelihoods of rural populations stands out even more. The growth of agricultural production in Central Asia ranged on average between 2% per year in Kyrgyzstan to 6% per year in Uzbekistan during the last 10 years. Crop and food production in the region grew by up to 1.62 times by 2010 as compared to 1999-2001. As a result, the Global Hunger Index indicators for the countries have been improving, and by now only Tajikistan is yet in the "serious" hunger index category (Table 1.1).

The region has 21 different agro-ecological zones (AEZ). However, just two of them – arid and semi-arid zones with freezing winters and scorching summers - cover almost 70% of the region. Most of the other AEZs are predominantly located in smaller niches in the higher altitudinal zones in the eastern and south-eastern parts of the region (Figure 1.2).

Rangelands occupy close to 65% of the region, while remote deserts, glaciers, urban settlements and other nonagricultural areas occupy 27% of the territory, leaving only 8%, or 32 mln ha, of the region's area under arable land. About 10.5 mln ha of these arable lands are irrigated, the remaining 21.5 mln ha are rainfed. About 20 mln ha of these rainfed areas are located in northern Kazakhstan, while the rest of the region predominantly depends on irrigated agriculture.

Central Asia has a sharply continental climate with high levels of variability. Mean winter temperatures throughout the region during the last century have ranged between -25°C to +7°C, while the mean summer temperatures were between +2°C to +31°C.

In the mountain areas, the minimum temperatures can be as low as – 45°C, and in the desert areas, the maximum temperatures can be as high as + 50°C (Gupta *et al*. 2009). Similarly, the mean annual precipitation during the last century has ranged between 60 mm to 1180 mm across different localities in the region.

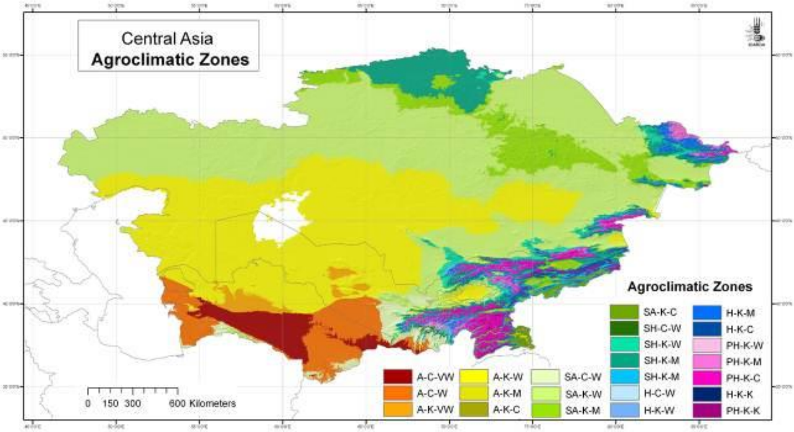


Figure 1.2. Agro-climatic zones in Central Asia

Source: ICARDA-GIS Unit, de Pauw (2007), Gupta *et al*. (2009). Due to large space requirements, the legend is given separately in Table 1.2.

Table 1.2. Legend to the Figure 1.2: Agro-ecological zones in Central Asia

Agroclimatic Zone	Description	Aridity index[1]	Temp. range coldest month	Temp. range warmest month	% of total
SA-K-W	Semi-arid, cold winter, warm summer	0.2 - 0.5	<= 0°C	20° - 30°C	37.9
A-K-W	Arid, cold winter, warm summer	0.03 - 0.2	<= 0°C	20° - 30°C	30.8
SA-K-M	Semi-arid, cold winter,	0.2 - 0.5	<= 0°C	10° - 20°C	6.6
SH-K-M	Sub-humid, cold winter,	0.5 - 0.75	<= 0°C	10° - 20°C	5.9
A-C-W	Arid, cool winter, warm summer	0.03 - 0.2	0° - 10°C	20° - 30°C	4.9
A-C-VW	Arid, cool winter, very warm summer	0.03 - 0.2	0° - 10°C	> 30°C	2.9
PH-K-C	Per-humid, cold winter, cool summer	> 1	<= 0°C	0° - 10°C	2.0
H-K-M	Humid, cold winter, mild summer	0.75 - 1	<= 0°C	10° - 20°C	1.6
SA-C-W	Semi-arid, cool winter, warm summer	0.2 - 0.5	0° - 10°C	20° - 30°C	1.5
SH-K-W	Sub-humid, cold winter, warm summer	0.5 - 0.75	<= 0°C	20° - 30°C	1.4
A-K-VW	Arid, cold winter, very warm summer	0.03 - 0.2	<= 0°C	> 30°C	1.2
PH-K-M	Per-humid, cold winter,	> 1	<= 0°C	10° - 20°C	1.2
SH-K-C	Sub-humid, cold winter, cool summer	0.5 - 0.75	<= 0°C	0° - 10°C	0.5
SA-K-C	Semi-arid, cold winter, cool summer	0.2 - 0.5	<= 0°C	0° - 10°C	0.5
H-K-C	Humid, cold winter, cool summer	0.75 - 1	<= 0°C	0° - 10°C	0.5
H-K-W	Humid, cold winter, warm summer	0.75 - 1	<= 0°C	20° - 30°C	0.2
SH-C-W	Sub-humid, cold winter, warm summer	0.5 - 0.75	0° - 10°C	20° - 30°C	0.1
A-K-M	Arid, cold winter, mild summer	0.03 - 0.2	<= 0°C	10° - 20°C	0.1
PH-K-K	Per-humid, cold winter, cold summer	> 1	<= 0°C	<= 0°C	0.1
PH-K-W	Per-humid, cold winter, warm summer	> 1	<= 0°C	20° - 30°C	0.0
A-K-C	Arid, cold winter, cool summer	0.03 - 0.2	<= 0°C	0° - 10°C	0.0

The ratio of the mean annual precipitation over the mean annual potential evapotranspiration

The climate of the region has been changing more rapidly than global averages since 1950s (Gupta *et al*. 2009). There are big uncertainties in the projections of potential impacts of climate change on the region, especially in terms of precipitation and irrigation water runoff dynamics. Some studies indicate that climate change may lead to higher temperatures, more erratic rainfall, as well as to lower volumes of runoff water for irrigation (Lioubimtseva *et al*. 2005, Cruz *et al*. 2007). Moreover, the biggest climate-related problem in the region is already an intrinsic part of its climate: regional temperatures and precipitation are highly volatile and prone to sharp extremes. Climate change may further increase this volatility and significantly raise weather-related risks for agricultural production. The historic climate trends and future climate change projections for Central Asia are analyzed in detail in Chapter 2 of the thesis.

1.2. Problem statement

Agriculture plays an important role in the regional economy and for the livelihoods of its predominantly rural population, especially for the poor. Agricultural production is sensitive to weather and climate volatility, which are already quite high in the region. Temperature and precipitation dynamics are key climate factors for rainfed areas, while for irrigated areas availability of reliable irrigation water becomes an important additional and related risk factor. Climate change may increase these risks even further. If not adapted to, increased climate volatility and change may have a negative impact on agricultural production and rural livelihoods in many parts of the region. In extreme cases, it may strain fragile food security in the poorer countries of Central Asia. Even in areas where climate change may have positive impacts, there is a need for actions on adapting to avail of these new opportunities.

1.3. Research objectives, hypotheses and questions

Aspiring to address the above problem statement, this study seeks to assess the potential economic impacts and ways of managing climate volatility and adapting to climate change in Central Asia, with emphasis on agriculture. So far, there have been only a handful of studies on this important topic for the region. Moreover, most of the previous studies estimated impacts of climate change on Central Asian agriculture based on crop yield losses only and did not consider fully the potential adaptive responses of agricultural producers to climate change (for example, Bobojonov *et al.* 2012, Nelson *et al.* 2010). Thus, the key purpose for this research is to contribute to filling this research gap. The study is also motivated by the need to provide sound, evidence-based research findings to regional decision-makers on the potential impacts of weather volatility and climate change, as well as adaptation options in agriculture, thereby supporting them in developing appropriate medium and long-term policies. The main hypothesis of this research assumes that appropriate and well-implemented adaptation and climate risk management policies which would be based on so called no-regret measures, i.e. those policies that would be beneficial to agricultural and economic development in the region even with perfect mitigation, will make it easier to deal both with the current and future impacts of climate change and weather volatility in Central Asia.

It is important that the policies to address climate issues in agriculture take into account the heterogeneity of agricultural and social systems, as well as the dynamics of change and adaptation. The natural, economic and institutional conditions in various parts of Central Asia, and in some aspects even within individual countries, differ quite significantly and, therefore, blanket policies may not be productive. For this reason, the decision-makers could greatly benefit from research findings providing both impact assessment and adaptation options in a "quilt", rather than a "blanket" approach (Seo *et al*. 2009). Moreover, the impact of climate volatility and change varies not only geographically, but also within different social groups in each country. Although it is recognized that the impact may be more severe on the poorer groups in the society (Tol *et al*. 2004), there has been little research conducted in Central Asia, and also globally, to quantify this impact.

Based on the above problem definition and research challenges, the proposed study seeks to address the following research questions:

1. How weather shocks may affect agricultural commodity prices in Central Asia?
2. How climate change may impact Central Asian agriculture?
3. How does the climate volatility and related economic change affect the livelihoods of the rural poor?
4. What are the key factors facilitating or hindering adaptation to climate change?

It is hoped that the findings of this research will contribute to providing answers to the research challenges indicated above, among which crucially by its inputs on the impacts of climate change on agriculture and rural livelihoods in Central Asia. To achieve this, the study uses the conceptual framework presented in Figure 1.3 below.

The conceptual framework succinctly summarizes the key assumptions, hypotheses and research questions of the study. It starts with the now widely established evidence that climate is changing, resulting in changes in climate variables such as temperature and precipitation, potentially leading to higher incidences of weather shocks. These climatic changes and weather shocks have effects on crop yields and livestock productivity, but also on input use, management practices, and input and output prices through their impacts on agricultural product supply and input demand. This study specifically focuses on the interaction between the past climate characteristics, their dynamics and agricultural profitability, in order to draw evidence-based conclusions and make better educated projections about the possible impacts of expected climatic changes in the future.

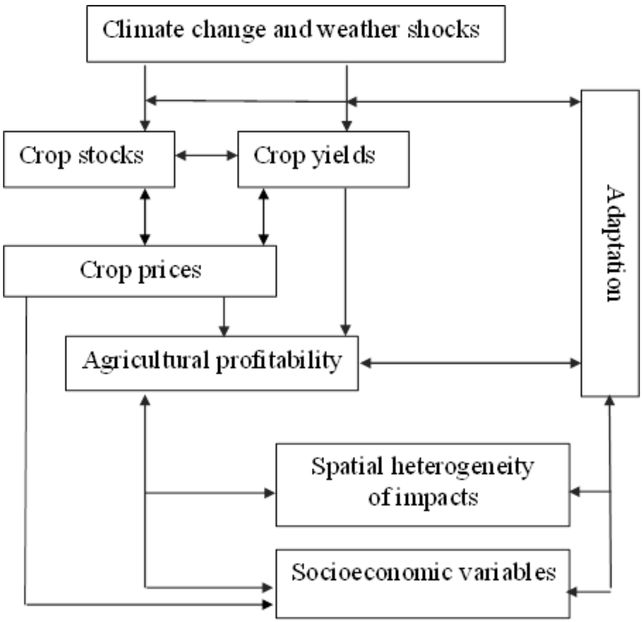


Figure 1.3. The conceptual framework of the study

Combined together, all these different dynamics influenced by changes in the climate variables will have an impact on agricultural profitability through their effects on crop yields and crop prices. For this reason, the effects of weather shocks on crop prices will be studied within the first research question. However, current climate parameters differ in various parts of Central Asia, and also future changes will be occurring in varying degrees, intensity, and directions. Some parts of the region may potentially loose from the climate change, some others may benefit. Therefore, it is important to identify these areas of risk and zones of opportunities. The impacts of climate change on agriculture in Central Asia as well as the spatial heterogeneity of these impacts are thus addressed by the second research question.

Potential social stratification of climate change impacts, namely the interaction between climate variables and rural poverty, mediated through the agricultural productivity and profitability, as well as agricultural product prices, is the main focus of the third research question. Finally, the fourth research question looks into which factors could facilitate and which others could hinder adaptation to climate change in the region.

1.4. Organization of the thesis

The chapters following this introduction address, one by one, each of the proposed research questions. In order to provide with a detailed climatological background for the ensuing economic analysis, Chapter 2 studies the past climate dynamics in the region over the last 150 years and reviews the climate change forecasts for Central Asia. Chapter 3, then, tackles the first research question and looks into how weather shocks might influences crop prices in the region. Chapter 4 addresses the second research question on the impacts of climate change on the regional agriculture. For this purpose, three methodologies of climate change impact assessment are employed and the results from these separate approaches are compared. Chapter 5 answers the third research question on the impacts of climate change on agricultural households and rural poverty within an agricultural household model framework. It identifies the potential livelihood impacts of climate volatility and change on agricultural producers, especially the rural poor. Chapter 6 looks into the adaptation constrains and factors leading to adaptation to climate changes using the household survey data. It presents policy conclusions for removing the barriers and facilitating adaptation. Chapter 7 concludes by summarizing the major results of the entire study and formulates the key policy-relevant findings of the study.

Chapter 2

2.1. Review historic climate change and volatility in Central Asia

This review of the historic climate and its change in Central Asia uses a relatively rich dataset of monthly and daily weather data from about 400 weather stations in the region and with the temporal coverage going as far back as 1842, though the densest coverage is since 1950s (Figures 2.1 and 2.2). The weather data have been compiled from various sources, such as Williams and Konovalov (2008), United States National Aeronautics and Space Agency´s (NASA) Global Summary of the Day, national hydro-meteorological services and other online sources such as www.rp5.uz and its sister websites for each country of Central Asia.

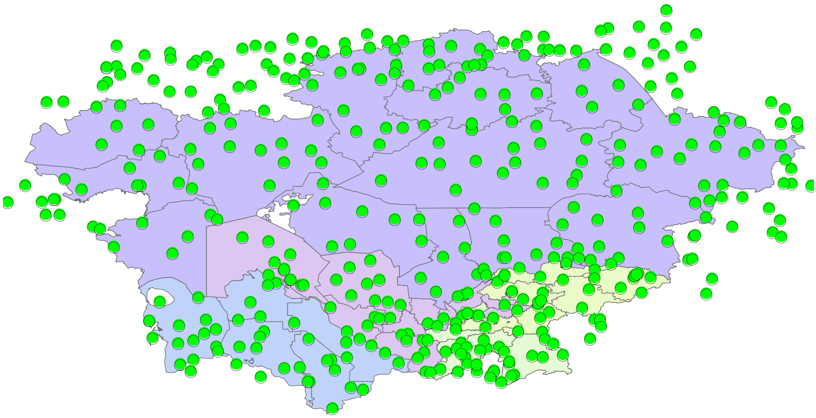


Figure 2.1. Weather station coverage in Central Asia

Source: author’s elaboration based on numerous sources

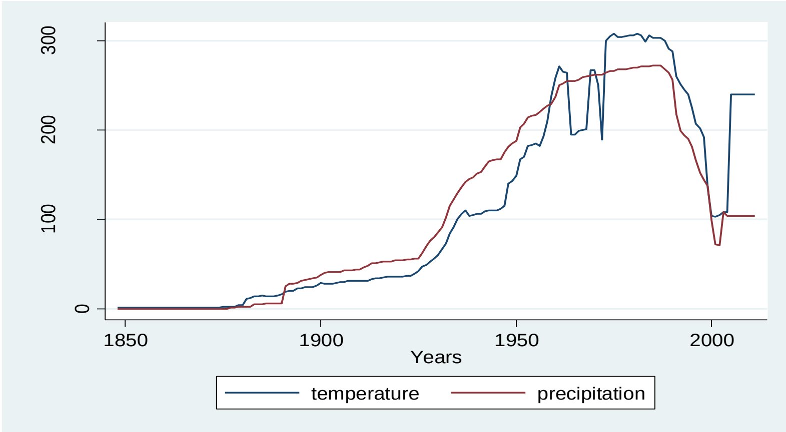


Figure 2.2. Temporal coverage density of used weather records for Central Asia

Source: author's elaboration based on numerous sources

2.1.1. Temperature

The mean temperatures in Central Asia grow gradually from south to north, but also from lower altitudinal western regions to mountainous eastern regions. Monthly and daily temperatures are subject to high degree of variability. Mean winter temperatures throughout the region during the last century have ranged between -25°C to +7°C, while the mean summer temperatures were between +2°C to +31°C. In the mountain areas, the minimum temperatures can be as low as – 45°C, and in the desert areas, the maximum temperatures can be as high as + 50°C (Gupta *et al*. 2009, Figure 2.3).

Since the amount of available weather data is too vast for analyzing at each individual weather station level, a method of k-means partition clustering was applied to segregate the data into clusters where observations belong to the cluster with the nearest mean. Seven clusters were, thus, identified based on mean monthly temperature.

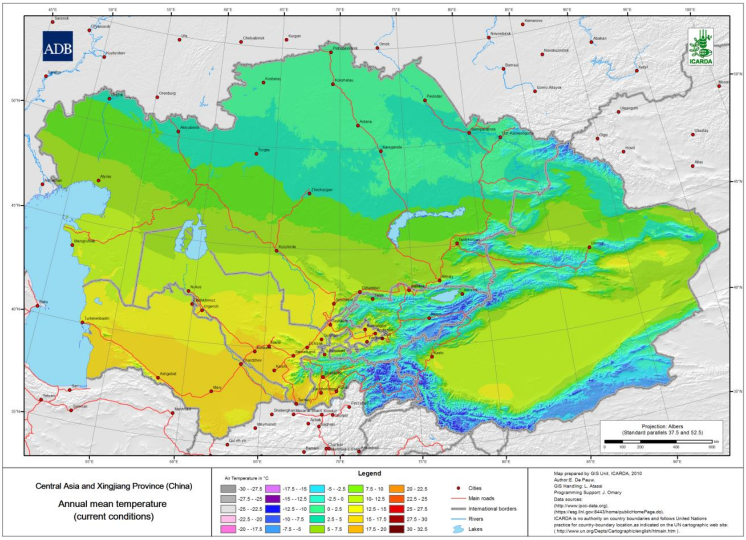


Figure 2.3. Current Mean Annual temperatures in Central Asia

Source: ICARDA, GIS-Unit, Eddy de Pauw, 2011

For representing the locations of these clusters cartographically, the cluster information was overlaid on the provincial map using the frequency of occurrence (mode) of each cluster within the province (Figure 2.4). For this reason, the weather transition is normally smoother at the borders of the provinces than what the map shows. However, there were no cases of conflicting modes, i.e. several equally frequent modes for the same province, and hence the map can serve as a satisfactory approximation of clusters by province. The resemblance of the map to much finer resolution temperature (Figure 2.3) and agro-ecology (Figure 1.2) maps also corroborates this conclusion. Temperature data from individual weather stations belonging to a particular cluster were averaged over each year of record to form a cluster-specific time series temperature data (Figure 2.5).

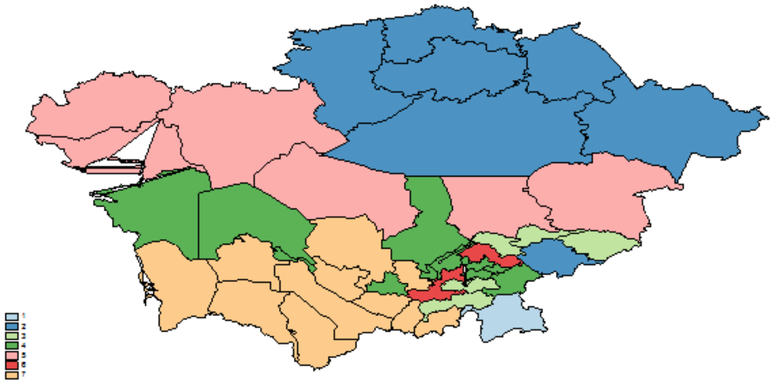


Figure 2.4. Geographical locations of clusters

Source: author's elaboration based on numerous sources

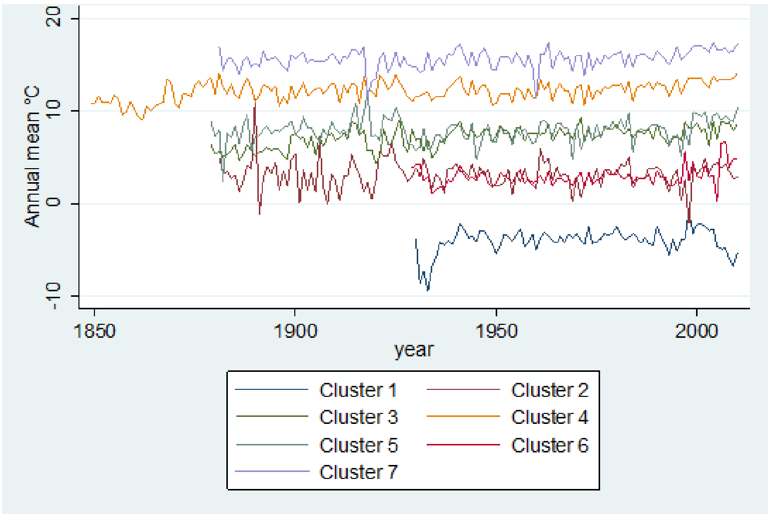


Figure 2.5. Mean temperature dynamics in by clusters in Central Asia

Source: author's elaboration based on numerous sources

The cluster analysis shows some distinguished patterns of temperature dynamics over the last century in the region (Table 2.1).

Table 2.1. Temperature dynamics in Central Asia (1880-2010)

	Over the last 130 years			Over the last 50 years			Volatility change over
	Mean Decadal Change	Mean Centennial Change	t	Mean Decadal Change	Mean Centennial Change	t	last 20 years
Annual °C							
Cluster 1	0.13	1.28	2.07	-0.1	-0.98	-1.01	(+)
Cluster 2	-0.02	-0.2	-0.54	0.02	0.19	0.14	(-)
Cluster 3	0.17	1.74	8.52	0.09	0.85	1.23	(+)**
Cluster 4	0.1	1	6.46	0.29	2.94	4.58	(+)***
Cluster 5	0.05	0.48	1.61	0.28	2.79	2.47	(+)*
Cluster 6	0.12	1.21	2.59	0.31	3.09	3.06	(+)**
Cluster 7	0.08	0.77	3.45	0.34	3.41	3.93	(+)***
Janury °C							
Cluster 1	-0.06	-0.55	-0.69	-0.35	-3.46	-2.49	(-)
Cluster 2	0.16	1.56	2.03	0.05	0.54	0.15	(+)
Cluster 3	0.18	1.77	4.42	0.01	0.13	0.08	(+)
Cluster 4	0.12	1.24	2.5	0.16	1.63	0.59	(+)**
Cluster 5	0.06	0.61	0.76	0.44	4.38	1.34	(+)
Cluster 6	0.02	0.17	0.18	0.04	0.35	0.16	(+)**
Cluster 7	0.2	2.2	3.07	0.31	3.09	1.07	(+)**
April °C							
Cluster 1	-0.25	-2.46	-3.92	-0.05	-0.48	-0.31	(-)
Cluster 2	0.14	1.43	2.24	-0.05	-0.48	-0.22	(-)
Cluster 3	0.13	1.3	3.62	0.23	2.31	1.76	(+)
Cluster 4	0.25	2.46	7.75	0.3	3.03	2.13	(+)
Cluster 5	0.09	0.88	2.05	0.07	0.75	0.41	(-)
Cluster 6	0.23	2.28	2.7	0.36	3.6	2.04	(+)*
Cluster 7	0.11	1.13	3.36	0.32	3.15	2.18	(+)*
July °C							
Cluster 1	-0.52	-5.22	-8.93	-0.3	-2.99	-2.3	(+)**
Cluster 2	0.05	0.46	1.25	-0.12	-1.16	-0.92	(+)
Cluster 3	0.23	2.33	7.47	0.05	0.48	0.48	(+)
Cluster 4	0.07	0.66	3.88	0.29	2.94	3.42	(+)*
Cluster 5	0.09	0.86	3.56	0.07	0.74	0.7	(+)
Cluster 6	0.25	2.55	3.86	0.72	7.2	6.29	(+)**
Cluster 7	0.06	0.6	3.02	0.2	1.99	2.59	(+)
October °C							
Cluster 1	-0.19	-1.95	-3.33	-0.11	-1.07	-0.66	(+)**
Cluster 2	0.04	0.37	0.88	0.47	4.68	2.88	(-)
Cluster 3	0.21	2.05	6.56	0.22	2.15	1.83	(+)
Cluster 4	0.07	0.69	2.68	0.33	3.26	2.44	(+)
Cluster 5	0.05	0.53	1.35	0.37	3.65	2.32	(-)
Cluster 6	0.1	1.04	1.39	0.43	4.32	2.73	(+)*
Cluster 7	0.09	0.92	2.46	0.43	4.3	2.82	(+)
Notes:		probably, no change				nificant * at 10%, ** at 5%, *** at	
		decrease					
		increase					

The overall conclusion is that mean annual temperatures are increasing in southern and western parts of the region, whereas the temperature changes in the north and high-altitude eastern parts if Central Asia, i.e. Clusters 1, 2 and 3, were not statistically significant over the last 50 years. Cluster 1 corresponds to the Pamir Mountains in the east of the region, where temperatures were rising considerably till early 1960s, but since then there was no statistically significant trend of mean annual temperatures.

Similarly, there seems to have been no significant mean annual temperature changes over the Tien-Shan Mountains, also in the east of the region, and rainfed wheat-growing areas in northern Kazakhstan (Clusters 2 and 3) during the last 50 years. Although, again as with the Pamir Mountains, the temperatures were rising considerably over the Tien-Shan Mountains during the first half of the 20th century. The Pamir and Tien-Shan mountain ranges are extremely important for agriculture in the region as most of region's water used for irrigation comes from these two mountain ranges.

The strongest mean annual temperature increases of about 3.41°C over the century are observed in Turkmenistan and Central Uzbekistan, i.e. basically Karakum and Kyzylkum deserts (Cluster 7). In terms of seasonal changes, temperature rises seem to be occurring mainly in spring and fall (April and October), with smaller rises in summer (July) and mostly no significant change in winter (January).

It is widely understood that the rate of temperature increases have accelerated globally in the second half of the 20th century. The Student's t-test was performed for mean annual temperature comparing the long-term mean temperatures (130 years) with mean temperatures for the last 50 years in Central Asia (Table 2.2). The results, in general, do not contradict the idea about the accelerated temperature increases over the last 50 years.

The volatility[1] of mean temperatures has been increasing in the region over the last 20 years (Table 2.1). A few cases of volatility decrease, notably in northern Kazakhstan, were found to be statistically non-significant. This volatility analysis should, however, be understood in

[1] Volatility can be defined either as deviation from long-term mean or as deviation from trend. Chapter 2 concerns specifically with climate change and climate volatility, which necessitates taking volatility as deviation from mean because climate is, by definition, the mean of long-term weather series. A deviation from trend would not be a measure of climate volatility, but a measure of current weather volatility as compared to weather volatility in the recent past. However, in the following chapters where responses and interactions of economic agents to climate and weather are discussed, volatility is taken as deviation from trend because economic agents are assumed to continuously update their cognitive perceptions so that their actions are shaped by changing trends in climate rather than long-term mean climate values which could become no longer relevant for their decision-making, especially in the context of accelerated climate change.

the light of the high levels of historic temperature variability intrinsic to most parts of the region, which is also illustrated by cluster-specific graphs of long-term temperature volatility change (Figure 2.6).

Table 2.2. Student's t-test of long-term (130 years-z1) and medium-term (50 years-z2) mean annual temperatures

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
z1	35	.7482857	.2525246	1.493955	.2350941	1.261477
z2	35	1.752	.3871733	2.290548	.9651692	2.538831
combined	70	1.250143	.2372634	1.985088	.7768153	1.72347
diff		-1.003714	.4622465		-1.926113	-.0813158

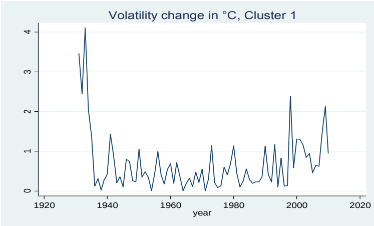
diff = mean(z1) - mean(z2)   t = -2.1714
Ho: diff = 0   degrees of freedom = 68

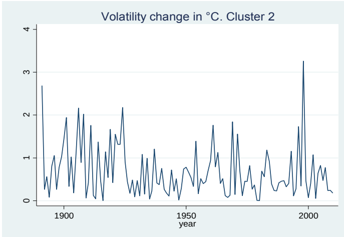
Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
Pr(T < t) = 0.0167	Pr(|T| > |t|) = 0.0334	Pr(T > t) = 0.9833

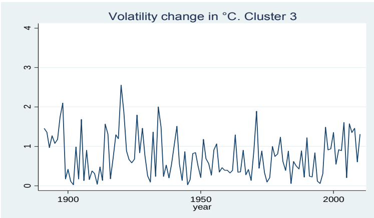
Note: z1 represents the long-term mean temperatures (130 years) and z2 mean temperatures for the last 50 years

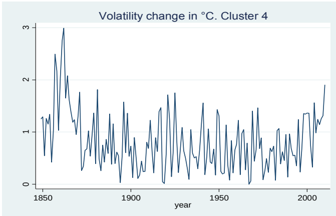
To create these volatility graphs standardized scores of mean annual temperatures were created for each cluster. Then, absolute values of deviations from their mean at zero were graphed. As can be seen, although increasing over the recent 20 years, the temperature volatility is within historic levels of recorded temperature volatility for most of the clusters. Only in Cluster 6 (piedmont areas corresponding to Sogd province of Tajikistan and Jalalabad province of Kyrgyzstan) the temperature volatility seems to have reached historically unprecedented levels.

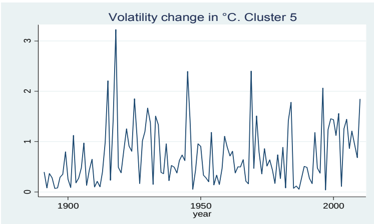
The general conclusion is that, over the last 50 years, the temperatures are rising in southern and western parts of the region, while the change is not significant yet over the northern and eastern areas. The highest temperature increases are occurring during the spring and fall periods. The volatility of temperatures is increasing but still within historic levels.

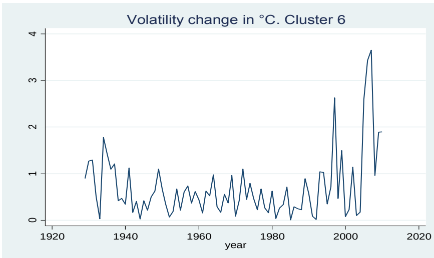












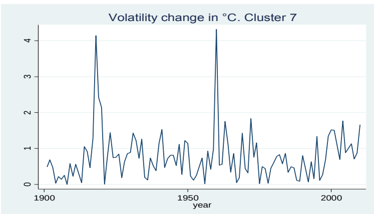


Figure 2.6. Change in the volatility of mean annual temperatures in clusters of regions in Central Asia

2.1.2. Precipitation

The mean annual precipitation during the last century has ranged between 60 mm to 1180 mm across different localities in the region. Central Asia, being located mostly in arid and semi-arid areas, receives less than 100 mm of precipitation in most of its south-western parts, covering Turkmenistan, central and north-western Uzbekistan, and south-western Kazakhstan, basically the areas surrounding what remains of the former Aral Sea. Northern part of the region, i.e. rainfed wheat producing areas of Kazakhstan receive on average 200-400 mm, while the precipitation in the south-eastern part of Central Asia, over mountains, can reach more than 1000 mm (Figure 2.7).

Meaningful clustering of rainfall data using the same method of k-means, as done for temperature data, was not possible. Therefore, the rainfall data was segregated to the same clusters as the temperature data. This approach has also an additional benefit of allowing the comparison of rainfall and temperature dynamics together. The clustered rainfall data shows that during the first half of the last century there has been a decrease in precipitation throughout the region, but starting from 1930s, the amount of rainfall seems to have increased across the region (Figure 2.8). The statistical analysis shows that the long-term (130 years) time trends for increase are significant at 1% in all clusters, except in cluster 5, corresponding to central Kazakhstan, where there was statistically non-significant decrease in precipitation.

The historic mean annual precipitation is distributed between 200 and 400 mm in most of the region while it is slightly higher over the northern provinces of Kyrgyzstan and Tajikistan. Outliers in the precipitation can be quite important. Figure 2.9 shows that in precipitation, as for temperature, the variation from year to year is quite high in most of Central Asia. Only in northern rainfed wheat growing areas in Kazakhstan and in mountainous Naryn province of Kyrgyzstan (Cluster 2) the historic variation seems to be lower, but with several outlier years, corresponding to drought years.

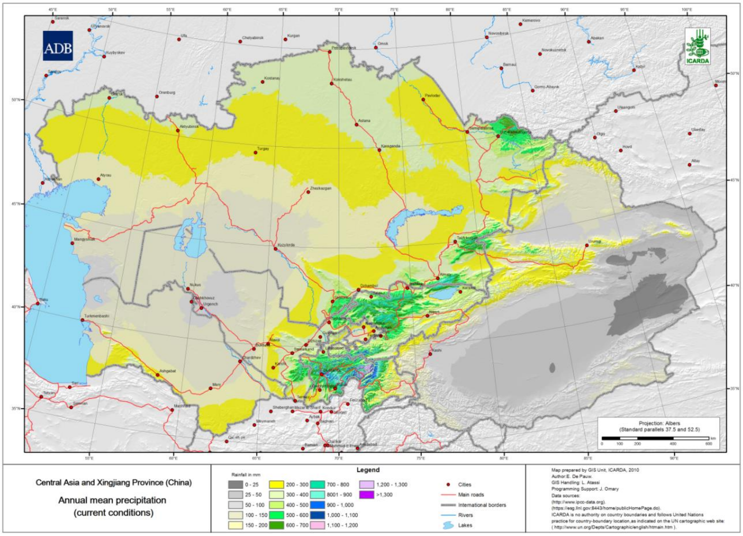


Figure 2.7. Mean annual precipitation in Central Asia
Source: ICARDA, GIS-Unit, Eddy de Pauw 2011

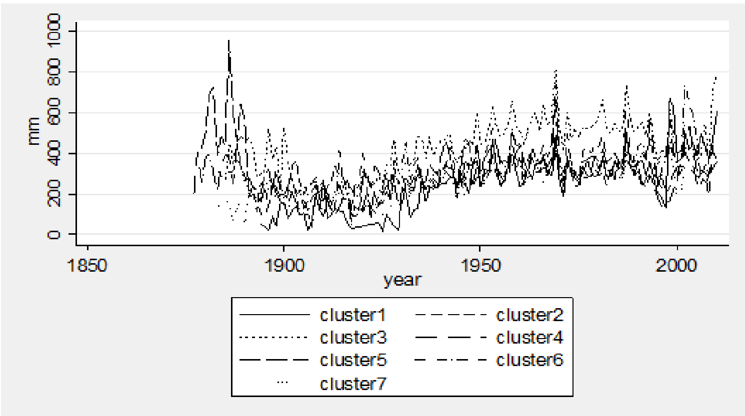


Figure 2.8. Long-term annual precipitation dynamics by clusters

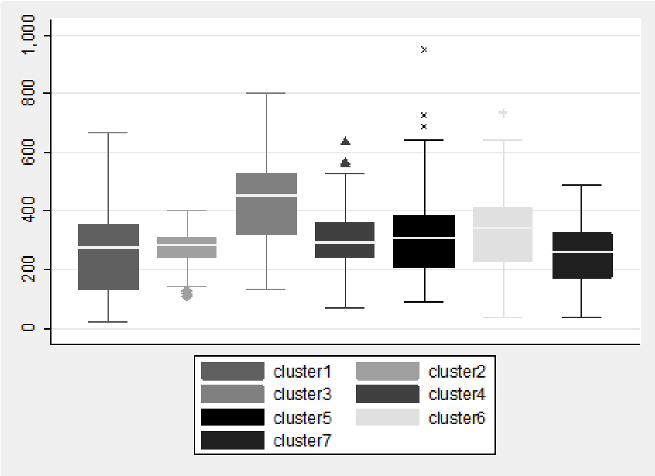


Figure 2.9. Mean annual precipitation distribution within clusters
Source: author's elaboration based on numerous sources

Volatility in precipitation is increasing in some clusters and decreasing in some others over the last 20 years. However, if compared with longer-term historic precipitation volatility, the current levels of precipitation volatility are within historic levels. (Figure 2.10).

Intra-seasonal distribution of precipitation can be quite important for agricultural performance, especially in the rainfed areas. There is an expectation that climate change will alter intra-seasonal patterns of precipitation, increasing the share of precipitation in non-vegetation period, while the share of precipitation during the vegetation period, when it matters the most, may be decreasing (Gupta *et al*. 2009). The see the evolution of intra-seasonal distribution of precipitation in Central Asia, the share of vegetation period precipitation in each cluster were analyzed and graphed in Figure 2.11. The vegetation period was considered to be from April to September, while the non-vegetation period from October to March. For most of the region, even if the intra-seasonal distribution of precipitation is changing, it is not yet very significant. Only in northern Kyrgyzstan and northern Tajikistan, there has been a clear shift over last 100 years from a precipitation falling predominantly during the vegetation period to one that is more equally distributed over the vegetation and non-vegetation periods.

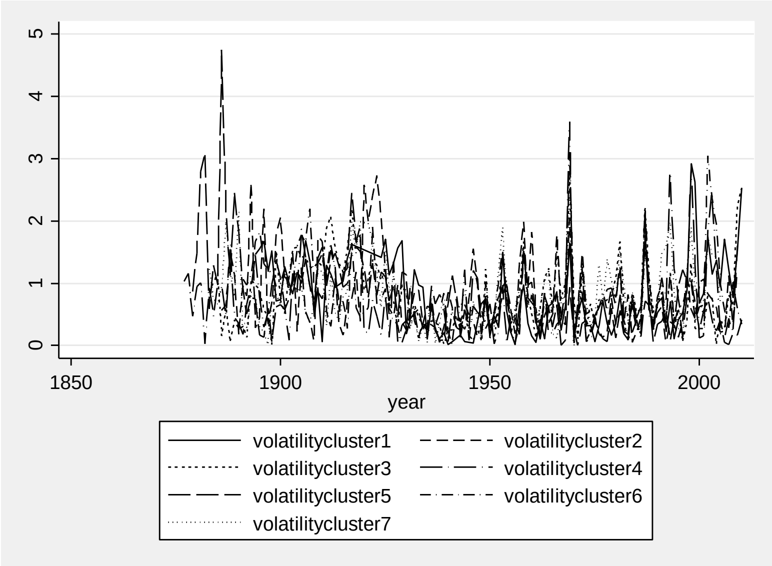


Figure 2.10. Volatility change in mean annual precipitation over the recorded precipitation history.

Source: author's elaboration based on numerous sources

As overall conclusion, the precipitation seems to have increased in most parts of the region over the last 100 years. The volatility of precipitation is increasing in some areas and decreasing in others, while remaining within historic levels. There have been no major shifts in seasonal patterns of precipitation in most of the region.

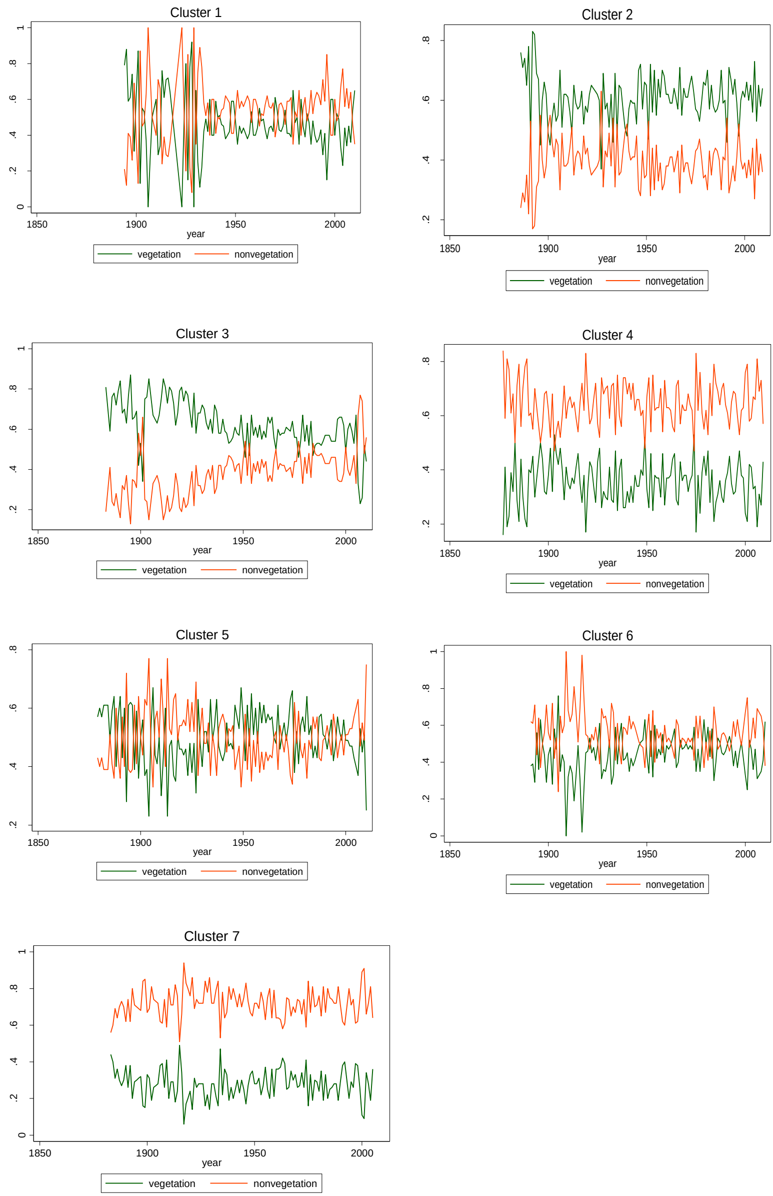


Figure 2.11. Dynamics in the share of vegetation and non-vegetation period precipitation

Source: author's elaboration based on numerous sources

2.1.3. River water flow

In most of Central Asia, the low levels of precipitation do not allow for crop production except only by supplemental irrigation. Irrigated agriculture is the mainstay of crop production in Uzbekistan, Turkmenistan, Tajikistan, Kyrgyzstan and southern Kazakhstan. Only in the northern Kazakhstan limited number of crops, mainly wheat and barley, are grown under rainfed conditions. This makes irrigation water availability extremely important for crop production in the region. There are five major river basins in Central Asia: Amudarya, Syrdarya, Balhash-Alakol, Ob-Irtysh, and Ural River basins (Figure 2.12).

During the last century, the area under irrigation in Central Asia has increased by almost 4 times from 2.9 mln ha to 10.5 mln ha. In the last 60 years alone, the area under irrigation doubled, while the water supply remained practically the same throughout the time. The expansion has been especially dramatic and highly consequential in the Amudarya and Syrdarya River basins (Figure 2.13).

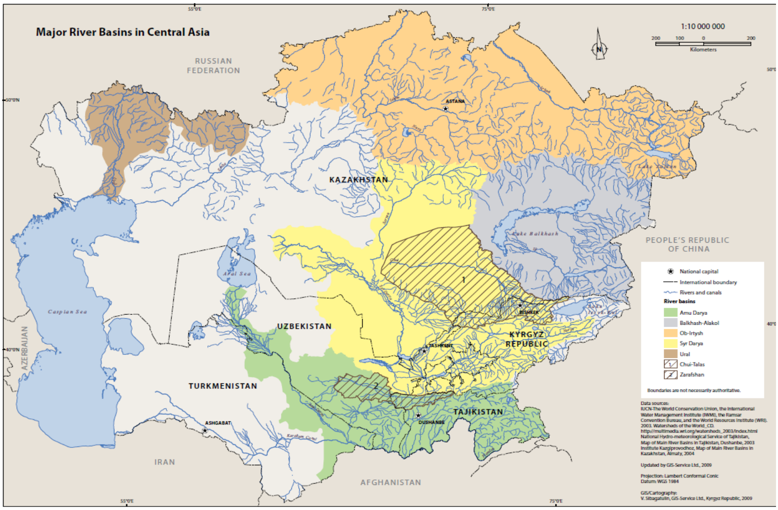


Figure 2.12. Major river basins in Central Asia

Source: ADB (2009b), map prepared by Sibagatulin.

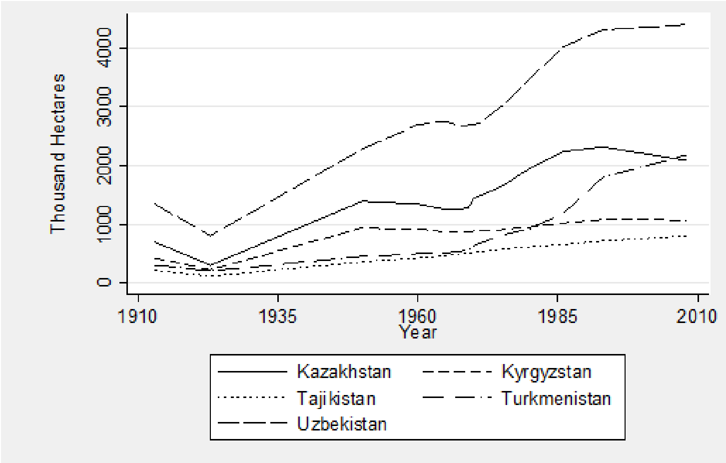


Figure 2.13. Expansion of irrigated areas in Central Asia

Sources: Statistical compilations "Narodnoye hozyaystvo SSSR" (various years), various statistical bulletins

Major irrigation areas in the region are given in Figure 2.14. These irrigation areas are located predominantly in the Amudarya and Syrdarya River Basins – almost 10 mln ha or 94% of the total, while only about 0.5 mln ha are located in Balhash-Alakol basin – Almaty province of Kazakhstan, and another 0.1 mln ha in the Ob-Irtysh basin, mainly Eastern Kazakhstan province.

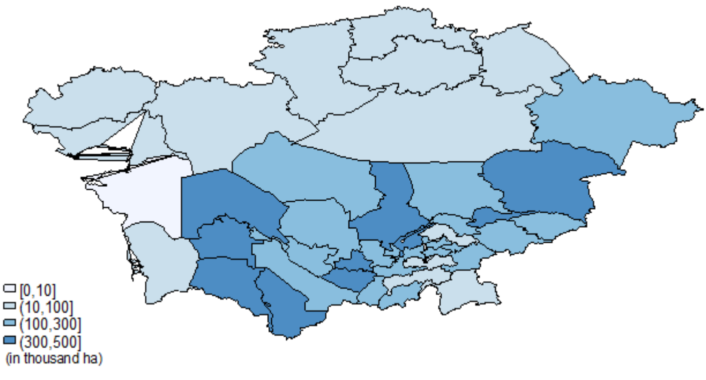


Figure 2.14. Area of irrigated areas in Central Asia

Therefore, the water flow dynamics of the Amudarya and Syrdarya Rivers are highly important for Central Asian agriculture (Figure 2.15). The long-term flow data from both rivers is punctuated by wet and dry years. Since the flow of these rivers mainly depends on the melting of snow and glaciers over the Pamir and Tien-Shan mountain ranges, the high volatility of temperature and precipitation is also reflected in the year-to-year variability of the river flow, which puts an additional risk factor for the region's agriculture. Most of the water-flow from these two river basins is practically used up even during high-water years (Table 2.3). During the dryer years, such as 2000-2001, the water shortages could lead to quite significant agricultural losses, and in extreme cases, even threaten the food security in more fragile parts of the region.

The water use proportions indicated in Table 2.3 are only for irrigation. If one includes other types of water use as well, such as domestic and industrial, then basically little shares of Amudarya and Syrdarya are left unused. As for the water use for irrigation in the other river basins of the region, there is still some room for expansion of irrigation if that would be desirable in the future.

In conclusion, irrigation is a key factor for crop production in most of Central Asia. So far, there has been no marked trend in the volumes of water run-off in the Amudarya and Syrdarya Rivers – the major sources of irrigation water in the region. Ups and downs of water flow, which are related to inherent climatic variability in the region, have been an important risk factor that needs to be managed. This becomes even more important if climate change would lead, as forecasted, to decreases in run-off volumes, increases in volatility, and seasonal shifts in the river flow.

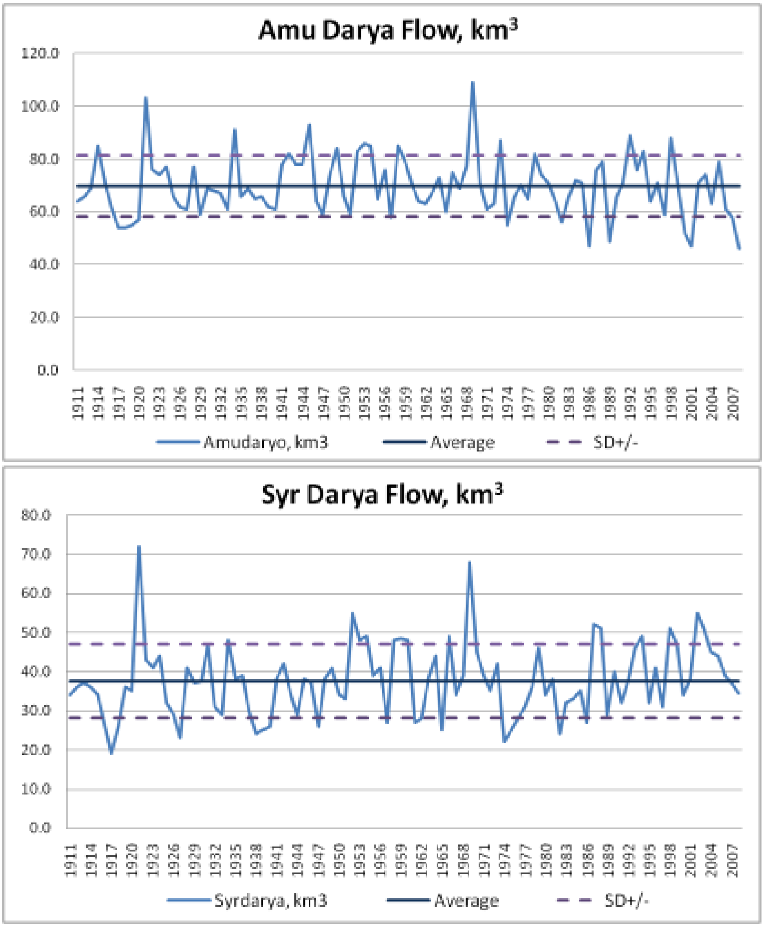


Figure 2.15. Long-term river flow of Amudarya and Syrdarya rivers
Sources: Bekchanov (2011, power point presentation), using data from SIC-ICWC

Table 2.3. Water flow and usage in the region's major river basins

River Basin	Average annual flow, km^3	The proportion used for irrigation
Amudarya	70	88%
Syrdarya	38	87%
Balhash-Alakol	30	17%
Ob-Irtysh	30	14%
Ural	15	9%
Total	182	58%

Source: SIC-ICWC, 2010; UNDP, 2005. Own estimates.

2.1.4. Extreme events

One of the key negative aspects of climate change, predicted by global climate change forecasting models, is that it would lead to increased number of extreme events, including heat waves, frosts, floods, droughts, etc. To analyze the dynamics of some of these extreme events in Central Asia, the number of days with more than 30°C and less -10°C was averaged per country for the last 50 years using daily weather data from around 250 weather stations in the region (Figure 2.16). The results showed that the number of days with more than 30°C has been increasing in all the countries. If in 1960 there were on average about 100 days with more than 30°C in Tajikistan, Uzbekistan, Kazakhstan and Turkmenistan, by 2010, this number has increased to almost 150 days (Figure 2.16). The number of days with less than -10°C is also increasing in all countries, except Tajikistan. This dynamic implies increasing probability of both heat waves and frosts in the region. This also implies that the climate in the region is getting even more sharply continental with increasing differentials between minimum and maximum temperatures.

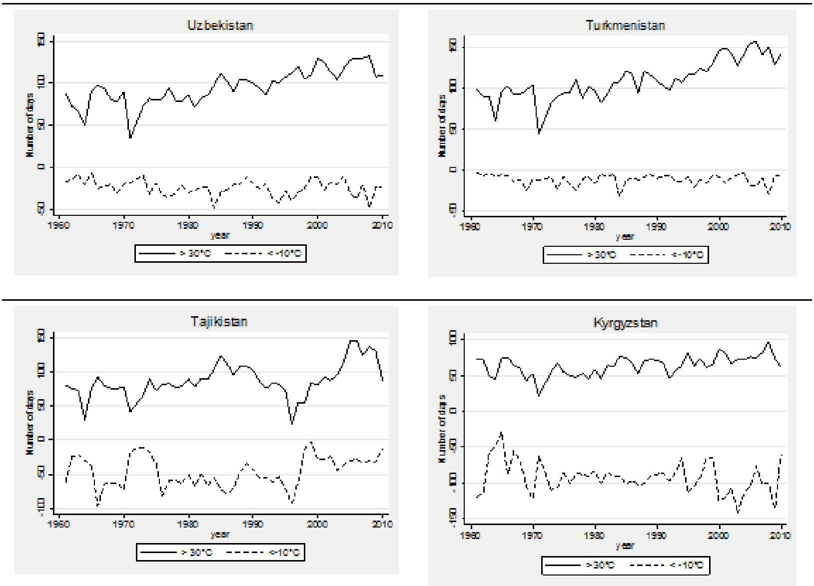


Figure 2.16. Change in daily temperature extremes*

*The number of days in a year with more than 30°C are plotted with connected lines above zero-line, and the number of days below -10°C are plotted with dotted lines below zero-line. Widening gap signifies the temperatures are becoming more extreme, and vice versa.

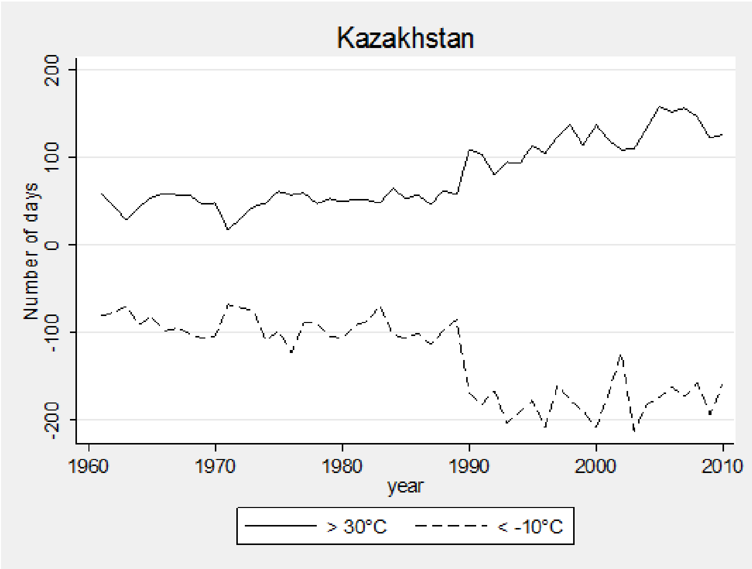


Figure 2.16. (cont.) Change in daily temperature extremes*

*The number of days in a year with more than 30°C are plotted with connected lines above zero-line, and the number of days below -10°C are plotted with dotted lines below zero-line. Widening gap signifies the temperatures are becoming more extreme, and vice versa.

Another important set of extreme events are linked to precipitation. The daily data for selected weather stations, which are thought to be broadly representative of big chunks of Central Asia, have been analyzed to construct mean daily precipitation intensity, which is the sum of the amounts of precipitation during each day when it rained divided by the number of days that rained. The higher number in this indicator would mean that bigger share of rainfall is falling during fewer days, implying increased probability of alternating periods of meteorological droughts with downpours, potentially leading to floods and landslides in susceptible areas. The time frame analyzed consists of daily observations for the last 85-120 years depending on the station (Figure 2.17)

Figure 2.17.(cont.) Dynamics in the mean daily precipitation

The daily rainfall intensity is showing different trends depending on the location. In some areas it is increasing, in others actually falling. However, the somewhat worrying sign that the rainfall daily intensity seems to be increasing in the hilly and slopy areas in Tajikistan (Dushanbe and Kurgantyube weather stations above), which are already prone to flooding and landslides. Increased rainfall intensity in other parts of the region, like in flat plain areas of desertic Chimbai, near the Aral Sea, probably will not cause as much damage.

2.2. Review of future climate change scenarios for Central Asia

2.2.1. IPCC and regional downscaled climate change projections for Central Asia

The Intergovernmental Panel on Climate Change (IPCC) reviews the latest science on climate change in its periodic reports, the last one being the Fourth Assessment Report in 2007. In this last report, the IPCC presented the projections on the future climate change using the results of 23 models. Future global climate change will depend on future greenhouse gas emissions – a big uncertainty. To take into account different potential paths of global development and greenhouse gas emissions, IPCC uses seven emission scenarios. In this section, the projected changes in temperature, precipitation and water flow as a result of climate change are reviewed based on IPCC projections and their downscaled versions for Central Asia. Under its Report by the Working Group II on Impacts, Adaptation and Vulnerability, IPCC (2007) provides a snapshot of temperature and precipitation changes in Central Asia under the highest future emission trajectory – A1FI, and the lowest future emission trajectory – B1 (Table 2.4). The major conclusion is that the temperatures in the region may be increasing under both scenarios, whereas the direction and magnitudes of changes in the precipitation are less certain.

Table 2.4. Projected changes in surface air temperature and precipitation for Central Asia under SRES A1FI (highest future emission trajectory) and B1 (lowest future emission trajectory) pathways

Season	2010 to 2039				2040 to 2069			
	Temperature °C		Precipitation %		Temperature °C		Precipitation %	
	A1FI	B1	A1FI	B1	A1FI	B1	A1FI	B1
Winter (DJF)	1.82	1.52	5	1	3.93	2.60	8	4
Spring (MAM)	1.53	1.52	3	-2	3.71	2.58	0	-2
Summer (JJA)	1.86	1.89	1	-5	4.42	3.12	-7	-4
Fall (SON)	1.72	1.54	4	0	3.96	2.74	3	0

Source: IPCC (2007)

The downscaling of IPCC forecasts for Central Asia was done by GIS-unit of the International Center for Agricultural Research in the Dry Areas (ICARDA) using the average of 5 Global circulation models under the emission scenarios A1b and A2 (Figures 2.18-2.19, de Pauw 2010), which imply increases of CO_2 levels by 2.3 and 3.4 times by

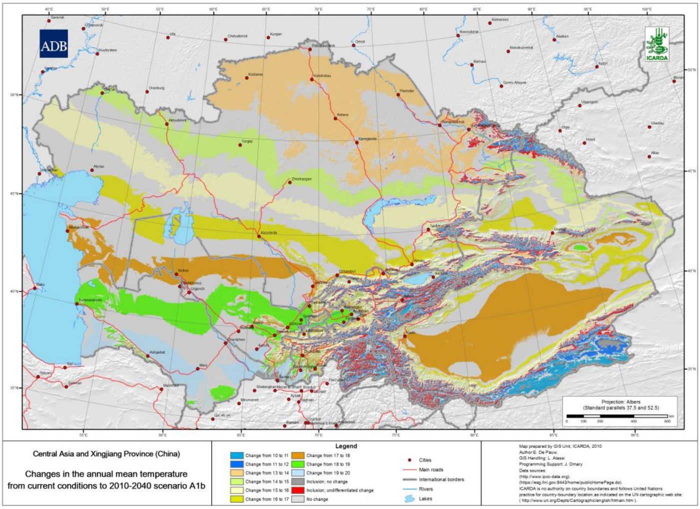


Figure 2.18. Change in Annual Mean Temperature by 2040, based on averaged output of 5 Global circulation models under Greenhouse gas emissions Scenario A1b.

Source: ICARDA, GIS-Unit, Eddy de Pauw, 2011

Note: grey areas mean no change, colored areas mean about 2.5°C increase)

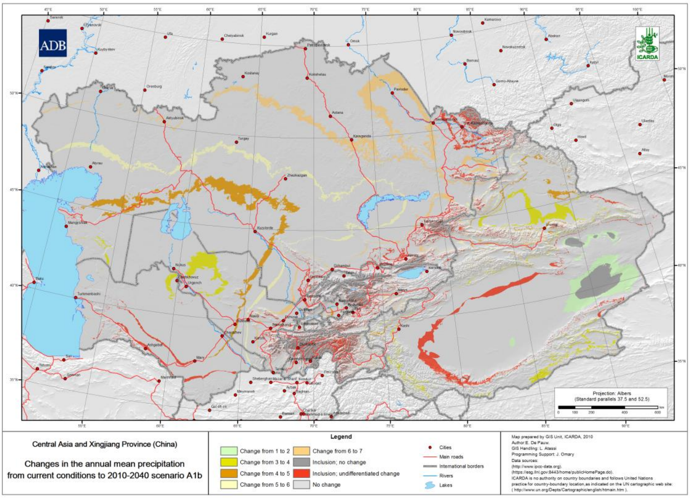
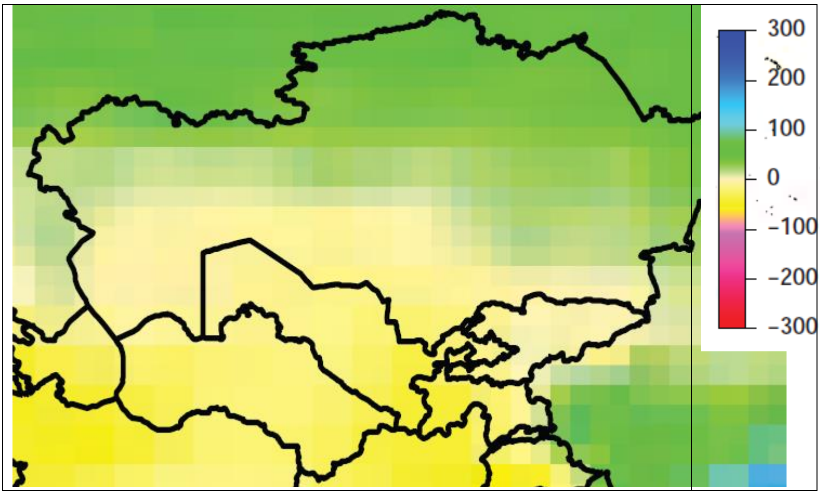


Figure 2.19. Change in Annual Precipitation by 2040, based on averaged output of 5 Global circulation models under Greenhouse gas emissions Scenario A1b.

Source: ICARDA, GIS-Unit, Eddy de Pauw, 2011

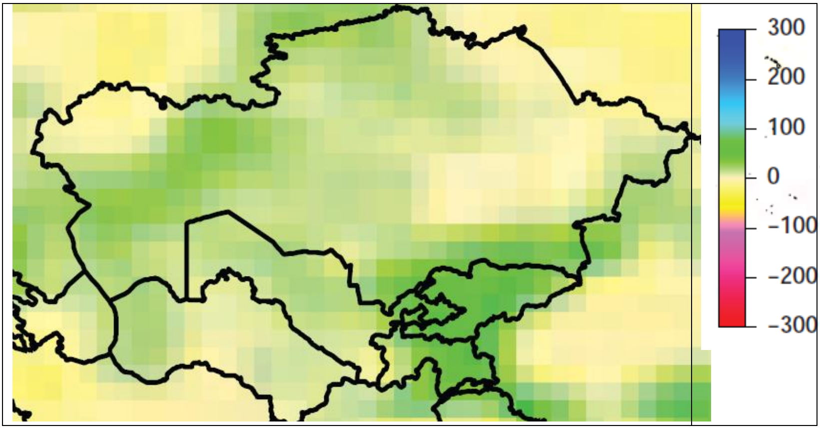
Note: grey areas mean no change, colored areas mean about 50-100 mm increase

2100 compared to their 2000-levels of 370 ppm. The results indicate that there may be likely increases in the average annual mean, minimum and maximum temperatures throughout the region, though the temperature increases would be lower in the west of the region near the Caspian Sea, and according to some models, higher in the north of the region. Summers may become warmer, and winters colder. The projected median increase in temperature is estimated to be about 3.7°C on average by the end of the century, with most of the increase to occur during summers (de Pauw 2010). In general, the precipitation may increase in the region, with higher increases in the north of the region, and possibly, some very slight decreases in the south of the region. Spring and fall precipitations are likely to increase while summer precipitation to decrease. Wetter winters may be more frequent, as well as drier springs, summers and autumns. However, unlike the temperature projections there are big disagreements among different models on the direction and magnitudes of precipitation changes in the region. This uncertainty is also illustrated by downscaled climate change forecasts for precipitation in Central Asia in Nelson *et al*. (2010), who compare Commonwealth Scientific and Industrial Research Organization (CSIRO) model and Medium Resolution General Circulation (MIROC) model projections under A1B scenario by 2050 (Figures 2.20-2.21). The MIROC model predicts precipitation decreases in the south of the region and increases in the north of Central Asia. The CSIRO model, however, forecasts precipitation increases basically all over the region, except in north-western and eastern Kazakhstan.



Source: Nelson et al (2010)

Figure 2.20. Change in average annual precipitation, 2000–2050, MIROC, A1B (mm)



Source: Nelson et al (2010)

Figure 2.21. Change in average annual precipitation, 2000–2050, CSIRO, A1B (mm)

In general, all IPCC model predictions for Central Asia, especially concerning precipitation, should be regarded cautiously, because "due to the complex topography and the associated mesoscale weather systems of the high-altitude and arid areas, GCMs [Global Circulation Models] typically perform poorly over the region" (IPCC 2007).

According to the IPCC projections, warming could increase the water run-off in Central Asia for decades, or even centuries as suggested by Gupta *et al*. (2009). However, the seasonality of runoff may change, with more runoff in spring and less in summer (ibid). Moreover, Stulina (2008) indicates that forecasts of the flow of the Amudarya and Syrdarya Rivers strongly vary depending on the model. For example, under the Geophysical Fluid Dynamics Laboratory (GFDL) model of the United States' National Oceanic and Atmospheric Administration (NOAA), there may be 1% increase in the average flow of Syrdarya and no change in the flow of Amudarya by 2030. In contrast, using the Canada Climate Change Model (CCCM) may lead to predictions of significant decreases in the flow of both rivers, – 28% and - 40% for Syrdarya and Amudarya, respectively (ibid.).

All in all, the climate change forecasts for Central Asia indicate that temperatures may be rising all across the region. There is no consensus in precipitation and water run-off predictions.

Chapter 3

3. Effects of weather shocks on agricultural commodity prices in Central Asia

3.1. Introduction

Weather shocks are considered to be one of the important sources of variability in agricultural commodity prices (Gilbert and Morgan 2010). Although there is no evidence that weather shocks alone have played a major role in the food price spikes in 2008 (Headley and Fan 2008), it seems, however, that they have contributed to the price spikes in interaction with other factors (Mitchel 2008, von Braun and Tadesse 2012). Climate change is likely to increase weather variability and incidences of extreme events (IPCC 2011), potentially leading to growing impacts of weather shocks on agricultural and food prices (von Braun *et al*. 2008, Torero and von Braun 2010). This may have considerable influence on poverty levels and economic performances of developing countries dependent on agricultural and agro-food sectors, especially if they are net food importers. Most of the existing research on the impacts of weather shocks on agricultural prices studies earlier historic periods and there are only few studies covering more recent periods (Roll 1984; Solomou and Wu 1999; Burgess and Donaldson 2010; Fox, Fishback and Rhode 2011; Jolejole-Foreman and Mallory 2011). Arguably, this lack of research attention is perhaps influenced by the fact that modern farm management techniques and more globalized agricultural markets have noticeably reduced the impacts of weather shocks on agricultural prices, especially in developed countries. Even in developing countries, generally more vulnerable to weather shocks, a major research concern has been with market integration and price transmission effects *per se*, without specific attention to weather impacts. Climate change and related increases in the frequencies and magnitudes of weather shocks are likely to necessitate a paradigm shift towards increasing research efforts on the effects of weather shocks on agriculture and agricultural prices, especially in developing countries.

Therefore, the main purpose of the present study is to advance the current knowledge through three contributions. First, the agricultural price transmission is linked to specific weather variables such as temperature and precipitation, and availability of irrigation water. The previous literature on the interaction of weather shocks and agricultural prices did not link price transmission to specific marginal changes in these variables. Second, an innovative, yet straightforward, method of assessing the impacts of weather shocks on agricultural commodity prices is suggested exploiting the idiosyncratic components of variables in a long panel setting. This approach allows for disaggregating short-term shocks in prices from long-term trends, thus providing a theoretically consistent way to estimate the effect of weather shocks on agricultural prices. And third, a focused treatment of transmission of weather shocks on agricultural prices is provided by using more recent contemporaneous data. In spite of these contributions, the present research has certain limitations, the key among them being its inability to distinguish between varying responses of public and private stockholders to weather and price shocks due to data constraints. Data limitations also concern commodity stocks and prices, as they were not always available at the needed scales and frequencies.

3.2. Relevant Literature

The study of price dynamics in economic literature has been framed within two competing theories providing alternative explanations of price formation, namely: the cobweb model of adaptive expectations (Ezekiel 1938, Cochrane 1958, Nerlove 1958) and the rational expectations model (Muth 1961). The cobweb model posits that the prices are formed by endogenous factors, namely, forecasting errors. For example, in response to high prices of a particular crop farmers increase their production which leads to lower prices for this crop in the next period. Responding to these lower prices, farmers reduce their production of this crop in the second period, only to see the rising prices in the third period as a result of this supply reduction, and so on (Barré 2011). The second model assumes that economic agents rationally use all the available information and price dynamics are caused by exogenous factors, especially weather shocks (ibid.). These two approaches also differ in the solutions they propose for tackling price volatility. The rational expectations approach advocates methods that allow for spreading the risks among a larger number of economic agents such as insurance schemes, temporal and spatial arbitrage, including storage and free-trade policies. In contrast, the measures proposed by the cobweb approach for price stabilization usually involve production quotas and other Government interventions for managing the commodity supply within the country (Mitra and Boussard 2012).

Both models were extended over time to account for their shortcomings. Nerlove (1958) extended the original cobweb model developed by Ezekiel (1938) and suggested that economic agents form their price expectations based on both the current prices and also their forecasting errors made during the last periods, i.e. they try to learn from their mistakes. Later on, the model was extended to include risk aversion (Boussard 1996) and non-linear curves (Hommes 1994). In spite of these improvements, Deaton and Laroque (1996) point out that the cobweb model still cannot reconcile its predicted negative first order autocorrelation in prices with the empirical evidence showing positive autocorrelation (Barré 2011). The key implication of the rational expectations model is that economic agents do not make systematic forecasting errors. However, this would imply stationarity of price series around a steady state, which is against the empirical findings of non-stationarity of most commodity price series. To account for this shortcoming, Barré (2011) informs that competitive storage model was developed to explain positive autocorrelations in prices (Muth 1961), as well as their kurtosis and positive skewness (Deaton and Laroque 1992). Frankel (1986) extended the competitive storage model by adding the overshooting hypothesis, which links the price dynamics in the commodity markets to changes in the monetary policy. Deaton and Laroque (2003) showed that it is also possible to represent positive autocorrelation, skewness, and kurtosis of observed data series with a rational expectations model without competitive storage. Other major challenges in empirical estimations are non-linear components, structural breaks or regime shifts.

In this larger context, the strand of literature that considers the impact of weather shocks on prices is relatively thin. Roll (1984) finds that cold weather shocks in central Florida, where virtually the entire US orange production occurs, affect the futures prices of frozen concentrated orange juice, though cold weather shocks seem to explain only a small share of the futures price variation. Webb, von Braun and Yohannes (1992) find that the upward effect of droughts on food prices in Ethiopia during 1980s was strongly exacerbated by infrastructural and administrative constraints to spatial arbitrage. Solomou and Wu (2003), in their comparative study of the effects of weather shocks on agricultural prices in Britain and Germany between 1870 and 1913, conclude that weather shocks had larger impacts on the German economy, because Germany was more dependent on agriculture, and German agriculture was more protected than British agriculture operating under virtually free trade conditions. Similarly, using historic data on weather and crop prices for the US during 1895-1932 under “unfettered” agricultural commodity markets, Fox, Fishback and Rhode (2011) find that local weather did not have a significant effect on the prices of internationally traded crops, namely, cotton and wheat. However, weather shocks significantly influenced the prices of maize and hay, which were mostly locally consumed. Burgess and Donaldson

(2010) indicate that openness to trade and better transport infrastructures (construction of railroads) in colonial-era India lowered the vulnerability of agricultural prices and incomes to rainfall shocks, and also dramatically reduced the incidences of famines. Jolejole-Foreman and Mallory (2011) show that positive rainfall shocks are associated with higher margins between farm-gate and retail prices, and reduced imports of rice in the Philippines.

Efficient price transmission between spatially separated markets and unhindered opportunities for spatial arbitrage (law of one price) are believed to lead to more competitive markets and hence more efficient allocation of resources and long-run growth (Samuelson 1952, Takayama and Judge 1964). Better market integration can allow for mitigating the impacts of weather shocks on local agricultural prices. Market integration may also reduce the need for food self-sufficiency (Fafchamps 1992). Several factors such as trade barriers, subsidies, exchange rate policies, poor infrastructure and non-competitive market structure are believed to impede price transmission (Rapsomanikis, Hallam and Conforti 2003).

Methodologically, the early research on price transmission was based on examining bivariate correlation coefficients of prices in different markets, where high correlation coefficients were regarded as a sign of price transmission (Rapsomanikis, Hallam and Conforti 2003). Another widely used approach was regressing the prices on each other, where coefficients closer to unity would imply a stronger co-movement of the prices (Mundlak and Larson 1992). Ravallion (1986) suggested an improved approach which also incorporated price lags in the regression analysis thus enabling to segregate short- and long-term price transmission effects, and relaxing the assumption of instantaneous adjustments in different markets. Webb, von Braun and Yohannes (1992) have further nuanced the notion of price co-movements in different markets, in the example of food prices in Ethiopia, indicating that these co-movements could be caused by covariate weather shocks even in the absence of market integration. Non-stationarity of much of the time series data and invalid tests of statistical significance resulting from applying simple regression techniques led to the development of the Error Correction Model (Engle and Granger 1987), which were later advanced to the Vector Autoregressive Model (VAR) and the Vector Error Correction Model (VECM). Non-linear aspects of price adjustments led to development of the Asymmetric Error Correction Model (Granger and Lee 1989) and threshold co-integration models (Enders and Granger 1998). Von Cramon-Taubadel (1998) applied the cointegration methods to testing for asymmetric price transmission, thus accounting for non-stationarity of price time series. Von Cramon-Taubadel and Meyer (2003) also highlight the importance of the level of aggregation in price series while testing for asymmetric transmission. In their analysis of retail and wholesale prices of chicken and lettuce in Germany, Taubadel and Meyer (2003) use weekly individual store prices and average retail prices during 1995-2000 and find that the individual store data reveals asymmetric price transmission, whereas the aggregated average retail price series do not show any sign of asymmetry. Relatively more recently, switching regime models and dynamic panel causality models were applied to test for price transmission.

3.3. Conceptual Framework

The theoretical model follows the rational expectations approach to price transmission which assumes that exogenous shocks, such as weather shocks, are potentially important determinants of price dynamics. Spatial and temporal arbitrages are expected to smoothen the effects of weather shocks on prices by stabilizing the supply of agricultural commodities and also calming down exuberant price expectations. However, storage may also result from hoarding behavior, especially in less developed markets, in which case, storage may actually play a destabilizing role on prices (von Braun and Tadesse 2012).

In general, factors affecting price dynamics can be classified into short- and long-term. Long-term factors include income levels, changes in tastes and preferences, technological change, population growth, and other similar trend-setting variables. Short-term factors are idiosyncratic shocks around the long-term trend. Extreme weather events are a major example of these idiosyncratic shocks. The extent by which short-term idiosyncratic shocks affect agricultural commodity prices depends on the institutional setting made up of national policies on trade, exchange rate, market structure, net food trading position of the country, amount of commodity stocks at the time of the shock and others. Weather shocks can affect crop prices through impacting their supply and by changing people’s perceptions and expectations about the future price dynamics, which is reflected through their storage decisions.

Time series can be decomposed into trend, seasonal, cyclical, and idiosyncratic components using unobserved-components method (Harvey 1989). This decomposition method can be usefully exploited in the current analysis. Weather shocks are expected to have random distribution and their effects on agricultural prices are only short-term. Although there are studies demonstrating that the effects of weather shocks on agricultural price volatility could potentially lead to long-term effects, for example, on children's health in poor countries (Jensen 2000), it may be safe to accept that weather shocks do not have permanent long-term effects on agricultural prices *per se*. Consequently, the effects of weather shocks on agricultural prices are fully captured by the idiosyncratic components of agricultural price series. Weather shocks themselves represent the idiosyncratic components of specific weather variables such as temperature and precipitation. Long-term factors affecting the prices such as income levels and population growth; or climate change in the case of the weather variables, are captured by the trend component of the time series. Hence, a straightforward way of assessing the effects of weather shocks on agricultural prices would be to decompose the variables in the model into their latent components, and look into only the idiosyncratic components of the variables in the regression analysis.

The analysis of weather impacts on agricultural prices using the panel data whose both cross-sectional and time dimensions are quite long (T-132 and N-38) effectively precludes from applying the conventional workhorse methods of price analysis such as VAR or VECM, but may necessitate the use of methods from the newly developing field of panel cointegration to account for potential non-stationarity aspects of very long panel data. The proposed approach is based on the idiosyncratic components of individual time series and hence the analysis is greatly simplified since the idiosyncratic components are by definition stationary and can be effectively tackled by simpler and time-proven panel regression techniques.

The conceptual approach is summarized in Figure 3.1. All the variables are represented by their idiosyncratic components. The conceptual framework schematically represents the following functional relationships between the employed variables of interest.

$$Y = f(T, R, Ir, E, In, P_{int}, d) \tag{3.1}$$

$$S = f(T, R, Ir, E, In, P_{int}, d) \tag{3.2}$$

$$P = f(\hat{Y}, \hat{S}, E, In, P_{int}, d) \tag{3.3}$$

where,

Y – shocks, or deviations from trend, in wheat or potato yields

S – shocks in commodity stocks

P – provincial prices for potato or wheat

T- shocks in mean monthly temperature

R- shocks in monthly accumulated rainfall amounts

Ir- shocks in the availability of irrigation water

E – shocks in national exchange rate

In - province level inflation rates

d – dummies standing for other country and time-specific unobserved shocks

$\hat{Y}$, $\hat{S}$ – fitted values for yield and stock shocks from the first stage of the model

Throughout this chapter, the shocks are defined as deviations from trend in the variables. For example, mean temperature in a specific month could be 2°C higher than what is otherwise expected based on the temperature trend. In the analysis this is considered as positive shock of 2°C, where the term "positive" is used in its strictly mathematical meaning, i.e. more than zero, without any normative connotations.

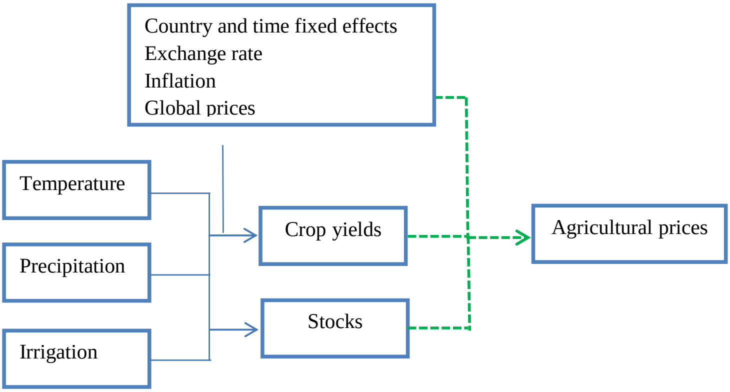


Figure 3.1. The conceptual framework of effects of weather shocks on agricultural prices

Note: The first stage of the regression is depicted with connected lines, while the second stage with dashed lines.

This approach at evaluating weather shocks as deviations from trend rather than deviations from the mean is based on the assumption that economic agents continuously update their cognitive perceptions so that their actions are shaped by changing trends in climate rather than long-term mean climate values which could become no longer relevant for their decision-making, especially in the context of accelerated climate change.

In the first stage of the analysis, the effects of shocks in temperature, precipitation and availability of irrigation water on yield and commodity stock shocks are estimated. The regression model also controls for the concurrent shocks in inflation, exchange rate, the international price for the corresponding agricultural commodity and for other unobserved time and country-specific idiosyncratic shocks that may have influence on stocking and production decisions.

Weather shocks could influence agricultural prices through two channels: i) through influencing expectations about the future prices, which gets reflected through stocking decisions, ii) through directly impacting the yields and hence the production of agricultural commodities.

The first channel, which can be called as expectations link, operates through both private and public decisions on stock holdings for the affected commodity. Both private and public agents utilize all the available information in their decision making process. In this regard, when confronted with weather shocks and their potential effects on future supply of agricultural commodities, economic agents respond to these shocks by adjusting their storage decisions. If a negative weather shock happens, for example, drier than usual weather or outright drought in the rainfed areas, private economic agents, seeking to maximize their profits, would expect a lower future harvest and thus future higher prices, which would lead them, *ceteris paribus*, to increase stocks, or at minimum, decelerate their destocking levels – which would put an upward pressure on the prices. On the other hand, the public agent's (i.e. Government) major political interest involves maintaining stable and affordable prices. Any upward movement in the prices that would be deemed excessive would result on releases from public stocks to bring the prices down. The final outcome would depend on the interaction between the private and public stockholders (Jayne and Tschirley 2009). Due to limitations on the availability of separate data on public and private stockholdings, the current analysis could not distinguish between these two types of stockholdings, but traces only the effects of weather shocks on aggregate stock levels.

In addition to the expectation link, there is also a direct production link between weather shocks and commodity prices through the effect of weather shocks on crop yields. Higher than usual rainfall amounts in rainfed areas (positive shocks), for example, could lead to bumper harvests thus increasing the supply of agricultural commodities, and potentially leading to lower prices.

The weather variables and availability of irrigation water are entered into the regression models both in their levels and also in quadratic forms to capture potential nonlinearities. A little bit more of rain could be beneficial for crop production, but if there is too much rain it may retard field operations, may lead to occurrence of plant diseases, such as yellow rust in Central Asia, may cause floods and landslides in hilly areas, etc. A full set of interactions between temperature, precipitation and availability of irrigation water is also included in the first stage estimation to account for their joint effects. The first stage of the regression also accounts for the effects of idiosyncratic shocks in exchange rate, inflation, the international price for the commodity and other unobserved time- and country- specific shocks, since they may also have influence on the stocking and production decisions, and their omission will bias the coefficient estimates (Baltagi 2002). For example, the Central Asian countries pursue various and numerous policies on import and export tariffs for agricultural commodities, on stabilizing domestic prices for key staple foods through stocks, production quotas, trading permits, etc – which the model does not capture explicitly, but strives to account for the effect of these factors implicitly through the inclusion of time- and country-specific dummy variables.

The second stage of the model has wheat and potato prices as dependent variables, and looks into how the latter are impacted by the fitted values of shocks in stocks and commodity yields, shocks in the global prices for the commodity, exchange rates and inflation. For tradable commodities, such as wheat, international price fluctuations are important factors in determining the domestic prices, especially in small open economies. For this reason, the shocks in the global prices of commodities are included to capture the effect of exogenous price shocks on commodity prices inside the country. Sensitivity of internal prices to changes in global prices also shows the level of integration between domestic and international markets, as well as the extent of national barriers for price transmission such as price controls, subsidies and other kinds of government interventions. In addition to external shocks, the model also needs to account for internal macroeconomic shocks that may affect prices. Consequently, it also includes exchange rate and inflation fluctuations. The devaluation of the local currency against the US dollar decreases the local commodity prices in dollar terms if the major part of the national supply of that commodity is produced inside the country. However, devaluation would increase the prices of commodities if they are mainly imported from outside. Regarding inflation, including the current levels of the inflation directly into the model may create endogeneity problem between the dependent variable – commodity price, and inflation as the explanatory variable, as commodity prices may actually drive the inflation dynamics. This is true especially in the case of food commodities in the poor countries, where food constitutes a major portion of aggregate consumer demand. To avoid this potential endogeneity problem, the lagged values of inflation are included in the model. The relationship between stocks and commodity prices, between commodity prices and yield shocks may also be endogenous. The use of the two stage model provides with a key advantage of instrumentalizing these endogeneities by using fitted values of stocks and yield shocks conditioned on weather and other variables. Following Roberts and Schlenker (2009) the model includes the interaction of stock and yield shocks in order to capture any possible joint effects. It is expected that that larger stocks, bumper harvests and their interaction terms are negatively associated with commodity prices. The model also includes country and time dummies to account for the effect of directly unobserved country- and time-specific idiosyncratic shocks. Finally, in both stages of the estimation, the lag structure of all the explanatory variables is considered, where the selection of the number of lags is guided by Akaike Information Criterion (Akaike 1974).

3.4. Econometric strategy

The empirical estimation consists of three steps. First, all variables in the model are decomposed into their idiosyncratic components. Secondly, the idiosyncratic components are tested for the presence of unit root to make sure that the series are stationary and linear panel regression methods can, thus, be used. Finally, the parameters are estimated using Feasible Generalized Least Squares (FGLS) panel regression.

To decompose variables into their latent components by separating trend, cyclical, seasonal and idiosyncratic components, the unobserved-components model (UCM) approach is applied. The general form of the UCM is written as:

$$T_t = \alpha_t + \beta_t + \phi_t + \delta X_t + \epsilon_t \tag{3.4}$$

where, T_t, is the dependent variable, α_t represents the trend, β_t seasonal component, ϕ_t cyclical component, δ regression parameters for exogenous variables X_t, and ϵ_t idiosyncratic components. UCM does not have to have all these specified elements at the same time. Following Harvey (1989), the time series data are modeled as random walk. Separate unobserved components regressions are run for each of the variables in each of the cross-sectional units, i.e. provinces, and then the idiosyncratic components of these variables are collected for further analysis.

The second step in the analysis is to test the idiosyncratic components for the presence of unit root to make sure that the series are stationary. For this purpose, the recent developments in panel unit root tests are availed of. These methods allow for better handling of the cross-sectional dependencies and serial autocorrelations obviously present in spatial distribution of weather events and regional price dynamics. In addition, the use of panel approach in testing for the unit root, as compared to separate pure time-series based unit root tests, provides with a larger number of observations, thus increasing the degrees of freedom (Yetkiner and Erdil 2004). There are several methods of panel unit root tests. They can be broadly classified into two categories: those which account for cross-sectional dependence and those which do not. Such test as those developed by Choi (2002), Pesaran (2003), Bai and Ng (2004), Chang (2002, 2004), Moon and Perron (2004) are in the first category, and those developed by Maddala and Wu (1999); Breitung (2000), Hadri (2000), Choi (2001), Levin, Lin and Chu (2002) and Im, Pesaran and Shin (2003) are in the second category (Barbieri 2010). To be able to choose the right unit root test, the panels are first tested for cross-sectional dependence using the test developed by Pesaran (2004). After having identified the presence of cross-sectional dependence in the panels, testing for panel unit is conducted by accounting for cross-sectional dependence. Specifically, the Pesaran panel unit root test in the presence of cross-sectional dependence is applied (Pesaran 2003).

The final step involves estimating the model described earlier in the conceptual framework using FGLS panel regression. Econometrically, the first and second stages of the model are specified as follows (with appropriate lags):

1rst Stage:

$$Y = T + T^2 + R + R^2 + Ir + Ir^2 + T{**}R{**}Ir + T^2{**}R^2{**}Ir^2 + E + In + P_{int} + d \quad (3.5)$$

$$S = T + T^2 + R + R^2 + Ir + Ir^2 + T{**}R{**}Ir + T^2{**}R^2{**}Ir^2 + E + In + P_{int} + d \quad (3.6)$$

2nd Stage:

$$P = E + In + P_{int} + \hat{Y} + \hat{S} + \hat{Y}^2 + \hat{S}^2 + \hat{Y}*\hat{S} + \hat{Y}^2*\hat{S}^2 + d \qquad (3.7)$$

where,

Y – shocks, or deviations from trend, in wheat or potato yields
S – shocks in commodity stocks
P – provincial prices for potato or wheat
T- shocks in mean monthly temperature
R- shocks in monthly accumulated rainfall amounts
Ir- shocks in the availability of irrigation water
E – shocks in national exchange rate
In - province level inflation rates
d – dummies standing for other country and time-specific unobserved shocks
$\hat{Y}, \hat{S}$ – fitted values for yield and stock shocks from the first stage of the model

The choice of the FGLS panel regression method is based on its several advantages. As we shall see further, decomposition of the variables into their idiosyncratic components, in addition to being theoretically sensible approach in this context, also resolves the issue of non-stationarity in the variables, since idiosyncratic shocks are expected to be stationary. However, there still remain several problems in the data series for which the estimation approach employed should account for. These problems are dependence in the cross-sectional units, autocorrelation and heteroscedasticity. Feasible generalized least squares approach is the technique that is capable of adequately handling all these remaining problems, which motivates the choice of the technique for the empirical estimation.

Idiosyncratic components of the variables can have positive or negative signs, signifying that fluctuations in the variables are either above or below the expected trend lines, respectively. When using squared terms or interactions of the variables, unless due care is taken, multiplication results could artificially change the sign in the squared variables or interactions. Addressing this issue is quite straightforward for quadratic terms: all what is needed to do is to specify that squared terms should be of the same sign as the levels being squared. However, it is more complicated to adequately handle the signs in the interactions, since one variable may have a positive sign whereas the other may have a negative sign. To account for this situation, before interacting the variables, i.e. multiplying them, I added to the variables being interacted a number sufficiently large to bring the entire distribution above zero while keeping the relative magnitudes of the numbers exactly the same. For example, the lowest number in the precipitation shocks was -91.4, while in the temperature shocks the lowest number was -9.89, so + 91.5 was added to the precipitation variable and + 9.9 to the temperature variable to bring the entire distributions above zero, so that when interacting these two variables, there is no problem with changing signs. In other words, the intercept of the distribution was shifted, without any change in the slope of the distribution. This data treatment procedure was used specifically for creating the interacting variables; the variables themselves enter the regressions in their original values. This procedure will ultimately have some effect on the constant term in the regression models, but in no way would bias the coefficient estimates. However, if no care is taken to address the artificial sign change while interacting the variables, the coefficient estimates will be biased.

3.5. Data

The dataset used consists of monthly panel variables for the 38 provinces in Central Asia for the period of 10 years between 2000-2010 as described in detail in Table 3.1 below.

Table 3.1. Information on the variables used in the analysis

Variables	Sources	Notes
Wheat and potato prices	National Statistical Committees, local non-governmental organizations, price sections of various local newspapers, as well as the international databases such as FAO´s Global Information and Early Warning System (GIEWS).	Converted to US Dollar using the average exchange rate for the corresponding month
Global wheat prices	Index Mundi online database (www.indexmundi.com). Original source: United States Department of Agriculture (USDA) Market News	Wheat, No.1 Hard Red Winter, ordinary protein, FOB Gulf of Mexico, in USD Dollars per metric ton
Global potato prices	National Statistics Committee	Potato is not a globally traded commodity.

Variables	Sources	Notes
	of Kazakhstan	Russia is an obvious candidate for potato trading for Central Asian countries because it is one of the leading potato producers in the world, and the most accessible country in terms of transport infrastructure and common customs procedures. So the monthly prices for potato in Kurgan, the center for Kurgan province of Russia, bordering with Kazakhstan is used as the international price for potato. The prices were originally available in USD.
Exchange rates	National central banks as well as international online databases such as www.oanda.com.	National level exchange rates were assumed to be the same for all provinces within the country
Inflation rates	National central banks, national statistics agencies	Province-specific Consumer Price Index (CPI) was used. Whenever province-level CIP was not available, national CPI was used.
Weather variables	Williams and Konovalov (2008), NASA´s Global Summary of the Day, national hydro-meteorological services and other online sources such as www.rp5.uz and its sister websites for each country of Central Asia	Monthly mean temperature and total accumulated monthly rainfall. From about 400 weather stations across Central Asia. Mean monthly temperature and total monthly rainfall data from individual weather stations were spatially projected to the digital map of Central Asia using spatial interpolation technique of inverse weighted distance. Following this, the pixel-level weather variables were averaged for each province. However, before the spatial interpolation, all the weather stations located at 1000 meters above the sea level were removed from the dataset to avoid potential bias in the analysis that may be caused by high-altitude weather stations located in areas with little or no agricultural production and population settlement. However, in cases where the entire region is located in high mountain altitude areas, specifically the Gordo-Badahshan Autonomous province of

Variables	Sources	Notes
		Tajikistan, all the weather stations were kept.
Monthly amount of available irrigation water	Scientific-Information Center of the Interstate Coordination Water Commission of the Central Asia (SIC ICWC) available at http://www.cawater-info.net and the reports of national water management authorities	For some provinces of Kazakhstan with overwhelmingly rainfed agriculture, there were data only on annual amounts of irrigation water applied. These annual amounts were disaggregated into monthly using within month distribution of available irrigation water in the neighboring provinces for the corresponding year.
Wheat and potato stocks	National statistical agencies as well as international databases, such as FAOSTAT	The data on stocks was not always available in monthly frequencies at provincial level. In some cases it was available only at national level on annual basis. To correct for this discrepancy, the annual data disaggregated into monthly frequencies using the intra-monthly distribution of stocks from the other years when monthly data were available or from neighboring countries with similar cropping calendar, farming systems, and net trading position, and the share of the province in the production of wheat and potato was used as the weight to calculate the provincial share of the stocks.
Yield shocks	National statistical agencies	The annual wheat and potato yield series were decomposed into their idiosyncratic components. The corresponding values of these annual idiosyncratic shocks in crop yields were assigned to all the months of the same cropping year. In applying this procedure, it was assumed that crop yields at the point of harvest are influenced by all previous events that have taken place throughout the immediate cropping year.

Although this dataset is the first such a relatively rich and detailed long-term monthly dataset available for Central Asian countries, it has limitations and contains gaps, primarily in the stock and price variables. Therefore, in cases of provinces where there were missing points in any of these variable series, the missing data were imputed using the fitted values from the OLS regressions involving the variables for the neighboring provinces for which these data were available. There were fewer number of gaps in the available price series for the provinces of Kazakhstan, Tajikistan and Kyrgyzstan, while more gaps were in the price data for the provinces of Uzbekistan. The major underlying assumption behind the applied imputation method for missing data is the existence of strong price co-movement between the neighboring provinces. This seems to be a valid assumption, especially in the case of Uzbekistan where differences in agricultural prices within the provinces inside the country are small (Grafe *et al.* 2005). This conclusion is also corroborated by my own analysis of a separate dataset of retail prices for major 24 agricultural commodities between 2009-2010 in Uzbekistan. The average provincial cross-correlations in retail prices for these 24 agricultural commodities range between 0.81-0.98, and are reported in Table 3.2. Moreover, there is some evidence that the level of integration in agricultural consumer prices among the countries of Central Asia is also high (ibid.). As with most available cereal stock data (Wiggins and Keats 2010), there may be unknown measurement errors in the stock variables, especially in terms of accurately estimating the extent of private stocks in the country. Importantly, the available data, unfortunately, does not allow for separating private and public stocks in order to econometrically account for differing aspects in the behavior of public and private stockholders, thus constituting a limitation of this study.

Table 3.2. Average cross-correlations of major 24 agricultural commodities among the provinces of Uzbekistan between January, 2009 and January, 2010*.

Provinces	Kar	And	Buh	Jiz	Qash	Nav	Nam	Sam	Sur	Sir	Tosh	Far	Hor
Karakalpakstan	1.00												
Andijon	0.88	1.00											
Buhoro	0.88	0.95	1.00										
Jizzah	0.83	0.92	0.89	1.00									
Qashkadaryo	0.84	0.96	0.96	0.88	1.00								
Navoi	0.91	0.96	0.95	0.86	0.96	1.00							
Namangan	0.86	0.98	0.96	0.91	0.95	0.93	1.00						
Samarqand	0.83	0.95	0.96	0.92	0.98	0.93	0.95	1.00					
Surhandaryo	0.83	0.95	0.97	0.90	0.97	0.93	0.95	0.97	1.00				
Sirdaryo	0.83	0.98	0.95	0.92	0.96	0.94	0.98	0.97	0.97	1.00			
Toshkent	0.81	0.96	0.95	0.92	0.96	0.92	0.97	0.97	0.96	0.98	1.00		
Farg'ona	0.87	0.98	0.96	0.93	0.97	0.95	0.98	0.97	0.97	0.98	0.97	1.00	
Horazm	0.88	0.93	0.96	0.94	0.93	0.93	0.94	0.95	0.96	0.94	0.94	0.96	1.00

* The names of the provinces are abbreviated in the top row to fit the table into the page. The sequence of the provinces in the top row is the same is in the leftmost column.

In spite of all these actual and potential data limitations, it is believed that the results presented below can adequately serve as first, even if rough, estimates of the effects of specific temperature, precipitation and irrigation water availability shocks on agricultural prices, in the example of Central Asia. Crucially, the suggested new estimation method could be fruitfully used in future work involving less constraining datasets.

3.6. Results and Discussion

Following the first step of the empirical approach, the time series are decomposed into their latent components. Figure 3.2 shows an instance of this decomposition in the example of wheat prices in Akmola province of Kazakhstan. All other variables for the remaining provinces in Central Asia are also similarly decomposed. Following this preparatory stage, the idiosyncratic components of the variables are tested for cross-sectional dependence (Table 3.3). The Pesaran test (Pesaran 2004) strongly rejects cross-sectional independence for all variables (Table 3.3), with p-values significant at less than 1%. The higher is the test statistic (CD-statistic), more strongly the panels are correlated. Similarly, the columns "corr" and "abs(corr)" show the estimated strength of the cross-sectional correlation. The test has shown that idiosyncratic shocks in the variables are correlated across the countries of Central Asia. Further, for checking the presence of unit root the Pesaran panel unit root test in presence of cross sectional dependence is employed (Pesaran 2003).

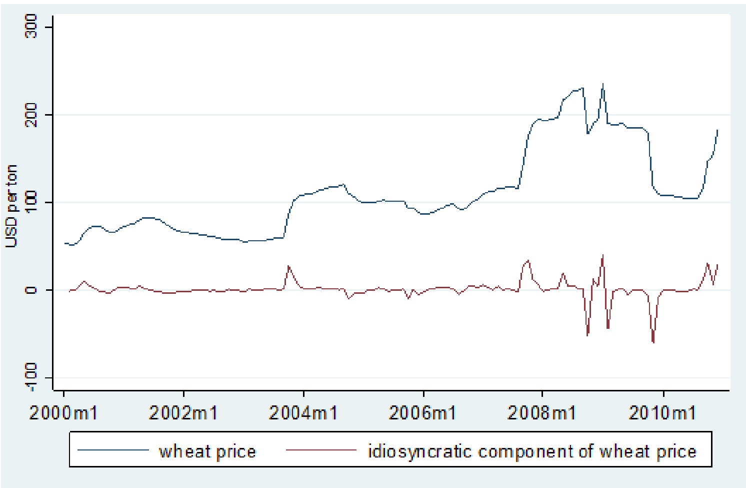


Figure 3.2. Decomposition of wheat price series into idiosyncratic components, Akmola province, Kazakhstan

Table 3.3. Pesaran test for cross-sectional dependence

Variable	CD-statistic	p-value	corr	abs(corr)
Wheat price	77.61	0.000	0.255	0.349
Potato price	77.87	0.000	0.256	0.272
Precipitation	76.34	0.000	0.251	0.268
Temperature	168.99	0.000	0.555	0.555
Irrigation water	99.23	0.000	0.326	0.343
Wheat stocks	172.09	0.000	0.565	0.567
Potato stocks	262.26	0.000	0.861	0.861
Inflation rate	117.53	0.000	0.386	0.386
Exchange rate	118.11	0.000	0.388	0.388

The test confirms that the idiosyncratic parts of the variables are stationary (Table 3.4). The important references to look in the table are the p-values. Selection of the right number of lags can be crucial for the unit root tests. The stationarity tests were run with up to 12 lags and in all cases the presence of unit root was rejected at less than 1%. In Table 3.4, the results of the unit root test based on two lags are presented.

Table 3.4. Pesaran panel unit root test in presence of cross sectional dependence

Variables	t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
Wheat price	-6.0	-2.1	-2.1	-2.2	-28.5	0.000
Potato price	-6.2	-2.1	-2.1	-2.2	-29.7	0.000
Precipitation	-5.9	-2.1	-2.1	-2.2	-27.6	0.000
Temperature	-5.2	-2.1	-2.1	-2.2	-23.2	0.000
Irrigation water	-6.2	-2.1	-2.1	-2.2	-29.8	0.000
Wheat stocks	-6.1	-2.1	-2.1	-2.2	-29.4	0.000
Potato stocks	-6.2	-2.1	-2.1	-2.2	-29.8	0.000
Inflation rate	-6.2	-2.1	-2.1	-2.2	-29.8	0.000
Exchange rate	-5.1	-2.1	-2.1	-2.2	-22.3	0.000

Note: 2 lags.

The tests confirm the theoretical hypothesis that idiosyncratic components of the variables are stationary. Thus, although non-stationarity is no longer a problem, there can be still other issues related with cross-sectional dependence, serial correlation and heteroscedasticity. The Pesaran test for cross-sectional dependence carried out earlier has also confirmed the presence of cross-sectional correlation in the dataset. Moreover, Wooldridge test for autocorrelation in panel data (Wooldridge, 2002) and Likelihood ratio test for heteroscedasticity after FGLS confirm the presence of autocorrelation and heteroscedasticity in both wheat and potato models both at the first and second stages of the estimation. Based on these characteristics of the dataset, the feasible generalized least squares (FGLS) is adopted as the estimation method.

The first stage regression results using FGLS are presented in Table 3.5. They indicate that weather variables and availability of irrigation water may play a statistically significant role in storage decisions and yield shocks.

Shocks in temperature, precipitation and irrigation seem to have a convex relationship with shocks in wheat stocks. Higher than usual temperature and precipitation amounts, better than usual water availability could lead to expectations of higher wheat yields and lower future wheat price and thus provide incentives for lowering wheat stocks. This is also confirmed by statistically significant positive association between positive shocks in wheat yields (i.e., higher than usual wheat yields) and higher temperatures, precipitation and water availability. On the same token, lower water availability could encourage aggressive stock accumulation against expected supply shortfalls. Several interactions of temperature, precipitation and irrigation water availability are also statistically significant; however, mostly they are somewhat ambiguous. For example, the interactions generally have convex relationship with yield shocks when two variables such as temperature and precipitation, temperature and irrigation, and precipitation and irrigation are interacted. However, the relationship is concave when all three are interacted. In general, signs of the interactions in nonlinear models are strongly influenced by the nonlinearities in the model and should be taken with caution (Ai and Norton 2003). Shocks in international wheat prices did not have a statistically significant effect on stock dynamics, however, they are positively associated with yield shocks, signifying that wheat producers may be responding to the changes in the international prices by modifying their production decisions, for example by applying more fertilizers when the prices go up. Kazakhstan is the only Central Asian country which may be considered as non-small supplier of wheat to the international market. Even allowing for this, the endogeneity between regional wheat yield shocks and international prices is unlikely to be a problem since under endogenous relationship the association between regional yield shocks and international prices should be negative and not positive as in the regression model. The exchange rate's impact on wheat stocks is ambiguous since the signs of the coefficients change with lags; however, it seems shocks in exchange rate seem to be positively correlated with yield shocks. Structurally, the link between exchange rate shocks and yield shocks passes through expected prices for exported output and changing prices for imported inputs, such as fertilizers and other chemicals.

In the case of potato, they key variable determining stock levels seem to be international prices for potato, whose coefficient signs are negative signifying that higher international prices for potato may lead to lower stocks of potato in the region. Since the potato prices in a neighboring province of Russia are taken as international potato prices, this signifies that higher prices for potato in Russia may be providing with incentives to export the potato instead of holding it in stock in the region. Weather variables have basically no significant effects on potato stocks. However, irrigation availability, precipitation and temperature have statistically significant convex effects on potato yield shocks. While the effects of the interactions in the weather variables on potato yield shocks are opposite of their effects on wheat yield shocks: generally concave when two variables such as temperature and precipitation, temperature and irrigation, and precipitation and irrigation are interacted, but convex when all the three are interacted.

One possible explanation for negative association with higher water availability and lower potato yields could be that potato is mainly grown in mountainous and higher-altitude areas of the region, thus higher water availability and excessive rainfall could imply higher incidences of flooding in these areas leading to lower potato yields. Another explanation, being located in high altitude areas, potato producers have "preferential" access to water resources and tend to over-irrigate, especially during periods with high water availability. Over-irrigation has been shown to reduce potato yields (for example, Stark *et al*. 1993).

Table 3.5. First stage of the model: impact of weather and other variables on yields and stocks (* p<0.01, ** p<0.05, * p<0.1)**

VARIABLES	Potato yield shocks	Potato stocks (log)	Wheat stocks (log)	Wheat yield shocks
International price for the commodity				
Level	2.95E-05	-0.000608***	0.000665	0.000121**
Lag 1	6.41E-05	-0.000236**	0.000396	4.71E-05
Lag 2	1.76E-05	-0.000201**	-0.000524	0.000110**
Inflation				
Level	0.00054	0.00697**	0.00777***	-4.05E-05
Lag 1	-0.00239	0.00514	0.00321	-0.000168
Lag 2	-0.00224	0.00351	0.000756	0.000272
Exchange rate				
Level	0.00101	-0.00159	-0.00320*	0.000894***
Lag 1	0.000946	0.000716	0.00504**	0.000602***
Lag 2	0.0015	0.000799	-0.00177	0.000447**
Temperature				
Level	-0.0838***	0.00376	0.00929	0.0219***

VARIABLES	Potato yield shocks	Potato stocks (log)	Wheat stocks (log)	Wheat yield shocks
Lag 1	-0.0209	0.00168	-0.0113	0.0111***
Lag 2	0.00954	-4.03E-05	-0.0529***	0.00195
Precipitation				
Level	-0.0173***	0.000312	0.00315*	0.00157***
Lag 1	-0.00357	0.000334	-0.00148	0.000351
Lag 2	0.000716	5.39E-05	-0.00594***	-0.00043
Irrigation (log)				
Level	-0.0764***	-0.0043	0.0206	0.0231***
Lag 1	-0.00281	-0.00572	-0.0141	0.0122***
Lag 2	0.0113	-0.00739	-0.0357**	0.00317
Temperature, squared				
Level	0.00158***	-7.38E-05	0.00296***	0.000372***
Lag 1	0.000537	3.54E-05	0.000693***	5.14E-05
Lag 2	-0.000347	0.000114	0.000470**	-1.13E-05
Precipitation, squared				
Level	1.07e-05**	-6.24E-09	1.42E-06	-7.28E-07
Lag 1	8.61e-06*	8.78E-08	1.20E-06	-9.29E-07
Lag 2	-9.48E-08	-1.74E-07	2.52E-06	-8.59E-07
Irrigation (log), squared				
Level	-0.00262***	0.00114***	0.000741**	0.000170***
Lag 1	-0.00290***	0.000733**	0.000650**	0.000212***
Lag 2	-0.00141***	0.000443	-0.000471	0.000251***
Interactions				
Temperature and precipitation				
Level	0.00160***	-2.16E-05	-3.44E-05	-0.000138***
Lag 1	0.000587*	-3.89E-05	0.000172	-1.69E-05
Lag 2	7.01E-05	-3.22E-05	0.000641***	4.16E-05
Irrigation and temperature				
Level	0.00752***	-0.000511	-0.000654	-0.00313***
Lag 1	0.00364	1.04E-05	0.0015	-0.00189***
Lag 2	0.000879	0.000252	0.00470***	-0.000711**
Irrigation and precipitation				
Level	0.00203***	-5.74E-05	-0.000345**	-0.000232***
Lag 1	0.000847***	-1.96E-05	7.71E-05	-0.000130***
Lag 2	0.000255	1.98E-05	0.000384**	-4.88E-05
Temperature, precipitation and irrigation				
Level	-0.000195***	5.96E-06	2.64e-05*	2.17e-05***
Lag 1	-0.000101***	3.79E-06	-6.66E-06	1.14e-05***
Lag 2	-3.34E-05	9.49E-07	-4.67e-05***	3.96E-06
Temperature and precipitation, squared				
Level	2.10e-07***	-9.39E-09	-1.09e-07***	-3.12e-08***
Lag 1	1.74e-07***	-1.92E-09	-4.07e-08**	-2.89e-08***
Lag 2	9.07e-08***	3.66E-09	-3.63e-08**	-1.96e-08***
Irrigation and temperature, squared				
Level	6.65e-06***	-1.07E-07	-5.88e-06***	3.00e-06***
Lag 1	1.62E-06	-8.48E-07	-3.45e-06***	2.09e-06***

VARIABLES	Potato yield shocks	Potato stocks (log)	Wheat stocks (log)	Wheat yield shocks
Lag 2	-2.66E-07	-8.09E-07	-2.21e-06**	8.66e-07***
Irrigation and precipitation, squared				
Level	-2.15e-07***	5.15E-09	4.86E-09	3.28e-08***
Lag 1	-2.11e-07***	-4.80E-09	2.44E-08	3.16e-08***
Lag 2	-1.11e-07***	-7.02E-09	4.99e-08**	2.71e-08***
Temperature, precipitation and irrigation, squared				
Level	4.19e-10***	0	0	-6.93e-11***
Lag 1	4.66e-10***	0	-5.34E-11	-6.20e-11***
Lag 2	2.48e-10***	0	-7.69e-11*	-5.41e-11***
Country and time- effects	**yes**	**yes**	**yes**	**yes**
Constant	**-3.368*****	**0.102**	**-0.912**	**0.698*****
Observations	**4,940**	**4,940**	**4,940**	**4,940**
Number of panel	**38**	**38**	**38**	**38**

After collecting fitted values of shocks in stocks and yields for potato and wheat, which allows for instrumentalizing against potential endogeneity between wheat stocks and prices, yield shocks and prices, and also trace the link with weather variables, wheat and potato prices are regressed on these fitted values, shocks in international prices for these commodities, in exchange and inflation rates. Country and time-specific effects are also included to account for unobserved shocks during the period. The results of the second stage are given in Table 3.6.

The results indicate that wheat and potato markets, as a whole, in Central Asia are affected by shocks in the international prices for the respective commodities. There is about 0.11 USD of contemporaneous price transmission to local prices for every 1 USD of price shock in the international potato and wheat prices. Similarly, lagged price transmission is also statistically significant with 0.08 USD and 0.09 USD for every 1 USD price increase for wheat and potato in the preceding month, respectively.

The effect of inflation on prices is positively signed on both level and lag; both for potato and wheat. Potato prices seem to be more sensitive to inflationary pressures (less “sticky”) than wheat prices, which may indicate that Government policies target price controls on wheat as a socially more important commodity. Exchange rate devaluation is negatively associated with local wheat prices, both in current and lagged forms, whereas for potato prices, although the association is negative in the current level, it becomes positive in the lagged form. Upward shocks in exchange rates make current local wheat and potato prices denominated in local currency cheaper in USD terms. For potato, however, during the next period prices tend to rise. This is perhaps for two reasons: cheaper local prices make it more profitable to export potato abroad or less profitable to import from abroad, thus in both cases reducing local supply. Wheat export and import are strongly regulated and usually conducted by the Governments themselves in Central Asia through their specialized agencies, whereas potato trading is conducted virtually without any barriers by individual entities. Secondly, upward exchange shocks increase prices of imported goods, including inputs, etc, thereby leading to higher prices for potato in the following periods. Inputs for wheat production to some extent are subsidized in virtually all countries of the region. Shocks in stock levels and crop yields have statistically significant effects on commodity prices. If for wheat current and lagged positive shocks in stocks and crop yields lead to price decreases, for potato the situation is more ambiguous as the signs change with lags. The effect of positive shocks in wheat stocks and wheat yields on wheat prices is convex, as the squared terms are also statistically significant and are positively signed. The interactions of yield and stocks shocks are significant for both potato and wheat, however, the signs of interactions are opposite to the signs of individual variables, but similar to the signs of their quadratic terms, implying that interaction of stock and yield shocks moderates any dynamic effects of the individual variables on the prices. The relationship between potato stocks, potato yield shocks and prices may point at imperfections in the potato markets in Central Asia. Thus, combining the two stages of the model, positive shocks in irrigation water, temperature and precipitation, i.e. warmer temperatures, more rainfall and irrigation water availability seem more likely to lead to lower wheat prices, whereas for potato the effects of changes in weather variables and irrigation water availability are more ambiguous and would more strongly depend on other market conditions.

The elasticities of changes in wheat prices with regard to changes in the key variables of the analysis, namely: temperature, precipitation and availability of irrigation water, are striking (Figure 3.3-3.6.). If the impact of higher temperatures on wheat prices is small and somewhat ambiguous with confidence intervals diverging at 0, the impact of lower precipitation and reduction in the availability of irrigation water are clear and, in fact, quite big. For example, reduction in precipitation by 100 mm may increase wheat prices by 64 to 318 USD per ton in the region. Similarly, a 30% reduction in the availability of irrigation water may lead to dramatic price hikes, ranging from 364 to 1650 USD per ton, all other things being equal. The availability of irrigation water seems to have the biggest potential impact on wheat prices. To show this, Figure 3.6 homogenizes the relative scales of price changes.

Table 3.6. Second stage of the model: impact of shocks in stocks in yields and other variables on shocks in provincial wheat prices

VARIABLES		Wheat	Potato
International prices for the commodity (USD/t)			
	Lag 0	0.11***	0.11***
	Lag 1	0.08***	0.09***
Inflation			
	Lag 0	0.1	.94*
	Lag 1	0.65***	.45
Exchange rate (log)			
	Lag 0	-3.8***	-8.7***
	Lag 1	-1.8***	5.2**
Yields (t/ha)			
	Lag 0	-249***	159***
	Lag 1	-389***	-177***
Stocks (log)			
	Lag 0	-48***	167***
	Lag 1	-63***	-216***
Interaction of stock and yield shocks			
	Lag 0	572*	-971***
	Lag 1	2074***	1,247***
Yield shocks, squared			
	Lag 0	2,870***	-160***
	Lag 1	915	214***
Stock shocks, squared			
	Lag 0	131***	-373*
	Lag 1	-27	1356***
Interaction of stock and yield shocks, squared			
	Lag 0	-1,264	3.240***
	Lag 1	-21,472***	-5,118***
Country and time effects		yes	yes
Constant		-33,1***	1.46
Observations		4,902	4,902
Number of panel		38	38

*** p<0.01, ** p<0.05, * p<0.1

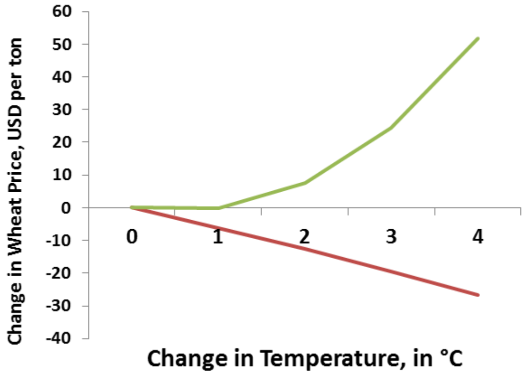


Figure 3.3. Impact of changes in temperature on changes in wheat prices

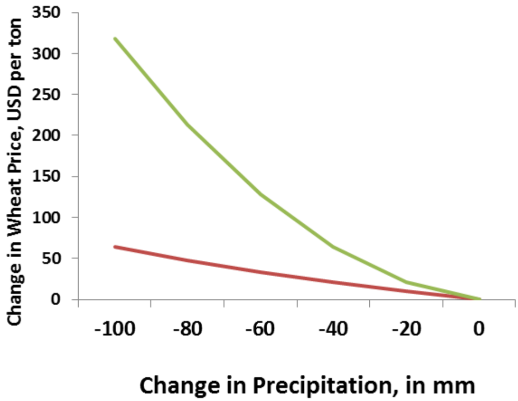


Figure 3.4. Impact of changes in precipitation on changes in wheat prices

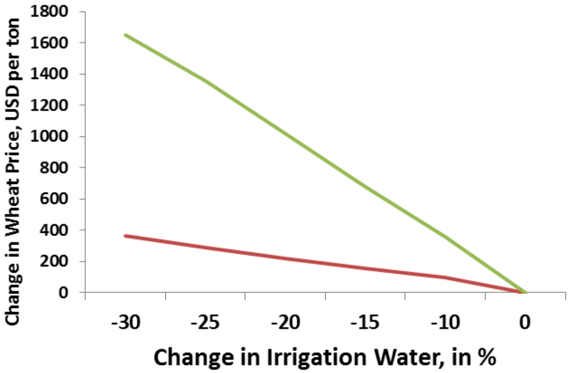


Figure 3.5. Impact of changes in temperature, precipitation and availability of irrigation water on changes in wheat prices

Note: Two lines represent higher and lower confidence intervals. Calculated based on the current lags.

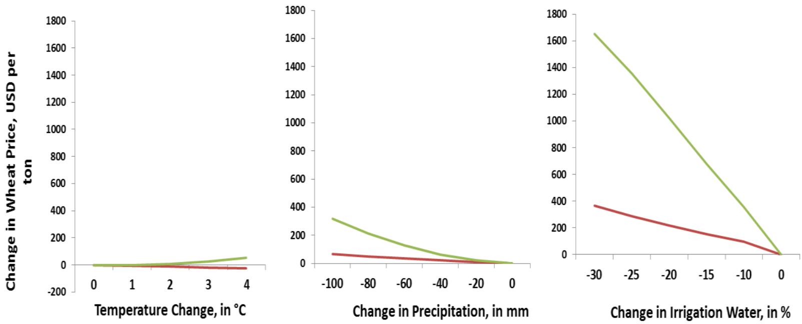


Figure 3.6. Comparison of the impacts of changes in temperature, precipitation and availability of irrigation water on changes in wheat prices

Note: Two lines represent higher and lower confidence intervals. Calculated based on the current lags.

The magnitudes of changes simulated in Figure 3.6 encompass the full range of potential negative climatic changes predicted by various global circulation models for Central Asia. The highest elasticity is shown by changes in the availability of irrigation water, implying that any sizable reductions in irrigation water could lead to dramatic increases in wheat price in the region.

3.7. Conclusions and Implications

Weather volatility and fluctuations in the availability of irrigation water have statistically significant effects on wheat and potato prices in Central Asia. Negative shocks in irrigation water availability and precipitation could create conditions for higher wheat prices, whereas for potato their effects are more strongly conditioned by other prevailing market factors. Lower availability of irrigation water could encourage irrigation-dependent countries of the region to raise wheat stocks to face expected supply shortfalls thus leading to higher prices. This effect could be further aggravated by negative effects of lower water availability on wheat yields. Moreover, the results show that wheat prices in the region are very sensitive to the availability of irrigation water, implying that hydrologic drought years have a strong potential to cause wheat prices spikes in the region. In order to counteract such developments, it is necessary to maintain storage policies and open trade arrangements in agricultural commodities in the region to minimize price volatility resulting from drought shocks.

Chapter 4

4. Assessment of climate change impacts on Central Asian agriculture

4.1. Introduction

The general view on the economic impacts of climate change on global agriculture since the very beginning of such economic assessments was one of cautious optimism. Unlike many studies based purely on the response of ecosystems or crops to environmental change, the studies of human and social response to climate change have emphasized various forms and mechanisms of adaptation. Darwin *et al*. (1995) had summarized this strand of economic research by stating that although climatic changes may certainly have an important impact on agricultural systems, however, individual and social adaptation are capable and likely to prevent any catastrophic damage to global food security, as long as climate change is not catastrophic. A key characteristic of climate change is defined by its differentiated distributional effects. Temperate areas are likely to gain from climate change, while tropical and arid areas are likely to lose (IPCC 2007). After seventeen years and extremely rich and lively debate in the literature, the consensus in climate change economics continues to generally coincide with this assessment (Mendelsohn *et al*. 2006, Mendelsohn 2009). Reviewing and compiling the climate change impact estimates, Cline (2007) indicates that, by 2080, the total effect of baseline global warming on global agricultural production could range between – 15.9% to – 3.2% for the scenarios without carbon fertilization and with carbon fertilization, respectively. However, there are big regional and country variations, ranging from - 56.1% in Sudan to + 27.5% across Scandinavia (ibid.). More recently, Nelson *et al*. (2010) suggest that climate change, together with population pressure, may lead to higher food prices between now and 2050, ranging from 31.2% increase for rice to 100.7% rise for maize. In addition, the climate change may lead to 8.5%-10.3% increase in the number of malnourished children in developing countries by 2050 relative to perfect mitigation (ibid.). Climate change may also dramatically alter food commodity trade flows. Without perfect mitigation, cereal exports from developed countries, mainly the United States, may fall by almost 140 mln tons. This is because climate change scenarios that are wetter on average are especially dry for central United States (ibid.). Nelson *et al*. (2010)

conclude that with adaptive actions leading to higher agricultural productivity, involving yield increases and improved irrigation efficiency, the negative effects of climate change could be alleviated. For example, overall increase of 40% in crop productivity between 2010 and 2050 could reduce the number of malnourished children by 16.2% by 2050 relative to the baseline results.

Central Asia is mainly located in arid and semi-arid areas, with agriculture being an important economic sector and source of livelihoods in the region. Therefore, climate change may become one of the key development challenges confronting the regional agriculture. Moreover, even within the region, the distributional effects of climate change are likely to be skewed against the poorer areas and poorer farmers with less financial resources and adaptive capacities. Hence, an analysis of the impacts of climate change should be able to capture these geographically-differentiated effects.

The main contributions of this study are three-fold. Firstly, previous studies of climate change impacts have been based on only one of the existing methodologies of economic assessment. In this study, several methods of climate change impact assessment are employed using data from the same geographic area at different levels of aggregation for obtaining more comprehensive and robust results. This will also allow for more objective evaluation and drawing common conclusions from the results of these different methods of climate change impact assessment. Secondly, this study looks into the effects of not only long-term climate change but also short-term weather variability. Thirdly, the study strives to fill an important geographic gap in the analysis of climate change impacts. Central Asia remains one of the regions of the world where impacts of climate change have so far been understudied. This is an important geographic and economic gap given the region´s potential to significantly contribute to global food security. The study also has several limitations. Although the methodologies applied in the study allow for implicit accounting for full adaptation to climate change in the estimates, the study does not explicitly quantify the costs of these adaptation actions. Specifically, it does not quantify crop substitution effects under climate change which may serve as the key adaptation measure. Finally, each of the applied estimation methods suffers from its methodological weaknesses which are described in detail in the Literature Review section.

4.2. Relevant Literature

The previous literature for assessing the impacts of climate change on agriculture was built around four major approaches. The following sub-sections review the results of the earlier studies using each of these methodologies.

4.2.1. Integrated assessment

The first approach can be termed as integrated assessment (Adams *et al*., 1990). This approach usually uses a suite of interlinked models including climate, crop-response and economic models, based either on partial or general equilibrium, to assess the climate change impacts. The climate model is usually represented by various Global Circulation Models (GCMs). Occasionally, these global models are downscaled to higher resolutions using various statistical techniques. The crop model is calibrated to simulate crop yields under different crop management practices and climate realizations in order to make economic forecasts about the impacts of climate change. The physical impacts of climate change, such as changes in crop yields, are introduced into an economic model exogenously as 'Hicks neutral technical changes (Kumar 2009). This approach has its strengths and weaknesses. Among the strengths are the possibility to control for non-climate factors, test for different CO_2 levels, linking climate change impacts to actual biophysical processes in crops, while weaknesses include arbitrary modeling of adaptation, the divergence of projected yields from the actual, and difficulty of capturing spatial heterogeneity of impacts (Mendelsohn and Dinar 1999). The inability of this approach to include all potential adaptation options to climate change in its estimation may lead to a downward bias in its results, i.e. this approach exaggerates the negative impacts of climate change.

4.2.2. Econometric yield models

The effects of weather variables on crop yields can be captured by the use of crop simulation models, as indicated under the integrated assessment method. They can also be captured by statistical regression models (Cabas *et al*. 2007, You *et al*. 2009). The advantage of the statistical regression models is that they can integrate not only biophysical variables such as soils, temperature and precipitation, the length of the growing period, but also socio-economic and institutional factors that crop models cannot capture directly. Socioeconomic and institutional factors can have significant impacts on crop yields through influencing human incentives. For example, Cabas *et al*. (2007) cite the study by Kaufman and Snell (1997) which found that climate variables explained 19% of variation in maize yields, while the social factors accounted for 74% of the variation in the mid-western part of the United States. The effect of temperature on crop yields is considered to be nonlinear. Yields are expected to increase with rising temperatures up to a certain threshold and decline beyond that threshold.

4.2.3. Ricardian approach

The Ricardian approach was suggested by Mendelsohn, Nordhaus and Shaw in mid 1990s (Mendelsohn *et al*. 1994). The Ricardian approach makes use of cross-sectional data to capture the influence of climatic as well as economic and other factors on land values or net farm income. The land value is assumed to reflect the productivity of the land. Since this observation was first made by David Ricardo, the approach was named as Ricardian. The main assumption of the Ricardian method is that variation in space can reflect the variation in time (ergodic assumption). Its strengths and weaknesses include capacity to capture efficient adaptation, albeit implicitly, and take the spatial heterogeneity into account. Its weaknesses include a potential bias resulting from omitted variables that are correlated with climate, inability to measure carbon fertilization effects (Mendelsohn and Dinar 1999, Mendelsohn 2007, Deschênes and Greenstone 2007). Ricardian approach can measure only long-run equilibrium conditions and cannot capture the trial and error process accompanying any adaptation, for example, it cannot capture short-term coping adjustments to weather shocks (Mendelsohn 2007). Early Ricardian models were criticized for omitting irrigation in their estimations, which can considerably distort their predictions for irrigated areas (Cline 1996). Later Ricardian studies confirm that in the irrigated areas, the effect of temperature and precipitation changes may be largely dwarfed by the impact of irrigation (Benhin 2008). The Ricardian method assumes constant prices, hence overestimates climate change impacts on both directions (Mendelsohn 2009). Moreover, Deschenes and Greenstone (2007) suggest that since the key vulnerability of the Ricardian approach is omitted variables correlated with climate, the climate coefficients in the Ricardian estimates may be biased. More alarmingly, one does not know the direction of the bias (ibid.). The predictions of the Ricardian studies have generally been more optimistic than those made by the integrated assessment method, showing less damage from climate change impacts. Mendelsohn *et al*. (1994) believe this is due to accounting for full and efficient adaptation under the Ricardian approach. The Ricardian studies have used two types of cross-sectional data: aggregate secondary statistics usually at county/district level or individual farm data obtained through custom-made surveys (Mendelsohn 2009). In some cases, both sources of data were analyzed separately for the same country with contradicting results. To illustrate, Wang *et al*. (2008), using farm-level data, conclude that global warming may be slightly harmful for Chinese agriculture, especially in rainfed areas, while Liu *et al*. (2004), using county-level data, find the effects of warming to be beneficial.

4.2.4. Panel approach

Finally, the panel approach suggested by Deschênes and Greenstone (2007) builds on the Ricardian approach by using panel data to estimate the effect of weather on agricultural profits and yields, conditional on district and province by-year fixed effects. Under this approach, the weather parameters are identified from the district-specific deviations in weather about the district averages after adjustment for shocks common to all districts in a province. This variation is presumed to be orthogonal to unobserved determinants of agricultural profits, so offering a possible solution to the omitted variables bias in the Ricardian approach (Deschênes and Greenstone, 2007). Its strengths include, in addition to addressing the omitted variables bias of the Ricardian method, robustness to a wide variety of specification checks and incorporation of spatial heterogeneity, while weaknesses are that it allows only for the partial adaptation to weather fluctuations by farmers and miss the long-term adaptation to climate change, cannot model carbon fertilization, and also may be missing the short-term price effects of production and yields (Deschênes and Greenstone 2007). Using the sales values in the current year, Deschenes and Greenstone (2007) also omit the possible effect of storage (Fisher *et al*. 2009). Since the panel approach based on annual weather realizations captures only short-term adjustments to weather, it may not be able to capture long-term adaptation to climate change, thus exaggerating the effects of climate change on the negative side. Table 4.1 broadly summarizes a considerable number of studies conducted using each of these approaches, without pretending being all-inclusive. In general, the most negative impacts are predicted by integrated assessment methods, while Ricardian and Panel approaches forecast less negative relative magnitudes of climate change impact.

Table 4.1. Summary of previous literature on economic assessments of climate change impacts (selective)

Authors	**Method**	**Location and Sector**	**Impact of Climate Change**
Nelson *et al*. (2010)	Integrated assessment method (IAM)	Global	Higher food prices between now and 2050, ranging from 31.2% rise for rice to 100.7% increase for maize. About 8.5-10.3% increase in the number of malnourished children in all developing countries by 2050 relative to perfect mitigation.
Cline (2007)	Review	Global agriculture	by 2080, ranges between – 15.9% to – 3.2%
Kane *et al*. (1992)	Integrated assessment method (IAM)	Global GDP	-0.47% to + 0.01%
Ringler *et al*. (2010)	IAM	Sub-Saharan Africa	cereal yields reduced by 3.2% in, leading to 15% higher prices for wheat by 2050
Adams *et al*. (1988)	IAM	US agriculture	- 5% to - 28%
Mideksa (2009)	IAM	Ethiopia's GDP	-10% (Gini coefficient + 20%)
Breisigner *et al*. (2011)	IAM	Yemen's GDP	- 0.01% annually between 2010 and 2050
Butt *et al*. (2005)	IAM	Mali's GDP	-1% to -2%
Zhai *et al*. (2009)	IAM	China's GDP	-1.3% by 2080

Authors	**Method**	**Location and Sector**	**Impact of Climate Change**
Oktaviani *et al*. (2011)	IAM	Indonesia's GDP	-2% by 2030
Lobell and Field (2007)	Econometric	global	global warming between 1981-2002 had already led to annual losses of about 5 bln USD
Mendelsohn *et al*. (1994)	Ricardian	US agriculture	- 6% in the pessimistic scenario
Aurbacher, Lippert and Krimly (2010)	Ricardian	Germany	Net agricultural income + 5 to + 6% between 2010-2040
Benhin (2008)	Ricardian	South Africa	1% increase in temperature would raise farm incomes by 80 USD per hectare, further increases harmful
Seo *et al*. (2009)	Ricardian	Africa	by 2100, hotter and dryer climates may reduce net agricultural revenues across Africa by 27%
Andersen *et al*. (2009)	Ricardian	Peru	incomes + 13% to – 20%, with an average impact of -2.3% by 2058
Deschênes and Greenstone (2007)	Panel	US	annual agricultural profits + 4% by 2099
Kumar (2009)	Panel	India	uniform 2°C increase in temperature and 7% increase in precipitation across India would result in 3%-9% decline in farm net revenues annually

Table 4.2. Previous assessments of climate change impacts in Central Asia

Authors	Method	Location	Impact of Climate Change
Bobojonov *et al*. (2012)	IAM	Uzbekistan, agricultural gross incomes	Climate change under IPCC scenarios A1b and A2 is likely to increase expected gross margins for wheat, cotton and potato during 2010-2040 relative to the baseline. However, gross margins are likely to decline for cotton under the same scenarios during 2040-2070. In all cases, it is likely that variance of gross margins may increase. A decline of 30% in irrigation water availability is likely to lead to 4%-17% reductions in expected incomes during 2010-2040, and to 35%-55% reductions during 2040-2070.
Bobojonov *et al*. (2012)	IAM	Central Asia, agricultural gross incomes	During 2040-2070, the climate change may increase agricultural incomes in northern rainfed areas of Central Asia (in some areas by up 50%), and reduce incomes in the southern irrigated areas, especially under the conditions of water scarcity (in some areas by more than 17%).
Sommer *et al*. (2012)	IAM	Central Asia	Wheat yields may grow on average by +12% across Central Asia, ranging from – 3% to + 27%.

Authors	**Method**	**Location**	**Impact of Climate Change**
Kato and Nkonya (2012)	IAM	Central Asia	Potato yields in mountainous areas of Tajikistan may increase by +10% to +70% depending on crop management practices, while they may decrease by 8% in plain areas of Kazakhstan. Cotton yields may decrease by up to 40%.
Nelson *et al*. (2010)	IAM	Global, including Central Asia, crop yields	By 2050, climate change may lead to higher rainfed wheat yields in Kazakhstan and Kyrgyzstan (by 0%-11%), while in Tajikistan, Turkmenistan and Uzbekistan rainfed wheat yields may decline (by 8%-18%). The yields for irrigated wheat may decrease in all countries (by 7%-14%), except in Uzbekistan (+1%). The detailed results are presented in Table 4.3.
Hunink and Droogers (2011)	IAM	Uzbekistan	During 2010-2050, winter wheat yields may increase, on average, from 1% to 7% under low climate change scenario (no explanation is given of what is considered "low"). However, under "high" climate change winter wheat yields may range from -6% to +6%. Similarly for potato, yields may vary from -1% to +1% under "low" climate change to -3% to -4% under "high" climate change. For cotton, yields may range

Authors	Method	Location	Impact of Climate Change
			from -2% to +1% under "low" climate change to -3% under high climate change. These calculations assume constant irrigation rates and do not take into account the carbon fertilization effect.
Chub (2007)	IAM	Uzbekistan	In most areas of Uzbekistan, the yields of cotton may increase by 10%-15%, of cereals by 7%-15%.

Table 4.3. Estimates of climate change impacts on the yields of selected crops in Central Asia by Nelson *et al*. (2010)

see the note in the next page

	Rainfed Wheat			Irrigated Wheat			Irrigated Rice			Irrigated Maize		
Country	**Baseline**	**Pessimistic**	**Optimistic**	**Baseline**	**Pessimistic**	**Optimistic**	**Baseline**	**Pessimistic**	**Optimistic**	**Baseline**	**Pessimistic**	**Optimistic**
Kazakhstan	11%	8%	8%	-14%	-14%	-14%	-9%	-9%	-9%	0%	0%	0%
Kyrgyzstan	0%	0%	0%	-14%	-14%	-14%	-12%	-12%	-12%	-7%	-8%	-7%
Tajikistan	-18%	-17%	-17%	-8%	-8%	-8%	9%	8%	9%	13%	12%	12%
Turkmenistan	-12%	-12%	-14%	-7%	-7%	-7%	-14%	-14%	-14%	8%	8%	8%
Uzbekistan	-11%	-8%	-11%	1%	1%	1%	-5%	-2%	-8%	7%	6%	7%

Note to Table 4.3: Calculated by the author based on crop yields under various scenarios by Nelson *et al*. (2010) provided in http://www.ifpri.org/climatechange/casemaps.html (accessed on 10 August 2012). First, yield changes under various climate change scenarios are calculated relative to the perfect climate change mitigation scenario, then, these relative changes are averaged across baseline, pessimistic and optimistic storylines. Optimistic storyline refers to the world with high GDP and low population growth. Pessimistic: low GDP and high population growth. Baseline: medium population growth and low GDP growth. In fact, Nelson *et al*. (2010) use exactly the same low GDP growth rates in the baselines scenario as in the pessimistic scenario for all countries of Central Asia, except for Kazakhstan, for which high optimistic GDP growth rates are taken as the baseline.

Similarly, Table 4.2 summarizes the results of several previous studies on climate change conducted in the countries of Central Asia. All of these previous studies were based on the integrated assessment method, involving mainly integration of climate and crop models. Only the studies by Bobojonov (2011) and Nelson *et al*. (2010) also include economic assessment components. Broadly, these studies demonstrate that climate change is likely to have differentiated impacts on various crops and regions in Central Asia, with possible yield gains, especially for rainfed wheat, irrigated maize and potato, whereas the cotton yields may be impacted more negatively, especially in the long-term (2040-2070). Table 4.3 summarizes the results of the study by Nelson *et al*. (2010) concerning yield effects of climate change for a detailed illustration. The few previous economic assessments of climate change impacts on Central Asia or explicitly including Central Asia, such as by Bobojonov *et al.* (2012) and Nelson *et al.* (2010) are based on integrated assessment method and, as explained above, may not be able to account for full set of adaptive actions against climate change impacts, thus producing downwardly biased estimates, i.e. exaggerating the negative impacts of climate change.

The present study compares three of the four approaches to economic assessment of climate change impacts reviewed above, namely: econometric yield models, Ricardian and panel approaches. The integrated assessment approach with multiple interlinked models involving global circulation model, crop-simulation modeling as well as economic modeling is beyond the scope of this study in terms of explicit inclusion. Instead, the study makes use of the results of ICARDA-IFPRI project (Sommer *et al*. 2012, Kato and Nkonya 2012) on "Climate change impacts in Central Asia and People's Republic of China" and the results by Nelson *et al.* (2010), which followed integrated assessment method, specifically while comparing the crop modeling results within that project with the results of the econometric yield model developed here. In the following sections, the individual analyses using each of these approaches are conducted, while the final section brings together and compares all of the results.

4.3. Econometric yield model

4.3.1. Conceptual framework

Crop yields are influenced by a wide range of different factors. Among these factors one can enumerate weather parameters such as temperature, precipitation, as well as their variations. Another set of important factors is agro-ecological conditions such as soil types and quality, length of growing periods. Crop management factors such as application of fertilizers and irrigation, use of machinery, different seeding rates, and chemical treatment with pesticides may all influence yields. Last but not least, various institutional factors can have crucial impacts on yields through influencing human incentives. These institutional factors may include market access, land tenure arrangements, availability of extension services, etc. While looking into the impacts of climate and weather on crop yields, it is, hence, crucial to be able to adequately account for a wide number of these other factors. Another important analytical challenge is to account for increased weather variability due to climate change. Arguably, it is higher weather variability and its impact on crop yields that is the major element of climate change impacts rather than only a gradual change in mean weather values.

In order to take these elements into account within this analysis, Just-Pope stochastic framework using Cobb-Douglas production function (Just and Pope 1978) is employed in the present analysis. This approach allows estimating the impact of weather variables on mean yields and their variances while accounting for other important variables either explicitly or implicitly through fixed-effects by including province and time dummy variables. Fixed-effects approach can help by accounting for time-invariant unobserved effects, such as for example the effect of soil types, however, there may be unobserved factors that vary with time such as fertilizer application rates. The estimated model explicitly accounts for key crop management inputs that may influence yields such as fertilizer and irrigation water application rates. It also includes time trend to account for technological change and potential institutional and policy shifts. The formulation of the Just-Pope model follows the generalized form as presented by Cabas *et al*. (2007):

$$y = f(X, \beta) + \mu = f(X, \beta) + h(X, \alpha)^{0.5}\epsilon \qquad (4.1)$$

$$\text{so that } E(y) = f(X, \beta) \text{ and } Var(y) = Var(\mu) = h(X, \alpha)\sigma^2 \qquad (4.2)$$

where y stands for yields, X is a vector of explanatory variables, f (X, β) is the deterministic component of the production function – which will give the mean yield function - and β is a vector of parameters related to this deterministic component, μ is a heteroscedastic error term with a mean of zero; h(X, α) is the stochastic component of the production function – showing yield variance - and α is a vector of associated parameters, ϵ is a random error with zero mean and variance σ^2. The Just-Pope framework also allows for distinguishing between variance-increasing and variance-decreasing factors in the production model, helping with better assessment of production risks in the analysis (Pope and Kramer 1979).

4.3.2. Estimation strategy

There are two ways for estimating the Just-Pope function: maximum likelihood estimation (MLE) or a three-step estimation procedure using feasible generalized least squares (3SFGLS) under heteroscedastic disturbances (Just and Pope 1978). Maximum likelihood estimator is considered to be more efficient and unbiased than 3SFGLS with small samples (Cabas *et al*. 2007). The dataset used in this study is sufficiently large consisting of 903 observations; hence, following Judge *et al*. (1985) and Cabas *et al*. (2007), the 3-stage feasible generalized least squares approach is used. In the first stage, yields are regressed on the explanatory variables. In the second stage, squared residuals from the first stage are regressed on their asymptotic expectation h(X, α) with h() taken as an exponential function $\ln \sigma^2 = Z'\alpha$ (Cabas *et al*. 2007). In the third stage, predicted error terms from the second stage are used as weights for generating the FGLS estimates for the mean yield equation (Just and Pope 1978). In estimating all these models, robust standard errors are applied.

4.3.3. Data

The study uses a 20-year provincial panel dataset of crop yields for the period of 1990-2010 covering 38 provinces across Central Asia and all major crops or crop categories in the region. The dependent variable is the yield per hectare. The explanatory variables include climate variables such as temperature and precipitation, as well as input use variables including fertilizers and water. The weather variables have been compiled from about 400 weather stations across Central Asia for the period under examination. The weather data come from national meteorological agencies, Williams and Konovalov (2008), NASA´s Global Summary of the Day, and online sources such as www.rp5.uz and its sister websites for each country in Central Asia. Mean monthly temperature and total monthly rainfall data from individual weather stations were spatially projected to the digital map of Central Asia using spatial interpolation technique of inverse weighted distance. Following this, the pixel-level weather variables were averaged for each province and across four seasons of the year, namely, winter, spring, summer and fall. However, before the spatial interpolation, all the weather stations located at 1000 meters above sea level were removed from the dataset to avoid potential bias in the analysis that may be caused by high-altitude weather stations located in areas with little or no agricultural production and population settlement. However, in cases where the entire region is located in high mountain altitude areas, specifically the Gordo-Badahshan Autonomous province of Tajikistan, all the weather stations are kept in the interpolation. In addition to mean weather variables, variations of these variables from their trend values are also used. These variations are decomposed using Hodrick-Prescott filter into the trend and idiosyncratic components (Hodrick and Prescott 1997), and then idiosyncratic components are used in the analysis. The annual amounts of per hectare applied irrigation water are also used in order to account for the importance of irrigation in agricultural production in southern parts of Central Asia. The estimation also explicitly includes the annual per hectare application rates for fertilizers in the econometric model. These data were compiled from various statistical bulletins and reports of the National Statistics Agencies and Ministries of Agriculture. The data on the use of these inputs by individual crop are not available; hence, the total amounts of input use for all the crops in the province are used, where it is assumed that the year-to-year shocks in input use amounts captured by this variable can accurately approximate input use change dynamics for each crop.

In constructing the weather variables one could weight them using crop distribution maps, such as, for example, by Monfreda *et al*. (2000). However, I prefer to use average provincial temperatures for two reasons. First, during the period under consideration the crop distributions have been changing. For example, in northern Kazakhstan many areas that were under crop production were abandoned for most of 1990s and only since mid-2000 they are again beginning to be gradually brought back under cultivation – so existing crop distribution maps do not show an accurate crop plantations over the period of 20 years. Another reason, it might also be true that weather variables in areas which do not produce a particular crop may have effects on the yields of that crop through modified management by farmers who are aware of weather changes in the neighboring areas and their potential effects on complementing or substituting crop prices, as well as farmers' expectations about the spread of the weather conditions from the neighboring area to their area. Provincial and time dummy variables are also included to account for time-invariant unobserved factors as well as for the effect of technological change and potential institutional and policy shifts.

4.3.4. Results and Discussion

The results of the Just-Pope model estimation indicate a strong influence of weather variables on mean crop yields. The mean yield model also has a very strong explanatory power with R-squared of at least 97% for all the crops studied (Table 3.2). In contrast, the yield variance model has much weaker explanatory power with fewer numbers of explanatory variables showing statistical significance (Table 3.3).

The coefficients of the mean yield model, in general, show expected signs. However, the model also indicates that the same weather or input variables could have differentiated effects on different crops. Per hectare fertilizer use has a concave relationship with most of the crop yields studied, however, in a few cases, notably for grape yields, even the squared terms have a positive sign. This could presumably be due to the fact that grapes usually receive very little chemical fertilization in the region. In terms of water use, the relationship is, as expected, concave for majority of the crops. Here again, grape and fruit yields seem to show a convex relationship and any further increases in water application would lead to lower yields. The variable for crop area stands for the importance of that crop in the province and also accounts for the effects of specialization or other comparative advantages of producing a particular crop in the province. For most crops the relationship is concave conforming to the general expectation that larger planting areas under a crop should lead to lower average yields because more marginal and less suited land is thus brought under the cultivation of that crop. However, for vegetables, melons and maize the relationship is convex. Time and province dummies are statistically significant in almost all cases. Time dummy is usually interpreted in the literature as the effect of technological and/or institutional changes on crop yields. Following that logic, one can deduce that average annual yield growth due to technological and/or institutional change across the region as a whole has been about 3-4% for cereals, wheat, potato, vegetables and maize; about 5% for rice; 8% for melons, 13% for fruits, but only 2% for grapes from their 1990 levels[2]. However, cotton has registered a mean annual decline of about 0.5% in yields. The most widely believed reason in the region for this decline in cotton yields is that it is due to land degradation, or more specifically to secondary salinization of irrigated lands. However, it seems to be only a proximate cause for cotton yield declines, the fundamental cause being the institutional changes that allowed for this land degradation to take place in the first place such as weakening of services responsible for the good maintenance and upkeep of irrigation and drainage networks, but also, and equally importantly, the push-back of cotton to more marginal areas to make space for expanding wheat cultivation, for example in Uzbekistan, Turkmenistan and Tajikistan. In general, these annual increments in yields for most of the crops in the region provide optimistic outlook for the future. If similar pace of yield growth, potentially due to technological change, is maintained, the yields of wheat would double in about 20 years by far compensating even the more pessimistic climate change impact forecasts.

Weather variables for different seasons have varying effects on different crops. If for cereals, wheat, rice, maize (i.e. grain crops) and melons higher temperatures in winter and spring seem to increase yields and higher temperatures in summer and fall decrease the yields, the opposite seems to be true for vegetables. Cotton is negatively affected by spring and summer temperatures. For potato and grapes, higher temperatures look harmful throughout the year except in fall. While fruits temperature variables for all seasons of the year are signed negative.

[2] Yield growth rates were obtained by multiplying time coefficients by average yields of the corresponding crop.

Table 4.4. Mean yield model

*** p<0.01, ** p<0.05, * p<0.1

VARIABLES		Cereals	Wheat	Cotton	Potato	Vegetables	Fruits	Rice	Melon	Maize	Grapes
Fertilizer use per ha, kg		0.0140***	0.00856***	0.00511***	0.0151***	0.0199***	0.0304***	0.00205	0.0378***	0.00353	0.00730**
Squared Fertilizer use per ha, kg		-2.52e-05***	-1.09e-05***	-8.99e-06***	-2.35e-05***	1.73E-05	-3.61e-05***	7.14E-06	-8.51e-05***	4.10e-05***	7.88e-05***
Water use per ha, m3		3.87e-05***	1.75e-05***	4.12e-05***	0.000354***	0.000441***	-0.000110***	0.000340***	0.000325***	4.39E-05	-0.000445***
Squared water use per ha, m3		-7.87e-10***	-5.55e-10***	-1.23e-09***	-1.40e-08***	-1.41e-08***	6.87E-10	-9.71e-09***	-1.50e-08***	-2.12E-10	1.31e-08***
Area		3.01e-07***	3.70e-07***	2.02e-06*	0.000397***	-0.000167***	9.87e-05***	2.13e-05*	-0.000437***	-6.26e-05***	0.000216***
Area squared		-0***	-0***	-0**	-8.18e-09***	1.00e-08***	-2.40e-09***	0	1.25e-08***	8.13e-10***	-2.69e-09***
Time dummy		0.0517***	0.0669***	-0.0127**	0.362***	0.540***	0.468***	0.159***	0.772***	0.0893***	0.129***
Province dummy		0.00308**	0.0297***	0.000541	0.00667	0.0272**	0.0685***	-0.0374***	0.0700***	-0.0689***	0.0557***
Temperature	winter	0.263***	0.254***	0.0391	-0.0324	-0.426***	-0.140*	0.451***	0.458***	0.769***	-0.425***
	spring	0.239***	0.0869***	-0.0667*	-0.0498	-0.911***	-0.362***	0.863***	1.170***	1.228***	-0.521***
	summer	-0.784***	-0.763***	-0.645***	-0.463***	1.585***	-2.752***	-1.397***	-4.156***	-2.135***	-0.709**
	fall	-0.193***	-0.0903***	0.0531	0.290***	0.747***	-0.0546	-0.882***	-1.364***	-1.025***	0.577***
Precipitation	winter	-0.0224***	-0.0202***	0.0117***	0.0255***	0.123***	0.0703***	0.0168***	0.0274**	-0.0128*	0.0091
	spring	0.00767***	0.00136	-0.0231***	-0.00497	-0.0949***	-0.130***	0.0172	0.0270**	0.118***	0.00147
	summer	-0.00167	0.000212	0.0436***	0.00909*	0.0362***	0.0818***	0.00579	0.0871***	-0.0250***	-0.0430***
	fall	0.0238***	0.0241***	0.00498***	-0.0375***	0.0277***	-0.0182**	0.0259***	0.127***	-0.0109	-0.0416***
Temperature squared	winter	0.00217***	0.00344***	-0.00452***	-0.00948***	0.00676**	-0.0106***	0.0211***	-0.0159***	0.0167***	-0.00453*
	spring	-0.000156	-0.000211	0.00121**	0.00299***	-0.00112	0.00474***	-0.00974**	0.0188***	-0.0171**	0.00662***
	summer	0.0143***	0.0148***	0.0140***	-0.00566	-0.0429***	0.0628***	0.0259***	0.104***	0.0509***	8.88E-06
	fall	0.000148	0.000223	-0.00125**	-0.00309***	0.00109	-0.00462***	0.00945**	-0.0187***	0.0164**	-0.00665***
Precipitation squared	winter	-6.40e-06***	-5.83e-06***	-1.25E-06	-5.99e-05***	-0.000143***	4.52E-06	3.74E-06	-0.000217***	-4.46e-05***	6.35e-05***
	spring	9.19e-06***	2.70E-06	-9.67e-06***	2.86e-05***	-1.68E-05	6.68e-05***	-5.09e-05***	-1.64E-05	-1.43E-05	-0.000102***
	summer	8.01E-07	3.02E-07	-5.47E-05	-0.000105***	6.58e-05*	0.000347***	3.65E-05	-0.000413***	-9.77e-05***	-0.000105**
	fall	-7.88e-06***	-7.60e-06***	-5.80e-06***	4.24e-05***	-0.000194***	8.42e-05***	-7.92e-05***	-0.000254***	-8.33e-05***	8.37e-05***
Temp. variation	winter	-0.201***	-0.187***	-0.00941	0.0012	0.444***	0.366***	-0.311***	-0.509***	-0.538***	0.493***
	spring	-0.219***	-0.0599***	0.0507*	0.0696	1.009***	0.12	-0.567***	-1.455***	-0.699***	0.364***
	summer	0.159***	0.132***	-0.0590**	0.675***	-0.00412	-0.038	0.397***	0.0903	0.317***	0.743***
	fall	0.177***	0.0649***	-0.027	-0.281***	-0.822***	0.256*	0.645***	1.648***	0.615***	-0.422***
Precip. variation	winter	0.0238***	0.0204***	-0.0131***	-0.00222	-0.103***	-0.0820***	-0.0202***	0.0424***	0.0264***	-0.0354***
	spring	-0.00826***	0.00152*	0.0256***	0.0043	0.118***	0.124***	-0.00214	-0.015	-0.117***	0.0253***
	summer	0.00327***	0.000899	-0.0421***	0.0316***	-0.0352***	-0.122***	-0.0128	-0.0364***	0.0478***	0.0623***
	fall	-0.0206***	-0.0199***	-0.00194	0.0398***	0.0414***	-0.0037	-0.00317	-0.0585***	0.0316***	0.0185**
Constant		-95.68***	-124.3***	34.75***	-705.1***	-1,070***	-894.9***	-311.6***	-1,523***	-171.7***	-230.5***
Observations		742	685	401	740	708	215	209	482	309	348
R-squared		0.99	0.989	0.938	0.982	0.998	0.974	0.958	0.991	0.99	0.998

Table 4.5. Yield variance model

**** p<0.01, ** p<0.05, * p<0.1**

VARIABLES		Cereals	Wheat	Cotton	Potato	Vegetables	Fruits	Rice	Melon	Maize	Grapes
Fertilizer use per ha, kg		0.0100**	0.00336	0.000363	0.00296	0.0021	0.013	-0.00108	-0.0209***	0.0259***	-0.00582
Squared Fertilizer use per ha, kg		-2.14E-05	5.36E-06	1.09E-05	-1.82E-05	5.30E-06	-1.57E-05	8.95E-06	8.53e-05***	-7.40e-05***	3.38E-05
Water use per ha, m3		5.57E-05	4.67E-05	0.000142	6.75E-05	5.21E-05	-0.000185**	-0.000375**	-4.78E-05	-8.59E-05	-0.000245***
Squared water use per ha, m3		-2.85E-09	-3.77e-09*	-4.00E-09	-2.45E-09	-2.15E-09	6.08e-09**	9.44E-09	3.23E-09	3.13E-09	6.05e-09**
Area		-2.61E-07	-1.17E-06	-2.20E-05	-6.81e-05*	-0.000194***	6.15E-06	0.000124***	-0.000187***	-4.88E-05	5.89E-05
Area squared		0	0	9.96E-11	8.06E-10	5.98e-09***	-4.66E-10	-9.20e-10**	4.71e-09**	8.01E-10	-1.22E-09
Time dummy		-0.0425	0.0528	-0.0399	0.0901*	0.00489	0.171**	-0.0951	0.0461	-0.0692	0.00679
Province dummy		-0.0275*	0.0174	-0.0044	0.022	0.00914	-0.0289	0.0114	0.0449**	-0.0326	0.0112
Temperature	winter	0.0744	-0.0298	0.127	0.304***	-0.000934	0.334	0.347	-0.316**	0.243	-0.013
	spring	-0.0348	-0.168	0.799**	0.679***	0.345**	0.731*	0.227	-0.339	0.149	-0.0309
	summer	-0.752***	-0.642**	1.749	-0.773*	0.0985	-1.428	-2.056*	-0.624	-0.324	0.377
	fall	0.0483	0.0606	-0.752*	-0.691***	-0.274*	-0.900*	-0.0502	0.237	-0.0243	0.00669
Precipitation	winter	-0.00822	-0.00349	0.00139	0.0362***	0.0118	-0.00824	-0.00333	0.0232	0.00832	0.00559
	spring	0.00796	-0.00119	0.00867	-0.0121	0.0217*	0.0358	0.0507	0.0139	-0.0286	0.00652
	summer	-0.00361	-0.011	-0.0582	0.0316***	0.0215*	0.0458	-0.0652**	-0.0426**	-0.0154	-0.0345**
	fall	0.00607	0.0269*	-0.00191	-0.0285**	-0.0232*	0.0497*	-0.0228	0.0188	0.0238	-0.00322
Temperature squared	winter	0.00259	0.00443	0.019	-0.00621*	0.00372	-0.00147	0.0151	0.00529	0.0185***	0.00232
	spring	0.00446*	0.00383	-0.0165**	0.00216	-0.000197	0.000378	-0.00778	0.00638**	-0.0119**	-0.00388
	summer	0.0166***	0.0200***	-0.0377	0.00281	-0.000949	0.0443*	0.0451*	0.0212	0.00726	-0.0135
	fall	-0.00450*	-0.00382	0.0166**	-0.00196	9.44E-05	-0.000402	0.00754	-0.00636**	0.0115**	0.004
Precipitation squared	winter	-3.87E-06	-3.66E-05	-1.38E-05	-4.00e-05**	1.55E-05	-2.08E-05	-8.78E-06	-1.56E-05	-2.07E-05	4.28E-06
	spring	-1.74E-05	-1.17E-05	5.16E-05	4.84e-05**	-1.92E-06	-9.74E-05	2.43E-05	-4.38E-05	4.96E-05	-2.84E-05
	summer	1.49E-05	5.50e-05*	0.000975***	-0.000138***	-3.40E-05	0.000116	0.000153*	0.000187**	5.19E-05	-1.52E-06
	fall	-3.66E-05	-1.98E-05	-3.87E-05	-1.41E-05	-4.12E-05	-4.85E-05	-6.32E-05	-0.000112**	-4.74E-05	-7.10E-05
Temp variation	winter	-0.105	0.0718	-0.132	-0.428***	0.0201	-0.224	-0.237	0.327**	0.113	0.0598
	spring	-0.0332	0.135	-0.306	-0.747***	-0.271	-0.568	-0.155	0.274	0.0347	0.00948
	summer	0.0244	-0.310**	0.419	0.773***	0.00575	-0.438	0.0882	-0.268	0.152	0.137
	fall	0.0259	-0.0279	0.248	0.722***	0.221	0.758*	0.0144	-0.165	-0.0907	-0.0109
Precip variation	winter	0.0154*	0.0193**	0.00232	-0.0253***	-0.0182**	0.00338	0.00618	-0.0193	-0.000885	-0.0166
	spring	-0.00356	0.00654	-0.0247	0.00185	-0.0197*	-0.00845	-0.0572*	0.0034	0.00186	-0.00356
	summer	0.00112	0.00368	0.00547	-0.00368	-0.0138	-0.0585	0.0266	0.0109	0.018	0.0362**
	fall	-0.000215	-0.0247**	0.0109	0.0282***	0.0295**	-0.0459**	0.0351**	0.00706	-0.0132	0.0205
Constant		90.48	-102.7	50.09	-174.2*	-16.94	-346.8**	209.3	-86.47	142.6	-11.19
Observations		742	669	401	740	708	215	209	482	309	348
R-squared		0.121	0.193	0.128	0.133	0.101	0.193	0.276	0.136	0.266	0.167

The effects of precipitation are also crop-specific. For cotton, winter, summer and fall precipitation are marginally useful while spring precipitation has more negative yield effects. For wheat, precipitation throughout the year is positive except in winter. For vegetables and fruits, higher precipitation is good in winter and summer, bad in spring, while in fall it is good for vegetables, but not so for fruits. Similarly, the effects vary strongly for other crops (Table 3.2).

What kind of “big picture” conclusion can we draw from these various model estimates? The net effects of weather change, and hence of climate change, on crop yields seem to have strongly varying inter-seasonal and inter-crop impacts. Season-specific effects need to be better understood and integrated into the economic models while also accounting for variation in the seasonal weather variables. The mean yield model also shows that variation in the weather variables have a strong influence on crop yields. Slightly, unexpectedly though, higher variation in weather does not always automatically imply negative effects on crops. In arid areas where the usual levels of precipitation are quite low, increased variation in precipitation could only come with additional rains. Probably for this reason and other less understood causes increased variation in weather variables can have different effects depending on season and crop. Sometimes and for some crops higher variation is positive, while for some others negative.

Higher input use is associated with increased yield variance for some crops, which is consistent with earlier findings (Cabas *et al*. 2009). However, in some cases higher input use is associated with lower variance in our model. The reason for this is probably because some crops are already furnished with inputs at near optimal level and hence any further increases would actually reduce the higher end of the yield distribution, making the distribution narrower. The time dummies in most cases are non-significant. Only for potato and fruits they show statistically significant increases in yield variance. Weather variables were not generally statistically significant except in the potato model. Higher winter and spring temperatures increased yield variation, while higher summer and fall temperatures decreased potato yield variance. If higher precipitation in winter decreased variation in potato yields, higher temperatures in fall increased potato yield variation. As a whole, weather and input variables explained only about 10-28% of crop yield variances. The main conclusion is that contrary to general belief that increased weather variation would lead to higher crop yield variances and most probably to lower mean yields, the results show that the situation may be much more nuanced. Probably this is due to the fact that agriculture operates under quite sub-optimal weather conditions in much of Central Asia. For example, winters and springs are quite cold and frosty in the northern areas of the region specialized in rainfed spring wheat cultivation. Hence warmer, thus more variable to the current baseline, temperatures in spring could actually allow for higher mean yields.

4.4. Ricardian approach

4.4.1. Conceptual Framework

The Ricardian method can be theoretically traced to hedonic models (Grilliches 1971, Rosen 1974). Hedonic models take their theoretical underpinnings from an approach to consumer demand theory proposed by Lancaster (1966), where a demand for a particular product can be attributed into demands for individual qualities or characteristics constituting that product. Hedonic models have been widely used in housing market analysis (Can 1992). Hedonic models characterize housing values to be made of a bundle of attributes, so that house price = f (a_1, a_2, ..a_n), where $a_1 \ldots a_n$ are various characteristics of the house, such as number of rooms, availability of parking lot, etc. Marginal price of each attribute, then, can be estimated separately within a multivariate regression framework (ibid.). Applying this thinking to land values, the Ricardian model considers climate to be one of the attributes making up the land values. Following David Ricardo, land values are assumed to represent the productivity of that land. Other things being equal, a change in climate variables would result in changes in the land values. Thus, marginal contribution of each climate variable to the land value can be estimated in monetary terms. The original Ricardian approach suggested by Mendelsohn *et al*. (1994) have been further modified to better account for the particularities of developing countries without functional land markets, hence, without the possibility of using land values as the dependent variable in the reduced form regressions. Instead of land values, net revenues per hectare were used as dependent variable (Kurukulasuriya and Ajwad 2007).

The similar approach is applied in this study since Central Asian countries also either do not have land markets at all or the functioning of existing land markets is strongly limited. In this modified version of the Ricardian model, where land values are replaced with net farm revenues, a production function of the farm can be denoted as a function of exogenous inputs such as climate variables (temperature, precipitation), soils, availability of irrigation, etc:

$$\pi = \sum(P * Q(I, C, E)) - Pr * I \qquad (4.3)$$

π – net revenue
P – vector of output prices
Q – vector of crop outputs
I - vector of purchased inputs
C- vector of climate variables
E – vector of other farm endowments such as soils, machinery, market access, etc
Pr – vector of input prices

The farmer seeks to maximize net revenues given the characteristics of the farm and market prices. The Ricardian model is a reduced form model that examines how several independent variables, such as input use, climate, farm endowments, etc affect farm net revenues. To reflect the nonlinear effects of climate variables, they enter into the regression model both in their linear and quadratic forms. The usual expectation is that climate variables would have a concave relationship with farm net productivity, since there are optimal degrees of temperature and levels of precipitation for each crop after which its yields would start declining. However, this relationship could vary across seasons and the shape of the temperature-yield curve could differ by crop. The impact of climate is measured as:

$$\Delta U = \pi (C_0) - \pi (C_1) \qquad (4.4)$$

where,

Δ U – change in the welfare
$\pi (C_0)$ – net profits under the current climate
$\pi (C_1)$ – net profits under the changed climate

Agricultural activities in a particular farm can be influenced by neighborhood effects. Proper estimation of the Ricardian model should be able to account for such spatial effects. For this purpose, village-clustered robust standard errors are incorporated in the estimation.

4.4.2. Empirical strategy

In the empirical analysis, the reduced form of regression of the Ricardian model given in (4.3) is estimated. The model is given as:

$$\pi = \alpha H + \beta C + \phi M + \eta A + \delta I + \mu G + \epsilon \qquad (4.5)$$

where,

π = net revenue

H = a vector of household characteristics

C = a vector of climate variables (temperature and precipitation, and their quadratic terms)

M= a vector of crop management variables, such as fertilizer application, irrigation, etc

A=vector of agro-ecological characteristics (length of growing period, soil characteristics, etc)

I = a vector of institutional variables (access to extension, land tenure, etc)

ϵ is the error term (robust village-clustered)

Following the literature on the Ricardian models, the country fixed effects G are also included in order to account for unobserved country-specific variables. α, β, ϕ, η, δ, and μ are vectors of corresponding parameters.

4.4.3. Data

The dataset used for this Ricardian analysis of climate change impacts in Central Asia comes from nationally representative agricultural household surveys carried out under the ICARDA-IFPRI project on "Impacts of climate change on Central Asia and People's Republic of

China", funded by the Asian Development Bank. The surveys were conducted in the four countries of Central Asia covering the 2009-2010 cropping season. The multi-stage survey sampling was conducted in a way to ensure representativeness of the survey sample with the overall population of agricultural producers: farmers, household producers, and cooperatives (where they exist) across different agro-ecologies and farming systems in each country. The confidence interval of 95% was used to calculate the sample size. The sample size varied between 380 and 385 respondents between the countries. To compensate for any missing or failed cases, the sample size for each country was determined to be 400 respondents, i.e. 1600 respondents in total.

Uzbekistan and Kazakhstan (bigger countries) were first divided into major agro-ecological zones – west, south, center and east for Uzbekistan, north, center, west, south and east for Kazakhstan. Then in each zone, one province was randomly selected. In the case of Tajikistan and Kyrgyzstan (smaller countries) all provinces were selected for further sampling of villages in each of them. The number of respondents was allocated to each province depending on the share of the agro-ecological zone (or province, in the cases of Tajikistan and Kyrgyzstan) in the value of the national agricultural production.

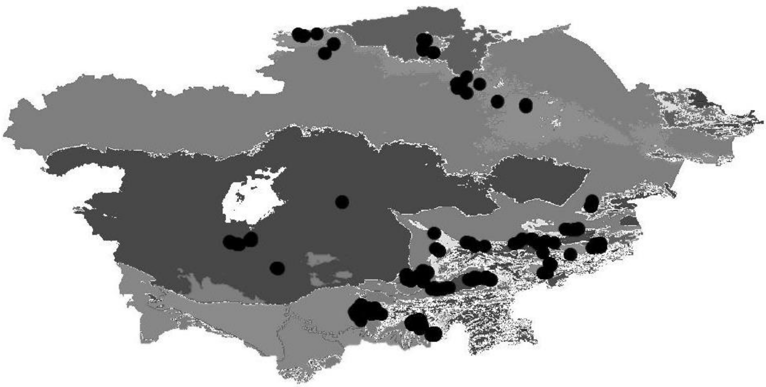


Figure 4.1. Location of surveyed households across agro-ecological zones in Central Asia

Following this, the total list of villages was obtained for each province selected. The villages in each province were numbered, and the corresponding numbers for the selected villages were randomly drawn using the appropriate Excel software function (35 villages in Kazakhstan, 22 in Kyrgyzstan, 25 in Tajikistan, 25 in Uzbekistan). The number of respondents per village was evenly distributed within each province. At the village level, the list of all agricultural producers, including household producers, were obtained from the local administrations; agricultural producers were numbered, and then from this numbered list, respondents were randomly selected. Due to civil unrest during most of 2010 in southern Kyrgyzstan, it was impossible to include the three provinces in the south of Kyrgyzstan in the sampling. Similarly, Gorno-Badahshan autonomous province of Tajikistan was also excluded from sampling due its trivial share in agricultural production and population, as well as extremely high surveying costs due to its location in high altitude areas with difficult access. In summary, in spite of these geographical gaps, the selected samples are well representative of the key areas in the region in terms of their share in the overall agricultural production, population, and different income levels (Table 4.6).

The dependent variable in the Ricardian model is net farm profits per hectare. The explanatory variables included into the model can be classified into the five categories as formulated in (*4.5*). These are vectors of household characteristics, climate variables, crop management variables, such as fertilizer and irrigation application rates, agro-ecological characteristics including length of the growing period and soil characteristics, as well as institutional variables. I am not aware of any other climate change impact assessment study, Ricardian-based or otherwise, which explicitly controls for such a wide variety of potentially influential factors. This will help to minimize any estimation bias resulting from omitted variables. Within each category of variables there is a set of variables each of which are described below in detail along with theoretical hypotheses about their behavior when regressed on net revenues as the dependent variable.

Table 4.6. Some characteristics of the selected provinces

Country	Provinces	Share in the national agricultural production (%)	Share in the national population (%)	Share of the national cropped area (%)	Share in the national GDP (%)	Number of observatio ns
Kaz	Akmola	8%	5%	23%	4%	87
	Almaty	15%	12%	4%	6%	85
	Karaganda	6%	10%	5%	12%	25
	Kostanay	15%	6%	23%	5%	88
	Kyzylorda	3%	5%	1%	5%	15
	S. Kazakhstan	11%	17%	3%	7%	108
	Total	58%	55%	59%	39%	408
Uzb	Andijon	10%	10%	6%	9%	78
	Toshkent	13%	10%	10%	14%	119
	Karakalpakstan	3%	6%	6%	4%	64
	Qashkadaryo	8%	10%	13%	12%	144
	Total	34%	36%	35%	35%	405
Kyr	Chui	26%	17%	35%	26%	160
	Issikul	14%	10%	16%	19%	109
	Naryn	7%	6%	9%	7%	59
	Talas	10%	5%	9%	7%	60
	Total	57%	38%	69%	59%	388
Taj	Khatlon	40%	39%	51%	45%	169
	RRP	25%	32%	17%	41%	127
	Sogd	33%	25%	31%	11%	102
	Total	98%	96%	99%	97%	398

Household characteristics

Age, education, and gender of the household head as well as the **family size** are standard variables used in most household survey analyses. In spite of this wide use of these household characteristics in numerous models analyzing survey data, most of Ricardian studies did not make wide use of these variables. There is no firm theoretical consensus on the direction of the impact of these variables on farm revenues or crop yields. In most cases, this is a matter of empirical analysis and can differ from one context to other. However, one may expect larger family size could have a positive effect on net revenues as more family labor could allow for more intensive land cultivation. Age is assumed to have a nonlinear effect on net revenues where higher age would proxy farming experience while it is expected that after a certain threshold more experience will be negatively counterbalanced with lower physical strength associated with more advanced age. For this reason age enters the model both at level and quadratic forms. There are no *apriori* expectations about the impact of gender, professional background and education on farm net revenues. In all Central Asian countries, 8-10 years of schooling is compulsory, a more advanced degree in, for example, medicine or pedagogy, may not necessarily contribute *per se* to higher farm revenues if the person decides to become a farmer. On the other hand, better knowledge of available agricultural innovations could become an important source for boosting farm revenues. The model uses the **number of technologies known** by the farmer to capture this effect.

Farm characteristics

Total farm size is expected to have a positive effect on net revenues due to economies of scale. Similarly, higher **soil fertility** is expected to boost farm net revenues through its positive effects on crop yields. The **number of crops grown** (crop diversification) is an important variable to include into the model, and generally it is believed that crop diversification would increase farm net revenues. However, crop diversification strategy could also be a consequence of risk-minimizing behavior and detrimental for profit maximization. Hence identification of the sign of this variable in the regression model could be an important contribution to the on-going debate about relaxing or maintaining monoculture-oriented State quota policies in the region. The costs of other inputs such as **labor, fertilizers, seeds, machinery, and fuel, as well as water cost** are also included.

Climatic characteristics

The climate variables consist of mean seasonal temperatures and accumulated seasonal precipitation, which have been compiled for about 400 weather stations across Central Asia for the period under examination. The data come from national meteorological agencies, Williams and Konovalov (2008), NASA´s Global Summary of the Day, and other sources. Average mean monthly temperature and average total monthly precipitation for the last 30 years from individual weather stations were spatially projected to the digital map of Central Asia using spatial interpolation technique of inverse weighted distance. The 30-year period is taken to represent the long-term climate normals. Following this, corresponding weather variables were extracted for each household using the GPS location of the household.

Agro-ecological characteristics

It is believed that many impacts of climate change would be felt along the **agro-ecological zones and farming systems typologies**, hence these variables are included to capture agro-ecology and farming system characteristics of agricultural production. **Length of the growing period** is similar to higher crop diversity in its effects leading to potentially higher net revenues. The model also controls for **soils**. A binary variable is included accounting for **rainfed and irrigated** areas in the model.

Institutional characteristics

Land tenure is a potentially important factor influencing farmers´ incentives and thus impacting their farm operations. Since farmers in Central Asia may often operate several plots with differing tenure regimes, a new variable – **share of privately owned land** – is created to capture the effect of land tenure. Better **market access** could allow for higher profits through lower transportation costs and higher prices in urban markets. The model seeks to capture the effects of better market access by interpolating distance to nearest urban markets for each household in the sample from the global dataset by Nelson (2008). The **country dummies** are included to implicitly account for other country-specific characteristics that are not included in the model explicitly.

4.4.4. Results and Discussion

Some major descriptive characteristics of the surveyed households are given in Table 4.7. The results of the Ricardian reduced form regression estimating the impacts of climate and other variables on net profit per hectare are given in Table 4.8.

Table 4.7. The households' key characteristics

Key indicators	Kazakhstan	Kyrgyzstan	Tajikistan	Uzbekistan
Average family size	5.7	5.5	7.8	6.2
Females to males ratio	1.18	1.13	1.04	1.06
Share of female household heads among the respondents	21%	8%	15%	6%
Age of household head	51	50	52	47
Dependancy ratio (definition?)	0.69	0.67	0.68	0.78
Family labor allocation, (%)				
off-farm work	26%	20%	23%	24%
employment abroad	0%	4%	4%	1%
farm work	73%	76%	73%	75%
Average farm size, (ha)	191	5	3	26
Average house value, (USD)	13044	5682	5836	14075
Average value of agricultural machinery owned, (USD)	25084	2287	514	10164
Average value of farm buildings, (USD)	38477	3715	127	3270
Average value of livestock owned, (USD)	5251	8973	852	6507

The relationship between precipitations and net profits per hectare seems likely to be concave for all seasons except for fall, when it is convex. Concave relationship implies that there is an optimal level of precipitation, any increase or decrees from that level would reduce net profits per hectare, whereas the convex relationship means that there is a minimally productive level of precipitation and any change from it in either direction may increase profits (Mendelsohn *et al.* 1994). As for temperature, the relationship seems likely to be concave in summer, during the crop vegetation period, and convex during the rest of the year.

Table 4.8. Ricardian regression results (* p<0.01, ** p<0.05, * p<0.1)**

VARIABLES	Coefficient	[95% Conf. Interval]	
Institutional variables			
Private land tenure	0.101***	0.0439	0.158
Crop diversity	0.0497***	0.0306	0.0688
Market access	9.68E-05	-0.00019	0.000379
Access to extension	-0.0224	-0.0647	0.02
Production characteristics			
Cropped area	-0.000380**	-0.00072	-3.83E-05
Cropped area, squared	2.19e-08**	2.15E-09	4.16E-08
Input costs per ha			
Fertilizers	0.000206**	1.86E-06	0.00041
Seeds	0.000720***	0.000524	0.000917
Machinery	-0.000203*	-0.00042	1.33E-05
Fuel	-0.00175***	-0.00246	-0.00105
Water	-0.000122	-0.00042	0.000173
Labor	-0.000237	-0.00056	8.49E-05
Input costs per ha, squared			
Fertilizers	2.19e-08**	2.15E-09	4.16E-08
Seeds	-6.63e-08***	-1.12E-07	-2.03E-08
Machinery	-1.21e-07***	-1.53E-07	-8.93E-08
Fuel	8.65e-08**	1.16E-08	1.61E-07
Water	2.78e-06***	1.59E-06	3.97E-06
Labor	3.25E-08	-1.07E-08	7.57E-08
Climate and weather variables			
Precipitation			
fall	-0.00815**	-0.0158	-0.00048
summer	0.00137	-0.00362	0.00636
spring	0.00178	-0.00242	0.00597
winter	0.00406**	0.000586	0.00753
Precipitation, squared			
fall	2.02E-05	-8.16E-06	4.85E-05
summer	-8.08E-06	-2.29E-05	6.74E-06
spring	-3.97E-06	-1.36E-05	5.61E-06
winter	-6.44e-06*	-1.39E-05	9.81E-07
Temperature			
fall	-0.0905**	-0.163	-0.018
summer	0.386**	0.0676	0.705
spring	-0.271**	-0.506	-0.0359
winter	-0.0254	-0.0926	0.0418
Temperature, squared			
fall	0.00776*	-0.00039	0.0159
summer	-0.00826**	-0.0161	-0.00044
spring	0.00865**	0.0015	0.0158
winter	-0.00885***	-0.014	-0.00368
Household characteristics			
Household head age	-0.000541	-0.00165	0.000567
Household head education	-0.00507	-0.0161	0.00596

VARIABLES	Coefficient	[95% Conf. Interval]	
Household head gender	0.0255	-0.0136	0.0647
Family size	0.00449*	-0.00043	0.00942
Agro-ecological characteristics			
Irrigated (0-no, 1-yes)	0.0579	-0.0312	0.147
Longitude	0.275***	0.118	0.432
Latitude	0.343***	0.143	0.543
Longitude*Latitude	-0.00549***	-0.0087	-0.00229
Soil fertility	0.0466***	0.0193	0.0738
Length of growing period	-0.00104	-0.00352	0.00143
Country dummies	Yes		
Soil dummies	Yes		
Agro-ecological zone dummies	Yes		
Farming system dummies	Yes		
Constant	-10.94**	-21.54	-0.345
Observations	1,531		
R-squared	46%		

Note: Dependent variable in log

In addition to climate and weather variables, the regression model also accounts for a rich variety of household, institutional, agro-ecological and production factors that may have an important impact on net profits. As expected, private land tenure was positively associated with higher net profits per hectare. Similarly, richer crop diversity also generated more net profits. The relationship between farm size and net profits per hectare is significantly convex. Smallholder and large-scale farmers seem to be generating more benefits per hectare than their medium-sized counterparts. It may be due to the economies of scales in large farms and the flexibility and much more intensive operation of small-scale farmers. Among the production inputs, fertilizers and seeds have statistically significant concave relationship with net profits, while fuel and machinery seem to have convex relationship. Among the household characteristics, only family size is weakly significant and positively associated with net profits per hectare. Among the agro-ecological characteristics, as expected soil fertility is positively associated with higher net benefits.

4.5. Panel approach

4.5.1. Conceptual framework

In contrast to the Ricardian model applied in the previous section, the panel model used in this section contains annual weather fluctuations as explanatory variables and not long-term climate parameters. Thus, if the Ricardian model can be said to represent equilibrium conditions and long-term adaptation to climate, the panel approach, as suggested by Deschenes and Greenstone (2007), looks into short-term impacts of weather and better represents short-term adjustments or coping strategies to weather events. Weather parameters represent seasonal or monthly deviations from their long-term values. The panel approach also corrects for the effect of the potentially omitted variables in the Ricardian model by using time and cross-sectional fixed effects. Although the use of province-level fixed-effects allows specifically focusing on the effects of weather on net revenues, the long-term climate is also captured by the fixed-effects, thus becoming entangled with all other province-specific time-invariant unobserved variables. The panel model does not use land values as its independent variable since land values reflect the influence of long-term climate rather than short-term weather fluctuations. Instead, the panel model uses net revenue per hectare as its independent variable. All in all, Deschenes and Greenstone (2007), indicate that the panel model would provide more conservative estimates of climate change than Ricardian models.

Although the assumption of constant prices under the panel approach may potentially provide with biased estimates of climate change impacts, Deschenes and Greenstone (2007) indicate that in cases when the climate change would have relatively small effect on crop yields, this shortcoming can be safely ignored. The present model also differs in some aspects from the panel model suggested by Deschenes and Greenstone (2007). The weather variables used here are deviations from climate trend in each specific province, rather than provincial weather deviations from the average weather realization in a country (Deschenes and Greenstone (2007) apply the latter approach on lower administrative scale of counties in a state, i.e. districts within a province).

4.5.2. Empirical strategy

In the empirical estimation, the agricultural revenues per hectare in each province are regressed on deviations from trend in seasonal mean temperatures and accumulated precipitation and a vector of crop management variables such as fertilizer and irrigation water application rates. The dependent variable was differenced to avoid potential estimation biases emanating from its non-stationarity in level form, and equally importantly, the differenced form would, arguably, better capture the effect year to year weather fluctuations on changes in net revenues. Weather variables enter the regression as deviations from trend, filtered using Hodrick-Prescott approach. The province and time fixed effects are used to account for the effect of time-invariant unobserved variables such as soils. The core model is formulated as follows:

$$y_{dt} = \lambda_d + \delta t + X'_{dt}\,\beta + \sum \theta_i f_i\,(W_{idt}) + \varepsilon_{dt} \qquad \textit{(4.6)}$$

where,
y_{dt} – agricultural revenues per hectare for province d at time t
λ_d - province fixed effects
δt – year indicator to control for annual differences in the dependent variable that are common across districts
X - vector of observable crop management practices (fertilizer and irrigation application rates)
Θ_i - effect of weather
W_{idt} – a vector of weather variables

The model is estimated using fixed-effects (FE) regressions estimator.

4.5.3. Data

The dependent variable in our panel model regression is annual provincial gross revenues from crop production (per ha) converted to US dollars using the average exchange rate during the corresponding year. Among the independent variables, weather variables – seasonal mean temperature and accumulated precipitation – represent deviations from long term climatic trend in each province. The weather variables enter the regression model both in level and quadratic forms. The regression model also includes time and province-by-time dummies to account for province fixed effects and for changes in the policy. The motivation for including these fixed effects is to control for all unobserved province specific time-invariant factors such as soils, for example, common annual differences across the years, such as changes in commodity prices (Deschenes and Kolstad 2012), as well as other time-variant province specific factors such as annual fertilizer or irrigation water application rates. Thus, our weather variables are purged of the potential biases resulting from these omitted variables.

4.5.4. Results and Discussion

The resulting model explains about a quarter of variation in agricultural revenues across Central Asia (Table 4.9). Almost all seasonal weather variables and their squared terms are statistically significant, but their magnitudes are not very big, implying that weather does not have a very big influence on year-to-year fluctuations on provincial revenues from crop production. This finding is in line with the earlier literature using panel data analysis (Deschenes and Greenstone 2007). Temperatures in winter, summer and fall have convex relationship with crop production revenues, while spring temperatures have concave relationship. Thus, rise in spring temperatures, up to a certain point, can increase crop revenues in Central Asia, for example, through allowing for earlier planting. While it seems further increases in temperatures during the rest of the year, especially during summer vegetation period seems to affect crop production revenues more harmfully. The model indicates that higher precipitation is positively associated with crop revenues throughout the year.

Table 4.9. Results of panel regression (Dependent variable in log)

VARIABLES	Coefficient	Confidence interval -95%	
Temperature			
winter	-0.0523***	-0.08324	-0.02143
spring	0.206***	0.147958	0.263874
summer	-0.156***	-0.21637	-0.09504
fall	-0.197***	-0.2494	-0.1446
Precipitation			
winter	0.00554***	0.002743	0.008342
spring	0.00314***	0.00083	0.00546
summer	0.00305	-0.00133	0.007419
fall	0.00603***	0.003363	0.008702
Temperature squared			
winter	0.0101***	0.002638	0.017626
spring	-0.00144***	-0.00204	-0.00085
summer	0.0153*	-0.00103	0.031583
fall	0.00129***	0.000723	0.001862
Precipitation squared			
winter	2.02e-05*	-3.05E-06	4.34E-05
spring	-9.42e-06	-2.9E-05	1.03E-05
summer	-7.12e-05**	-0.00014	-8.29E-07
fall	9.24e-05***	5.67E-05	0.000128
Year dummies	yes	yes	yes
Province-Year dummies	yes	yes	yes
Constant	23.27	-12.9392	59.47102
Observations	760		
R-squared	23%		
Number of panel	38		

*** p<0.01, ** p<0.05, * p<0.1

4.6. Comparison of Different Models

The Ricardian and panel models broadly agree on the signs of most of coefficient estimates for precipitation and temperature, even though there are disagreements on the magnitudes of coefficients. This is interesting especially since these two models look at different things. The Ricardian model looks at the impact of long-term climate change, whereas the panel model looks at the effects of short-term (annual) weather deviations from the trend. Table 4.10 below tabulates the coefficient estimates and the confidence intervals for temperature and precipitation, and their squared terms, for the panel and Ricardian models. Those areas where the two models disagree on the signs of the coefficients in a statistically significant way are marked in grey.

Table 4.10. Comparison of the Ricardian and panel model estimates for temperature and precipitation

Climate variables	Panel model			Ricardian model		
	Coeff.	[95% Conf. Interval]		Coeff.	[95% Conf. Interval]	
Temperature						
fall	-0.197***	-0.2494	-0.1446	-0.0905**	-0.163	-0.018
spring	0.206***	0.147958	0.263874	0.386**	0.0676	0.705
summer	-0.156***	-0.21637	-0.09504	-0.271**	-0.506	-0.0359
winter	-0.0523***	-0.08324	-0.02143	-0.0254	-0.0926	0.0418
Precipitation						
fall	0.00603***	0.003363	0.008702	-0.00815**	-0.0158	-0.0005
spring	0.00314***	0.00083	0.00546	0.00137	-0.00362	0.00636
summer	0.00305	-0.00133	0.007419	0.00178	-0.00242	0.00597
winter	0.00554***	0.002743	0.008342	0.00406**	0.000586	0.00753
Temperature squared						
fall	0.00129***	0.000723	0.001862	0.00776*	-0.00039	0.0159
spring	-0.00144***	-0.00204	-0.00085	-0.00826**	-0.0161	-0.0004
summer	0.0153*	-0.00103	0.031583	0.00865**	0.0015	0.0158
winter	0.0101***	0.002638	0.017626	-0.00885***	-0.014	-0.0037
Precipitation squared						
fall	9.24e-05***	5.67E-05	0.000128	0.0000202	-8.2E-06	4.9E-05
spring	-9.42E-06	-2.9E-05	1.03E-05	-8.08E-06	-2.3E-05	6.7E-06
summer	-7.12e-05**	-0.00014	-8.3E-07	-3.97E-06	-1.4E-05	5.6E-06
winter	2.02e-05*	-3.1E-06	4.34E-05	-6.44e-06*	-1.4E-05	9.8E-07

*** p<0.01, ** p<0.05, * p<0.1

Table 4.11 presents the most optimistic and pessimistic potential impacts of climate change based on the confidence intervals of the estimates of the yield, Ricardian and panel models. The climate change scenarios applied are for the year 2039 within B1 (lowest future emission trajectory) – optimistic, and A1FI (highest future emission trajectory) – pessimistic, scenarios, respectively, by IPCC (2007). These seasonal temperature and precipitation changes for the region are shown in detail in Table 2.4 in Chapter 2.

Table 4.11. Comparison of forecasts by different methods

Methods	Optimistic	Pessimistic
Panel	0.21%	-0.72%
Ricardian	1.21%	- 1.43%
Wheat yield	-27%	-54%
Cotton yield	-16%	-80%
Potato yield	+5%	-14%
Vegetables yield	+28%	0%

The Ricardian and Panel approaches indicate that the overall effect of climate change on crop revenues would be small. Reaching -1.43% in the pessimistic case, but also potentially increasing by up to 1.21% percent in the optimistic case. Interestingly, the results of the statistical yield model are broadly similar in the direction of the predicted impacts as the crop-simulation based studies conducted by ICARDA and IFPRI in the region, although the results of the statistical yield model are more pessimistic in the projection of the magnitudes of the impacts. Nelson *et al.* (2010) project that rainfed wheat yields may increase in Kazakhstan by up to 11% and decrease in the rest of the region by down to -18% (Table 4.3). ICARDA study of wheat predicts that wheat yields may increase on average by 12.5% across the region during the same period (Sommer *et al*. 2012). IFPRI study of cotton and potato yields forecasts that cotton yields may increase by 3.7% or decrease by -10.1%, with and without carbon fertilization effect, respectively, on average for the studied sites, while similarly, potato yields may increase by 15% and 9%, respectively, for with and without carbon fertilization scenarios (Kato *et al.* 2012).

There are many inherent uncertainties and strong assumptions in all of these yield predictions both those generated by econometric regressions and those generated by crop simulation modeling. Although simulation modeling-based forecasts are thought to provide more accurate estimates of climate change impacts on yields, usually they are calibrated using experimental data from controlled trials in research stations. In many cases, only the best and most successful experiments can provide the amount of data required by the crop modeling software. As a result, these yield projections are calibrated using the best end of yield distribution. The statistical model, on the other hand, uses production-level data resulting from the activities of millions of individual farmers, although it cannot link these estimates to specific biophysical processes. Perhaps for this reason, the projections of yield losses due to climate change made by the statistical model are higher than by the cited crop model-based studies. The main point of this economic study is not in estimating individual crop yields, but in indicating at the potential overall economic impact of climate change on agriculture. The estimates show that the impact of climate changes on crop production in Central Asia may be relatively low thanks to the evolving adaptive capacity of farmers and potential crop substitutions effects. Theoretical grounds for the crop substitution effect are depicted in Figure 4.2.

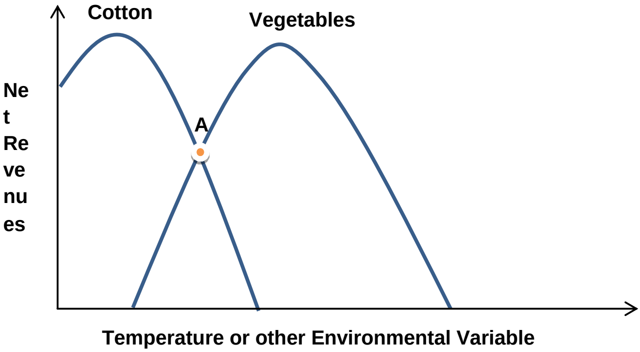


Figure 4.2. Crop substitution as response to climate change

Note: adopted from Mendelsohn *et al.* (1994)

As the temperature increases, farmers who grow cotton would continue growing cotton until the point A where net revenues from growing cotton would be the same as from vegetable cultivation. Any further increases in the temperature would bring the net revenues from cotton cultivation below those from vegetable cultivation, at which point a profit maximizing farmer would switch to vegetable cultivation. Although theoretical principles for crop substitution under climate change are understandable, the explicit quantification of crop substitution effects in Central Asia is beyond the scope of this study, but would be a very interesting topic to look into in future research based on the initial results of this study.

The climatic changes that have occurred over the last 20 years could be indicative of the future spatial distribution of impacts, especially in terms of delineating potential zones of risk and areas of opportunities. In my view, 20 years, especially the last 20 years between 1990-2010, are sufficiently large period of time to have already felt the effects of the ongoing climate change. The analysis of weather trends in the Chapter 2 also shows that the last 20 years were the period with the biggest changes in temperature and precipitation in the region over the entire history of recorded weather observations. There are other advantages of looking into the effects of actually occurred changes in the climate, through the example of weather variations around trend over the last 20 years, instead of, for example, making impact assessments till 2040 or 2080 using climate change scenarios. Firstly, *ex post* analysis is not so much vulnerable to huge uncertainties and beholden to subjective assumptions as are the *ex ante* assessments.

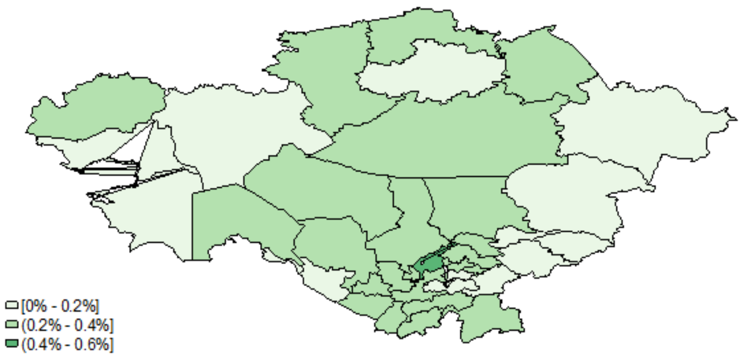


Figure 4.3. Average impact of weather variations from trend on agricultural revenues across Central Asia during 1990-2010

Secondly, analyzing immediate past and present impacts of climate change may be more relevant in terms of policymaking than making educated guesses about what will happen in 30 or 70 years from now, periods much beyond any policymaker's horizon of interest in Central Asia. Figure 4.3 presents the results of this *ex post* estimation for provinces of Central Asia based on panel data analysis of the average effect of weather variations from trend on changes in agricultural revenues over the last 20 years.

The results seem to indicate that on average the effect of weather variations from trend on changes agricultural revenues across the region during the last 20 years was minimal. The impacts of weather ranged from zero to + 0.6%. One point to bear in mind is that the map shows the effect of weather variations from trend, my separate estimations of weather variations from long-term normals shows only a slightly more nuanced picture, with impacts ranging between -2% to +2%. There may be several reasons for these relatively low impact estimates. Several institutional and technological shifts during the last 20 years may have contributed to increasing adaptive capacities in the region, such as agricultural privatization, reduction of price distortions in agricultural input and output markets, maintenance of open cross-border trade in agricultural products (in spite of occasional export bans), or from the technological side: adoption of elements of conservation agriculture on quite massive areas, large-scale crop substitution from cotton to wheat in Uzbekistan, Turkmenistan and Tajikistan, significant gains in wheat productivity due to development of new wheat varieties in Uzbekistan, etc. Importantly, Central Asia is already subjected to a sharply continental climate with extreme temperatures and erratic rainfall. In most of the region, as shown in Chapter 2, agricultural production occurs under sub-optimal climatic conditions with important year-to-year variations. As a key conclusion, agricultural producers operating in such inherently stressed environments may have more experience to dynamically adapt to erratic and changing environment.

4.7. Conclusions and policy implications

Even though the relative estimated impact of climate change on Central Asian agriculture by 2040 is in single digits, ranging between 1.21% to -1.43% of net crop production revenues, the absolute monetary impact is not negligible, estimated to range from + 180 mln USD annually in the optimistic scenario, to – 210 mln USD annually in the pessimistic scenario relative to 2010 levels. The results of this study are broadly in line with the previous assessments of climate change impacts on the region conducted by Bobojonov *et al.* (2012) and Nelson *et al.* (2010), although it reports more optimistic estimates of climate change impacts due to implicit incorporation of full adaptation to climate change in its estimates, which was absent in the previous studies. Moreover, these ranges of impact estimates are also in line with predictions for other temperate areas of the world (Mendelsohn *et al.* 1994, Deschenes and Greenstone 2007). However, contrary to general belief that increased weather variation would lead to higher crop yield variances and most probably to lower mean yields, the results from the statistic model show that the situation may be much more nuanced. Probably this is due to the fact that agriculture operates under quite sub-optimal weather conditions in much of Central Asia. For example, winters and springs are quite cold and frosty in the northern areas of the region specialized in rainfed spring wheat cultivation. Hence warmer, thus more variable to the current baseline, temperatures in spring could actually allow for higher mean yields.

The absolute monetary amounts of the projected impacts are non-trivial for the region, thus pointing at the need for more adaptive actions in the future then what may have been the case so far. Thus, additional investments into adaptation through, for example, agricultural research, with a view to enhance the potential positive effects and mitigate negative effects of climate change may be justified. Finally, most of the adaptation actions usually recommended in the literature for the region (Gupta *et al*. 2009, Christmann *et al*. 2009), such as for example, more efficient water use, development of drought-resistant cultivars, the adoption of sustainable land management practices and institutional reforms are highly useful for agricultural development in the region with or without climate change, thus could be implemented as no-regret options for adapting to climate change while reaping the benefits of these measures in terms of improved agricultural development in the region even in the case of perfect mitigation.

Chapter 5

5. Impact of climate change on rural livelihoods in Central Asia

5.1. Introduction

Agriculture remains a key source of livelihood for a majority of rural households in most of Central Asia. Impacts of climate change on rural poverty can be complex. From one hand, any price increases for agricultural commodities caused by weather shocks may reduce producers' income losses or even increase revenues. On the other hand, net food buying rural (and urban) households, especially the poorest ones for whom food is a major expense category, could be hit hard by rising food prices (von Braun *et al*. 2008). Moreover, households with subsistence-based agricultural activities and residing in areas with lower market access may be negatively affected by lower harvests potentially reducing their food consumption. At the macroeconomic scale, more expensive and scarcer food is also likely to put negative pressures on the rest of the developing economy, weakening industrial and investment competitiveness through higher minimum wages. A key impact of climate change would likely happen through increased weather extremes and variation. A better knowledge how current weather extremes and variations affect different categories of agricultural households could provide with clues about their reactions to increased weather variability under the climate change as well.

Potential impacts of climate change on the livelihoods of rural households need to be studied by fully accounting for different roles of agricultural households as both producers and consumers of agricultural products, as labor suppliers, as well as interactions between these three dimensions. Any such analysis would still be deficient unless it distinguishes climate change impacts depending on households' resource endowments, with especially careful look at the impacts on poor households. The previous literature has shown that different categories of households may respond differently to the same external shocks, with the poorer households having less resilience and adaptive capacities, thus being more vulnerable to negative shocks (Ahmed *et al*. 2009).

This study advances the current literature on the impacts of climate change in three different ways. First, it estimates the relationship between climate change and rural poverty using the agricultural household model framework. Most previous climate change studies ignore agricultural households' potentially interlinked decision making on production, consumption and labor supply and thereby their comprehensive adaptation actions. Moreover, even in broader climate change literature although almost each and every study does emphasize the poverty impacts of climate change, mostly this emphasis is based on qualitative judgments rather than quantitative analysis. Secondly, by disaggregating impacts of climate shocks according to different categories of households (poor, middle, rich; net food buyers or sellers) into the standard agricultural household model it distinguishes the impacts of climate change depending on these household characteristics, with emphasis on the poor households – so far, there have been only a few studies considering such socially differentiated impacts of climate change (for example, Ahmed *et al*. 2009). Third, it sheds a spotlight on Central Asia, a region that has so far been very little studied both in terms of responses of agricultural households to external shocks and especially on their reactions to weather and climate shocks. However, the study also has a limitation. It does not explicitly account for different risk attitudes of the households, which usually may play an important role in shaping households' decision making process; hence more future research is needed in this area.

5.2. Relevant literature

The relationship between climate and poverty is not straightforward leading to well-known debates about the role of climate and of geography as a whole in determining per capita incomes (Bloom and Sachs 1998). Mendelsohn *et al*. (2007) posit, based on data from USA and Brazil and reduced form regressions, that climate has statistically significant effect on rural incomes and climate change is likely to increase rural poverty. Thurlow *et al*. (2009) find that climate variability costs Zambia 4.3 bln USD over a 10-year period and may keep about an additional 2.3% of the population below the poverty line by 2016. Hertel *et al*. (2010) predict that a possible rise in major global staple prices by 10-60% by 2030, could increase the poverty rates for non-agricultural households in parts of Africa and Asia by 20-50%, while agriculture-specialized households elsewhere in Asia and Latin America could actually experience reductions in their poverty rates. Dell *et al*. (2012) find that higher temperatures substantially reduce economic growth in poor countries, while the same have no statistically significant impact on the growth rates in rich countries. Market failures also limit the ability of agricultural households to cope with risks and external shocks (Fafchamps 2005).

Climate change is expected to increase the frequency of extreme weather events (IPCC 2011). Weather shocks are widely considered to be one of the important sources of price volatility (Ahmed *et al*. 2009). Increased price volatility for agricultural commodities has long been argued to exacerbate poverty levels, chiefly in poor developing countries (von Braun *et al*. 2008, FAO 2008). In fact, Ahmed *et al*. (2009) indicate that climate extremes affect the welfare of poor households negatively, especially rural laborers and urban poor. Ito and Kurosaki (2009) find that faced with weather shocks, agricultural households, especially the smallholder and landless poorer households, seek to increase their off-farm labor supply, especially to non-agricultural activities. Akramov (2011) reports that as a result of food price spikes in 2007, partly caused by negative weather shocks in conjunction with other factors (Mitchel 2008, von Braun and Tadesse 2012), USDA's annual food security assessment indicated that in Kyrgyzstan, Tajikistan and Uzbekistan, food consumption for the poorest households fell beyond the nutritional target. More specifically, increases in the price of wheat, sugar, oils and fats during 2010-2011 led to 3.6% net increase in poverty in Tajikistan (Ivanic *et al.* 2012). Nelson *et al.* (2010) project that climate change may have negative effects on the eradication of child malnutrition in Central Asia.

Major share of poor people in developing countries are located in rural areas and derive their livelihoods from agricultural production. Most of these producers are semi-subsistence smallholders (Ahn *et al*. 1981). Over the last 30 years, there have been considerable advances in economic literature within the framework of agricultural household models

(AHM) leading to better understanding of incentives and behavior of such smallholder household farms in developing countries (Singh *et al*.1986). A key feature of agricultural household models is that they allow for making valid inferences when households' production decisions are not separable from their consumption decisions resulting from market imperfections due to high transaction costs (ibid.). Other advantages of AHM include better accounting for such smallholder household characteristics as diversified crop portfolio instead of specialization in one crop and preference to produce staple crops instead of potentially more profitable cash crops (Minot 2008).

Agricultural household models were first developed by Kuroda and Yotopoulos (1978) to explain the surprising finding that increasing crop prices did not lead to higher marketed surpluses of those crops in Japan (Taylor and Adelman 2003). The intellectual origins of agricultural household models could be traced back to the works of Soviet economist Alexander Chayanov[3] (1929) one of whose key insights was that agricultural households' production activities depend on the ratio between "eaters" and "workers" in the family, i.e. dependency ratio. Yan (2009) also opines that a later intellectual inspiration for agricultural household models came from the work on "family economy" by Becker (1965). If earlier agricultural household models were chiefly concerned with the impacts of agricultural price policies, later on they have also been applied to a very diverse range of issues such as missing markets and transaction costs (Sadoulet and de Janvry 1995), off-farm labor supply, technology adoption, nutrition, income distribution, migration, etc., thus, in fact, becoming the key starting point for microeconomic research of agricultural households in developing countries (Singh, Straus and Squire 1986, Taylor and Adelman 2003).

The estimations of AHM are extremely sensitive to assumptions about the integration of the households to product and factor markets, i.e. weather the agricultural household model is separable or non-separable. Therefore, there is a need for testing the separability of the agricultural household model. Several separability tests have been developed, each with its advantages and weaknesses. Vakis *et al*. (2004) classify these separability tests into three categories: 1) global tests not accounting for heterogeneity among households (Benjamin

[3] Chayanov was executed for his ideas during Stalinist repressions in Almaty, Kazakhstan, in 1937.

1992, Jacoby 1993). The usefulness of these tests is limited because market failures are usually idiosyncratic, and not covariate (Vakis *et al*. 2004). 2) Idiosyncratic tests accounting for heterogeneity across households (Feder *et al*. 1990, Maddala 1983, Sadoulet *et al.*1998, Labmert and Magnac 1994). This type of separability tests were used to test for failure in some specific markets or in any market. In cases when the test is used for some specific markets, for example, credit market (Feder *et al*. 1990), the problem is that the households that exhibit separable behavior in that specific market tested could actually have non-separable behavior in some other market. The problem with applications to any one market (and thus deducing the household behavior in all markets) lies in conceptual and empirical difficulty of implementation, sensitivity to specifications (Vakis *et al.* 2004). 3) Tests that reveal idiosyncratic non-separability on the basis of observed behavior as suggested by Vakis *et al*. (2004). These tests allow for drawing conclusions on the separability of decision making by heterogeneous households using a reduced form approach, are not confined to one specific market and make use of unknown sample separation.

5.3. Conceptual framework

While studying the impacts of weather shocks and climate change on the livelihoods of agricultural households, one needs to adequately account for heterogeneity of agricultural households, including differentiating impacts between poor, middle income, and rich; as well as net food-buying and net food-selling households. A key feature of agricultural households in many developing countries is that their production decisions may not be separable from their consumption decisions due to market imperfections (Singh, Straus and Squire 1986). The issue of separability of household decision making needs to be settled first as a starting point and guidance for further in-depth analysis. When the household decision making is separable, one can solve the production and consumption sides of the model separately. First, on the production side, one seeks to maximize the net agricultural profits of the households under risky weather and climate conditions, and then in the second stage, based on this maximized production one maximizes household's utility from consumption. The consumption decisions do not influence the production decisions. Households consider goods produced at home or outside as perfect substitutes. Similarly, family labor and hired labor are also considered as perfect substitutes. In the alternative case, when household decision making is non-separable, consumption side influences the production. For example, family characteristics and demographics may have significant effects on the household's choice of production technology, use of inputs and ultimately, production outcomes. The choice of the model to apply would be crucial for the final estimation results in terms of agricultural production values, consumption levels and poverty rates, as well as supply of family labor to different economic activities.

No matter whether decision-making is separable or non-separable, agricultural households' food consumption and poverty levels are affected by weather and climate shocks through their impact on agricultural households' farming profits. Structurally, this could be through the effects of weather shocks on crop yields and/or crop prices. Hence to see the potential impact of weather and climate shocks on households' food security, the income and price elasticities of households' food expenditures need to be identified. The previous chapters looked into the potential impacts of weather and climate shocks on agricultural prices and farming incomes in Central Asia. Here, the analysis is moved a step further to see how these income and price changes may translate in terms of households' access to food. Moreover, as discussed in the introduction, I also seek to differentiate these impacts by different household categories.

The cooperation between the households could serve as a basis for overcoming household specific transaction costs. The present model seeks to explore the effect of collective adaptation actions by agricultural households against weather shocks, and the potential consequences of such collective action on their poverty rates.

Risk attitudes of agricultural households may play an important role in their decision-making and economic performances. Risk-averseness may lead to sub-optimal economic outcomes for agricultural households. Therefore, poverty reduction may necessitate the use of methods to better manage such risks, for example through agricultural insurance (Ito and Kurosaki 2009), or other forms of collective action. Weather risks are usually covariate, while adaptive capacities, resilience and market failures are idiosyncratic. In contrast to idiosyncratic risks, agricultural households find it much more difficult to insure against covariate risks (Rosenzweig and Binswanger 1993). Difficulty to insure against weather risks leads agricultural households to factor in potential weather risks in their production decisions in an *ex ante* manner (ibid.). Incorporation of risk attitudes of households in the models estimated in this study is constrained by lack of adequate data, requiring more research in the future for explicitly accounting for households' risk attitudes.

5.4. Empirical Strategy

In econometric terms, the difference between separable and non-separable models is that in the non-separable model farming profits are endogenous with consumption. To address this issue of endogeneity, econometric estimation of non-separable model requires the use of instrumental variables that would be highly correlated with farming profits and not endogenous with the consumption. The instrumental variables should affect consumption only through their effect on production. Climate variables or specifically, long-term temperature and precipitation variability, can be obvious candidates for the role of instrumental variables in such a setting. Temperature and rainfall variability have important effects on agricultural profitability by influencing many aspects of agricultural production such as the choice of crop cultivars, planting dates, soil moisture content, etc, however, clearly local weather variability is not caused by current levels of consumption of households residing in that locality. Moreover, the use of climate variables as instruments in this context enables to link these climate variables to household livelihoods through their effect on agricultural incomes. Naturally, the validity of these suggested instruments is evaluated using various identification tests.

The empirical estimation involves four steps. The first step is to test for separability of the agricultural household model. Taking into account the recommendations from Vakis *et al*. (2004) about the importance of accounting for heterogeneous household behavior in testing for separability, giving preference to using a reduced form approach, and making sure that the estimation method is able to identify unknown sample separation for obtaining results on households' behavior which are not confined to one specific market, finite mixture regression is employed to identify latent idiosyncratic non-separability among heterogeneous households (Table 5.2). Finite mixture regression uses maximum likelihood estimation for identifying sub-populations within an overall population (Mclaclhan and Peel 2000). Finite mixture models (FMM) are especially useful for modeling unknown distributional shapes. While estimating FMM, one can give the number of latent components in the data within which observations behave differently. For example, within the agricultural household model framework, household behavior is classified into separable and non-separable, i.e. two components. However, one may not know which households behave in separable manner and which in non-separable manner. Using the results from the FMM regression, the households can be classified into these two categories: for example, those households whose family labor allocation to own on-farm agricultural production is influenced by their demographic characteristics in a statistically significant manner are thought to behave in non-separable manner, and vice versa.

Second, assuming non-separability, a two-stage model is run: in the first stage the endogenous variable (farming profits) is regressed on the suggested instrumental variables (temperature and rainfall variability), from which the predicted values for the farming profits are obtained. Then, the latter are plugged into the second stage regression, where I employ quantile regression of consumption expenditures per household member on a number of explanatory variables including the now instrumented farming profits, household characteristics, asset ownership, crop prices, and several institutional and community variables such as market access, etc. The reason for using quantile regression is to see the effect of these variables on different household categories, especially the poorest ones. When relationship and interactions between the right- and left-hand side variables are complex and can vary at different ranges of data distribution, the Ordinary Least Squares (OLS) estimation may miss the important differences on how different quantiles of the dependent variable react to the same explanatory variables (Cade and Noon 2003). In the present case, using OLS or other similar methods based on estimating the relationship between the variables at the means of these variables would completely miss whether poor or rich households in the sample are affected differently by the same external factors. Another advantage of quantile regression is that it is more robust to outliers than OLS.

In the third stage, separability is alternatively assumed and quantile regression of consumption is run without instrumenting for endogeneity between consumption and farming profits as above, but by using observed values of farming profits.

Finally, instrumented and non-instrumented versions of the quantile regressions are run following the results of separability test: instrumented version for households with non-separable behavior and not instrumented version for households with separable behavior.

5.5. Data

The data used in the analysis comes from the nationally representative agricultural household surveys conducted in the countries of Central Asia during 2010. The survey and the resulting dataset have been described in detail in Chapter 4. Table 5.1 provides some descriptive statistics from the dataset relevant for the analysis in this chapter.

The regression models include such standard household variables as **family size, age, gender and education of the household head**. It is expected that higher family size is associated with lower per head food consumption levels. **The value of the livestock** by the household can be a good indicator of the level of climate change adaptive capacities and income smoothing options after weather shocks. **Total farm size** is expected to have a positive effect on consumption levels as economies of scale could allow increasing per hectare farming profits and also enable the use of more productive agricultural machinery. **Number of crops grown** (diversity of crop portfolio), could positively influence consumption levels. Land tenure is a potentially important factor influencing farmers´ decisions. Farmers in Central Asia may operate several parcels with different tenure arrangements ranging from privately owned to those leased from the State. To instrumentalize this in one variable, **the share of privately owned land area** in the total farm size is calculated. Better market access could lead to improved opportunities for commercializing agricultural produce thus creating favorable conditions for higher farm earnings. The model seeks to capture the effects of better **market access** by interpolating the distance to nearest urban markets for each household in the sample from the global dataset by Nelson (2008).

In addition to these variables, several new variables are introduced which are expected to have a strong explanatory power in the estimated models. One of these variables is called as **rural development**, standing for the dynamism and institutional power of the rural areas, which can serve as a good proxy variable standing for availability of non-farm employment opportunities in the area. This variable is an interaction of the Nelson (2008) data on distance to major urban centers and intensity of night-time lighting[4]. A binomial variable was created for classifying households into **net sellers and net buyers** of agricultural commodities, chiefly food. This variable was created by subtracting the amount of money spent on food expenses from total agricultural sales. All households which sold more than bought were classified as net sellers, and vice versa. If farmers were growing crops but not selling them, they were classified as **subsistence farmers, and non-subsistence** farmers if they were selling any of their agricultural produce. **Cooperation** can be an important element of collective action for managing various risks and adapting to climate change. Farmers' mutual knowledge exchange and ability to learn from their peers can be a good proxy indicator for their willingness for collective action. The ratio of the number of SLM technologies farmers learned from other farmers divided by the number of all other SLM technologies they learned from all other sources is used to instrumentalize for farmers potential for collective action. In fact, Ringler *et al.* (2011) find that farmer-to-farmer extension increases the probability of adaptation to climate change. Within a cross-sectional setting, it is hypothesized that spatial variation of prices within a given area, such as a province: ratio between minimum and maximum prices in the province at a given time can also be indicative of the extent of market integration. Strong spatial variation is consequent to the existence of market failures or of isolated and disintegrated markets, which are more sensitive to local weather shocks, thus making them more vulnerable to inter-temporal price variations as well. Thus, high spatial variation in prices is indicative of **market fragmentation** and high transportation costs. So in the regression analysis this new variable is as a proxy for market integration. The **country**

[4] DMSP-OLS Nighttime Lights Time Series. NOAA's National Geophysical Data Center. Data collected by US Air Force Weather Agency. http://www.ngdc.noaa.gov/dmsp/downloadV4composites.html

dummies are included to implicitly account for other country-specific characteristics that are not included in the models explicitly. In addition, the **prices** for several key staple crops in the region are used to estimate price elasticities of consumption depending on different household categories.

5.6. Results and Discussion

Before going to the results of our econometric analysis, some descriptive statistics of several important variables are presented in order to provide an overview of the sampled households (Table 5.1). In most key parameters, characteristics of households across the four countries of Central Asia are quite similar. Notable exception is the average farm size in which average farm sizes in Uzbekistan and especially in Kazakhstan are much bigger than in Tajikistan and Kyrgyzstan. In Kazakhstan and Tajikistan, higher share of agricultural households are headed by females than in Uzbekistan and Kyrgyzstan. Per capita expenses for food and other consumption items in Kazakhstan sample are considerably higher than in the rest of the region.

The separability tests were conducted for both labor and goods markets using finite mixture model regression (Tables 5.2-5.3). While testing for separability using the household labor supply, the family size and dependency ratio were found to significantly influence the on-farm family labor supply for the households in the first category (n=415), while for those households in the second category (n=1125) none of the demographic characteristics were significant determinants of on-farm family labor supply. Those households for which household demographics are not significant in determining family labor force allocation can be classified as making decision in a separable manner, while those for whom household characteristics are significant determinants of labor supply can be thought to behave in non-separable manner. The results point out that the decision making among our households using this criterion is separable for households in Component 2, and non-separable for those in Component 1 (Table 5.2). Similarly, another separability test was conducted using the value of net agricultural trade balance, i.e. the difference between the value of agricultural goods sold and bought by the households. If the household behaves in separable manner, the household's demographic characteristics should not influence its net agricultural trade balance in a statistically significant way, since household would consider goods produced at home or outside as perfect substitutes.

Table 5.1. Household descriptive statistics

Key indicators	Kazakhstan	Kyrgyzstan	Tajikista	Uzbekistan
Average family size	5.7	5.5	7.8	6.2
Females to males ratio	1.18	1.13	1.04	1.06
Share of female household heads	21%	8%	15%	6%
Age of household head	51	50	52	47
Dependancy ratio	0.69	0.67	0.68	0.78
Family labor allocation, (%)				
off-farm work	26%	20%	23%	24%
employment abroad	0%	4%	4%	1%
farm work	73%	76%	73%	75%
Share of food expenditures in total expenses (%)	60%	67%	66%	62%
Average farm size, (ha)	191	5	3	26
Average house value, (USD)	13044	5682	5836	14075
Average value of agricultural machinery owned, (USD)	25084	2287	514	10164
Average value of livestock owned, (USD)	5251	8973	852	6507

Table 5.2. Separability test based on family labor supply to household own farm

Variables	Component 1	Component 2
Dependency ratio	-0.37**	-0.10
Female to male ratio	-0.02	0.09
Household head age	-0.06	0.04
Household head age, squared	0.00	-0.0003
Household head gender	-0.18	0.06
Family size	-0.15**	-0.07
Number of adults	0.16	0.03
Education of household head	-0.01	0.01
Average wage	0.96***	-0.001
Distance to markets	0.0	-0.001*
Rural development	0.0004***	0.00001
Country dummies	yes	yes
Farm size	0.0002**	-0.00001
Number of crops grown	1.54***	0.79***
Constant	-4.26	-0.92

Dependent variable: Supply of family labor to own on-farm activities *** p<0.01, ** p<0.05, * p<0.1

By this measure, 437 households (Component 1) in were found to behave in non-separable manner and 1095 households (Component 2) in separable manner (Table 5.3).

Table 5.3. Separability test based on household's net trade balance in agricultural goods

Variables	Component 1	Component 2
Dependency ratio	-0.0495	-0.01991
Female to male ratio	0.013439	-0.00287
Household head age	-0.00955	0.005218
Household head age, squared	1.82E-06	-5.2E-05
Household head gender	0.043274	0.027667
Family size	-0.46939**	-0.03816
Number of adults	0.059797	-0.00939
Education of household head	0.112691***	0.000917
Average wage	0.15069	-0.20578***
Distance to markets	0.000118	-2.8E-05
Rural development	0.00012*	1.45E-05*
Country dummies	yes	yes
Farm size	-1.43E-06	0.000364***
Number of crops grown	0.239087***	0.035535***
Constant	8.289252***	9.827911***

Dependent variable: Net balance in agricultural goods trade (in log) *** p<0.01, ** p<0.05, * p<0.1

The Pearson chi2 test rejected at 1% that the results of the two separability tests are independent from each other (Table 5.4), i.e. meaning that both tests mostly agreed, and in most cases the same households were found to behave in non-separable manner by both tests, and vice versa. At the same time, the tests showed that there are some households who may be behave in separable manner in the labor market, but behave in non-separable way in the goods market, and vice versa.

Table 5.4. Comparison of separability tests in labor and goods markets

	Goods market		
Labor market	non-separable	separable	Total
non-separable	147	268	415
separable	290	827	1117
Total	437	1095	1532

Pearson chi2(1) = 13.2795 Pr = 0.000

Before estimating the non-separable model, the validity of the instruments was checked using various identification tests. When both variation in temperature and precipitation were used, the model was over-identified with Hansen J-Statistic equal to 3.39 (p-value = 0.0653), when only variation in precipitation was used the model was under-identified with Kleibergen-Paap LM statistic equal to 1.094 (Chi-sq(1) P-val = 0.2956), whereas when only variation in temperature was used the model was exactly identified. In the latter case, the null hypothesis of under-identification was rejected at 1% both for i.i.d. and non-i.i.d. assumptions for error terms with corresponding LM statistic of Anderson canonical correlation and Kleibergen-Paap LM Statistic. The Sargan-Hansen test indicated that the model is exactly identified. The model was calculated also without instrumenting for farming profits (separable model), and then compared to the above instrumented version (non-separable model) using Hausman specification test resulting at rejection of the null hypothesis of no systematic difference in the coefficients at 1%.

The results of non-separable and separable model estimation are given in Tables 5.5 and 4.4, respectively. These two models assume that all household behave either in separable or non-separable manner. The major difference between separable and non-separable models is in the income[5] elasticity of food consumption and income coefficients depending on the population quantiles: in the non-separable model 1% change in production income would translate into about 0.39%-0.52% change in consumption. The income elasticity of the poorest households (10th percentile) is higher than that of richer households (Table 5.5). In the separable model, the elasticities are significantly lower, less than 5% and mostly non-significant (Table 5.6).

However, in practice, some households in the sample may behave in separable manner, while at the same time; the remaining households behave in non-separable way. Using the results of separability tests, households were divided into two groups: those with separable behavior and those with non-separable behavior, using the separation given by the separability test of the labor market behavior. Quantile regressions of per capita household food expenditures were run separately for each of these two groups. When estimated separately, the model for

[5] Net income received from agricultural production.

households with non-separable behavior confirms the results of the general non-separable model. The results of the separable model for only those households which were found to have separable behavior are broadly similar with the general separable model (Annex 1).

Since income from agricultural activities is the most important explanatory variable in the analysis, based on the above results one can draw some conclusions on the relative strengths of each of these models. It appears that non-separable models better explain households' behavior, especially for the poorer households, since the income elasticities of food consumption in the separable models are implausibly low, especially considering that for most households in the sample agricultural income is the most important source of livelihoods. Moreover, as the separability tests have demonstrated, some households who seem to behave in a separable manner in one market may show non-separable behavior in some other market. For these reasons, while interpreting the results, the preference is given to the non-separable models.

The general non-separable model indicates that the poorest households' food consumption is quite sensitive to agricultural income changes: 1% increase in the level of their farming profits may lead to about 0.52% increase in their per capita food consumption. For richer households, income from agricultural activities seems to have lower impact on their food consumption, about 0.39% increase for every 1% increase in farming profits (Figure 5.1).

The effects of the age, education and gender of household head are generally statistically non-significant at 5%. More households members working on-farm or non-farm seems to have statistically more significant effects, with more households members engaged in on-farm work decreasing per capita household food consumption, while more household members working in non-farm jobs leading to higher food consumption.

Table 5.5. Model estimation with instrumental variable assuming non-separability

Variables	Quantiles				
	10th	**30th**	**50th**	**70th**	**90th**
Farming profits (log, instrumented)	0.522***	0.494***	0.437***	0.378**	0.392**
Age of household head	0.0132	0.0105	-0.0122	-0.0185*	-0.0268
Age of household head, squared	-0.00016	-0.00015	0.000109	0.000176*	0.000271
Education of household head	0.00106	-0.108	-0.152**	-0.161**	-0.0503
Education of household head, squared	0.000218	0.0225	0.0345**	0.0355***	0.00862
Gender of household head (0-female, 1-male)	0.0846	-0.0427	-0.0508	-0.0456	-0.0842
Number of family members working:					
Non-farm work	0.0369	0.0371*	0.0525***	0.0590**	0.0457
On-farm work	-0.0417**	-0.0471***	-0.0557***	-0.0569***	-0.0551***
Distance to markets (log)	-0.0779**	-0.0929***	-0.0552***	-0.0426*	-0.0721**
Livestock value (USD)	5.99E-07	3.59E-07	2.44E-07	3.65E-08	1.95E-06
Value of total assets (log)	0.0632**	0.0735***	0.0567***	0.0392***	0.0468**
Market integration	-0.550***	-0.316***	-0.342***	-0.252*	-0.422***
Cooperation	0.00569	0.00843	0.0224	0.0338	0.0357
Net agricultural trade position (0-net buyer, 1-net seller)	-0.284***	-0.219***	-0.187***	-0.178***	-0.157*
Number of crops grown	0.0575**	0.0487***	0.0332	0.0222	0.00637
Subsistence farmer (0-yes, 1-no)	0.355***	0.409***	0.408***	0.348**	0.188
Vegetable price (log)	-0.0483*	-0.0223	-0.0153	-0.0088	-0.0102
Potato price (log)	0.395***	0.492***	0.310*	0.261*	0.217
Wheat price (log)	-0.0669	-0.0726	-0.196	-0.255	-0.165
Maize price (log)	-0.185***	-0.147***	-0.0865**	-0.0438	0.0298
Share of privately owned land	-0.218***	-0.175**	-0.134*	-0.0507	0.0783
Farm size (log)	-0.00192	-0.0165	-0.00925	0.0129	0.0382**
Constant	-4.042***	-3.141***	-2.292**	-1.549	-0.675
Pseudo R2	18%	20%	21%	20%	19%

Notes: Dependent variable: Food consumption expenses per household member, log. Country dummies included. Instrumental variable: Long-term variation in temperature. Bootstrapped 20 times. *** p<0.01, ** p<0.05, * .1

Table 5.6. Model estimation without instrumental variable assuming separability

Variables	Quantiles				
	10th	30th	50th	70th	90th
Farming profits (log)	0.0345	0.0370*	0.0427***	0.0443***	0.027
Age of household head	0.00892	0.00281	-0.00342	-0.0172***	-0.0101
Age of household head, squared	-0.00015	-6.91E-05	3.36E-05	0.000157***	0.000111
Education of household head	0.0982	-0.108	-0.136*	-0.116*	0.00848
Education of household head, squared	-0.0196	0.0253	0.0345**	0.0262*	-0.00031
Gender of household head (0-female, 1-male)	-0.0182	-0.0584	-0.0366	0.00104	-0.0258
Number of family members working:					
Non-farm work	-0.0229	0.0688**	0.0582**	0.0577**	0.0249
On-farm work	0.000288	-0.0529***	-0.0558***	-0.0565***	-0.0467**
Distance to markets (log)	-0.0382	-0.0826***	-0.0428	-0.00682	-0.0103
Livestock value (USD)	4.43E-07	2.58E-07	1.24E-07	-1.31E-07	-4.79E-07
Value of total assets (log)	0.0546***	0.0569***	0.0332	0.0320**	0.0337*
Market integration	-0.614***	-0.387***	-0.430***	-0.455***	-0.729***
Cooperation	0.00764	0.0328**	0.0274	0.0347**	0.0531*
Net agricultural trade position (0-net buyer, 1-net seller)	-0.326***	-0.341***	-0.267***	-0.239***	-0.188**
Number of crops grown	0.0746***	0.0342*	0.0171	0.0105	0.0226
Subsistence farmer (0-yes, 1-no)	0.380*	0.496**	0.391*	0.4	0.214
Vegetable price (log)	-0.0487	-0.0116	-0.0209	-0.0225	-0.00573
Potato price (log)	0.473*	0.496***	0.511***	0.293*	-0.0326
Wheat price (log)	-0.432	-0.298	-0.374**	-0.311*	-0.287
Maize price (log)	-0.123	-0.130**	-0.122**	-0.0921	-0.0507
Share of privately owned land	-0.405***	-0.273***	-0.227***	-0.146**	0.0182
Farm size (log)	-0.015	0.0109	0.00709	0.0223	0.0563***
Constant	-0.964	0.0925	0.473	0.75	1.005**
Pseudo R2	18%	18%	20%	20%	18%

Notes: Dependent variable: Food consumption expenses per household member, log. Country dummies included. Bootstrapped 20 times. *** p<0.01, ** p<0.05, * .1

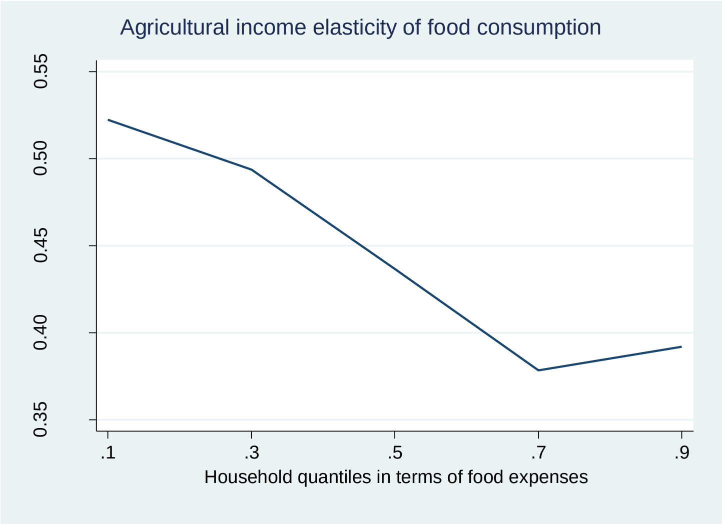


Figure 5.1 Impact of agricultural income on household food consumption (non-separable model)

Distance to markets is negatively associated with households' food consumption. Halving the time necessary to reach the nearest major urban market may likely increase the households' food consumption by about 5-10%. A separate analysis shows that this is probably because both of the possibility to get higher prices for agricultural produce in the urban markets, but also, importantly, the higher chances of having a family member working in a non-farm job in the city. As expected, the value of livestock owned is mostly positively associated with food consumption; however, the coefficients are statistically non-significant. Whereas the value of total assets owned has a clear positive association with higher food consumption across all household categories. The instrumental variable on market integration is negatively associated with food expenses in all models, i.e. higher market integration seems to be associated with lower expenditures on food. The instrumental variable on cooperation does not seem to be a good one, as it was non-significant in most cases, even though positively signed. Being a net seller of agricultural commodities (including non-food, such as cotton) seems negatively associated with food expenditures. Being a non-subsistence farmer, i.e.

commercializing at least some part of household's agricultural output and growing a more diversified crop portfolio both seem to lead to higher food consumption.

In all cases when vegetable, wheat and maize prices are statistically significant; they are negatively associated with food expenditures, which is consistent with classical demand theory. However, in most cases, potato prices are positively associated with food expenses, especially for the poorer households, pointing at the importance of potato in the agricultural production by poor households and as a source of their income.

The share of privately owned land was negatively associated with food expenses, perhaps pointing that those farmers who are able to rent more land then they own privately would have higher profits and thus higher food consumption. Confirming this idea, total farm size was positively associated with food consumption for the richest households. In all models, the country dummies are included to account for unobserved country-specific characteristics, and also all the models have been village-clustered and bootstrapped with 20 replications for achieving robust standard errors.

These results are presented graphically in Figure 5.2.

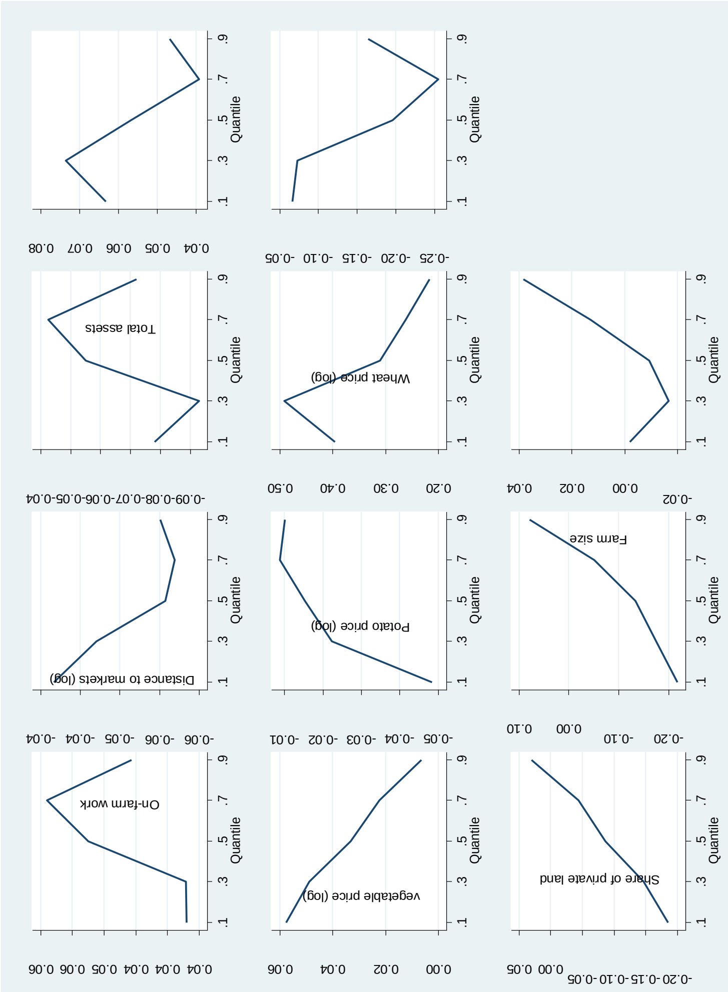


Figure 5.2. The results of general non-separable model.

5.7. Conclusions and policy implications

The study has confirmed that poorer households are more vulnerable to the impacts of weather and climate shocks since their food security more strongly depends on their agricultural incomes. The agricultural income elasticities of the poorest 10% of households in our sample is estimated to be about 0.52, meaning every 1% decrease in their farming profits is likely to lead to 0.52% decrease in their food expenses.

The models show that food expenses of all households are negatively associated with wheat, maize and vegetable prices, while potato prices are positively associated with the food expenses, epically of the poorest households, which points at the importance of potato for the livelihoods of the poorest farming households. Hence weather shocks leading to higher wheat, vegetable and maize prices are likely to reduce the food expenses of all household categories, whereas higher potato prices seem to be somewhat more beneficial for the poorest farmers. However, if the weather shocks would lead to significant reductions in farming incomes through lower yields, uncompensated by higher prices, it is likely to deal a crippling blow to the food security of the poorest farmers, whereas the richer households' food expenditures would not be so much impacted.

Improving market access and creating opportunities for diversified crop portfolio seem to positively contribute to improving food security among the rural farming households in Central Asia.

Chapter 6

6. Constraints and incentives to climate change adaptation in Central Asia

6.1. Introduction

Mitigation efforts being currently undertaken seem not to be sufficient to avert some degree of climatic change. Increasingly, achieving the target of not allowing 2°C rise in global mean temperatures, compared to the pre-industrial levels, seems illusory, spelling significant changes in the functioning of natural ecosystems. Hence, in order to prevent or lessen any negative effects of these changes on social and economic systems, there is a need for appropriately vigorous adaptation actions.

Agriculture is the most climate-sensitive sector in Central Asia. Given agriculture's importance for rural livelihoods, climate change could have important consequences on rural incomes, unless appropriate actions are taken to adapt to the changing climatic and weather conditions. As climate change is going to increase the frequency and magnitudes of weather extremes, agricultural households in Central Asia may be confronted by unprecedented weather shocks. The risks posed by weather shocks are covariate, while agricultural households' adapting capacities and resilience are idiosyncratic. Thus, the poorest households are more vulnerable to climate change because they have lower adaptive capacities. For this reason, any analysis of adaptation to climate change would be deficient unless it specifically looks into the factors that enable or prevent the poorest agricultural households from adapting to weather shocks and climate change.

In this light, the key contributions of this chapter consist of the following. First, factors constraining or stimulating adaptation to climate change are identified, including households' differing socioeconomic statuses and resource endowments. Secondly, I differentiate between absence of need among agricultural households to adapt and the truly limiting factors on their adaptive capacities. Most studies quantitatively assessing determinants of adaptation confound absence of need to adapt and capacity to adapt. Finally, potential ways of promoting incentives and overcoming the constraints to climate change adaptation are proposed, specifically targeting the Central Asian context, but which may also be useful in other settings. So far, to my knowledge, there have been no quantitative studies of determinants of climate change adaptation in Central Asia in the published literature.

6.2. Relevant literature

The literature on environmental risk perceptions have been growing since early 1960s (O'Connor *et al*. 1999). The main hypothesis behind this literature is that when people perceive better the risks they are facing, they are more willing to undertake actions to address them. Hence perception of climate change is an important precondition for farmers to adapt to it (Madison 2007). Therefore, adaptation can be considered as all changes an individual or an institution, such as government, makes to adjust to a changing environment (Osberghaus *et al.* 2010, Seo *et al*. 2011). However, when faced with "weak signal" uncertain risks such as climate change, raising public awareness could be necessary for correct attribution of the causes of on-going climatic changes and appropriate reactions to these changes. It also needs to be acknowledged, as suggested by Nhemachena and Hassan (2007) and Mertz *et al*. (2009), that adaptation measures undertaken by farmers may have other driving forces than actual climate effects. For this reason, adaptation actions are a function of both perceiving the risks associated with the climate change, but are also dependent on personal environmental knowledge and beliefs, as well as personal characteristics such as gender, age, education, etc. (O'Connor *et al*. 1999).

The research on climate change has been moving from a techno-centric approach that considered adaptation as merely a matter of technological change to a more comprehensive concept of adaptation as a dynamic socio-economic, cultural and institutional process (Gbetibouo 2009). In agricultural research, this also has led to a shift in attention from estimation of climate damages to deeper analysis of farm-level adaptation, including the ways farmers psychologically perceive climatic change and variability, the biophysical, socioeconomic and institutional factors that facilitate or hinder adaptation, as well as most plausible ways farmers actually take adaptation decisions and actions (ibid.)

Adaptation can be classified into two categories: i) private adaptation and ii) public adaptation (Mendelsohn 2000). Private adaptation is undertaken by individuals themselves seeking maximize their utility, while public adaptation is undertaken by the Governments seeking to achieve a higher public benefit for the entire society (Osberghaus *et al*. 2010).

Adaptation can happen *ex post* to a climatic shock or *ex ante* (Mendelsohn 2000). There are reasons to believe that most of the private adaptation may happen *ex post,* while Governments can potentially undertake *ex ante* adaptation measures, but also "nudge" and educate private individuals towards efficient levels of *ex ante* adaptation.

6.3. Conceptual framework

Changes in the climate do not automatically lead to adaptation actions, but they are mediated by perceptions of these changes by agricultural households (Hisali *et al*. 2011, Rogers 1975) and their capacities to adapt (Yohe and Tol 2002).

The vulnerability of agricultural production to climatic and weather changes is greatly modulated by timely adaptation and coping actions. However, when evaluating uncertain and low probability events individuals may often take decision based on their intuitive risk judgments, i.e. perceptions, rather than rational expected utility maximization (Tversky and Kahneman 1986, Slovic 1987, Botzen *et al*. 2009). Therefore, for better understanding of households' adaptive behavior, it is important to comprehend the factors that shape their perceptions of climatic changes (Botzen *et al*. 2009). Human perceptions are fashioned by two distinct but mutually reinforcing thought processes: experiential and analytical (Botzen *et al*. 2009), or as Kahneman (2011) puts it "fast and slow" thinking. If explained succinctly, the experiential process operates in an intuitive, affective and automatic manner, while the analytical process is based on logical, deliberate and rational processing of the available information (Botzen *et al*. 2009). Both of these processes are influenced by individual's previous experiences, education, age, gender, socio-economic, institutional, cultural and other characteristics.

Perceiving climate change is not by itself sufficient for adapting to it. One of the key incentives for successful adaptation is when agricultural producers do perceive that climate is changing and that this change is affecting their agricultural activities, necessitating them to take appropriate actions to modify their farming practices to better suit the new climate. Households start adapting only when the costs of inaction on the changes that they perceive outweigh the costs of adaptive actions. Even if households perceive certain changes in the climate, they may still be unwilling to incur costs of adapting to these changes if these changes do not pose a sufficiently high level of damage risk, especially since individuals tend to underestimate the occurrence of low probability events (Tversky and Kahneman 1986).

Even when households perceive the changes and are willing to take adaptive actions, they may still be constrained by low adaptive capacities. Households' adaptive capacities, in turn, depend on their resource endowments, specifically, their access to five "capitals": human, natural, financial, social and physical (Chambers and Conway 1991), which largely fashion households' resilience to external shocks, including weather and climate shocks. To illustrate, households' abilities to act collectively in cooperation with other households are the key part of their social capital and are essential for their climate change adaptation (Adger *et al*. 2003, Ringler *et al.* 2011). Such collective action requires flows of information and networks among individual households (Adger *et al*. 2003). Social networks could greatly facilitate the adoption of new technologies and the mobilization of resources for adaptation measures (Ringler *et al.* 2011), in fact, individuals embedded in stronger social networks were found to have higher awareness of climate change and higher likelihood of adaptation (ibid.)

Conceptually, this study is guided by its distinction of the four behavioral states in the adaptation process, i.e. first, households should perceive that climate is changing in order to adapt to these changes; second, even if they perceive the climate change, households may see no need to adapt unless costs of climate change are higher than the costs of adaptation; third, even if they see the need to adapt, after rational economic calculations, their adaptation may still be constrained by their low adaptive capacity; and finally, households perceive the changes, see the benefit in taking some action, and have certain adaptive capacities to take some specific adaptation actions (even though, the same households could still be constrained by their adaptive capacities to take a complete set of necessary adaptation actions).

I am able to differentiate between behavioral states 2 and 3 above using perceptions of households on climate change impact. If a household perceived climate change but did not adapt to it, while, at the same time, did not report any negative consequences due to climate change or indicated that the change has been positive, it is concluded that household did not adapt because it saw no need to do so. In case, when household perceived climate change and did not adapt to it even while reporting that climate change has had negative consequences on farm productivity, it is concluded that household sees the need to adapt but was constrained in its adaptive actions.

This conceptual framework also motivates the empirical strategy described in the following section.

6.4. Empirical strategy

As an initial step, an exploratory analysis of the survey datasets is conducted with the purpose of highlighting the major characteristics of the perceptions of the surveyed households about the climate change and its putative impacts, their coping actions as well as constraints on their adaptation.

Secondly, the key target variable of the analysis is created standing for the different behavioral states in the adaptation process as described in the conceptual framework. Thus, the newly created variable consists of four categories such as i) did not perceive climate change and did not adapt, ii) perceived climate change but saw no need in adapting, iii) perceived climate change but did not adapt because of insufficient adaptive capacity, and finally iv) perceived climate change and adapted. Households have been categorized as adapted to climate change if they have reported to have done any of the 33 adaptation options (plus, "any other" open-ended option) enumerated in the survey questionnaire such as change of crop variety, change of planting dates, etc.

The nature of the dependent variable requires the use of econometric methods appropriate for categorical variables, such as multinomial logit or independent probit models or their more suitable modifications. However, to identify exactly which econometric method to use, tests for Independence of Irrelevant Alternatives (IIA) are employed to check the validity of multinomial logit model, and also tests to check for the "proportional odds" assumption are used for verifying if models for ordinal categorical variables are more suitable. The standard multinomial logit model treats the categories of the dependent variable as nominal and un-ordered. In the present case, it seems very likely that these categories may not be completely independent of each other. The models used for ordinal categorical variables employing "proportional odds" method assume strict hierarchy among the categories of the dependent variable. However, in the present case, it is hard to say that the categories of the dependent variable represent sequential points in the distribution. Hence, if the non-suitability of both the multinomial logit model and of ordinal "proportional odds" methods are validated by the results of appropriate tests, then the dependent variable would require an estimation method that does not use "proportional odds", or "parallel regression" assumption, but also does not treat the categories of the dependent variable as completely independent of each other.

Stereotype logit model (Anderson 1984) is just the kind of maximum likelihood estimation method which overcomes both of the above limitations. According to Long and Freese (2006) the stereotype logit model was developed by Anderson (1984) to address the limitations of the ordinal logit model, where the dependent variable can be understood "in terms of latent continuous variable that is divided by thresholds leading to observed categories", whereas in the stereotype logit model, each of the categories of the dependent variable are subjectively "assessed" by the respondent. A standard application of stereotype logit model is in evaluating dependent categorical variables constructed using Likert scale: such as an "assessment" of quality of something – excellent, good, medium, and bad. Long and Freese (2006) propose that the model could also be applied in cases when the dependent variable is not "assessed", but when one is unsure of the relevance of the ordering of the categories or when some of the alternative categories may be similar (StataCorp 2011).

As Fullerton and Wallace (2007) indicate, rather than assuming constant coefficients across equations, stereotype logit model assumes that coefficients change by a common factor, ϕ, so that

$$\beta_k = \phi_k \beta. \qquad (6.1)$$

A stereotype logit comparing two categories, j and m, can be denoted as (following Fullerton and Wallace, 2007):

$$\log(P_{ij}/P_{im}) = (\varphi_j - \varphi_m) \sum_{k=0}^{K} \beta_k x_{ik}, \qquad (6.2)$$

Where constraints are imposed on the ϕ parameters to ensure ordinality. As in the present case, for example, in order to identify a model with four outcome categories, the stereotype model assumes that $\phi_1 = 1$ and $\phi_4 = 0$. To ensure ordinality, one assumes that $1 = \phi_1 > \phi_2 > \phi_3 > \phi_4 = 0$ (ibid.)

Two important aspects of the stereotype logit model are “indistinguishability” and “dimensionality” (Anderson 1984). The model is indistinguishable when the explanatory variables in the regression cannot differentiate between some pair of categories of the dependent variable; hence these categories can be combined leading to more efficient estimates (Fullerton and Wallace 2007). In the analysis, the distinguishability is tested by constraining adjacent ϕ parameters to be equal one another and comparing these results to the unconstrained model.

Another characteristic of the stereotype logit model is dimensionality. According to Fullerton and Wallace (2007), dimensionality is “the number of linear functions required to describe the relationship” (Anderson 1984). The maximum number of dimensions is the number of categories of the dependent variable minus one. In the present case, the maximum number of dimensions can be three. However, a stereotype logit model with the maximum number of dimensions allowed is equivalent to a multinomial logit model (Fullerton and Wallace 2007). To determine the appropriateness of the stereotype logit model, it is first identified how well the full stereotype logit model fits the data as compared to the null model. Then, it is evaluated if the multinomial logit model fits the data better than the stereotype logit model. In both cases the likelihood ratio statistics is used for comparing the models. If the stereotype logit model fits the data better than the null model and the multinomial logit model, then a single-dimension stereotype logit model is appropriate (Lunt 2001).

6.5. Data

Literature on the adaptation to climate change in agriculture is strongly based on the previous research on adoption of new technologies by agricultural producers, including under risky decision making contexts. Based on the previous lines of research and earlier work on agricultural adaptation to climate change *per se*, it is hypothesized that there are a number of variables which have a strong associative (if not causal) effect with adaptation to climate change. Of course, no list of variables will ever be sufficiently comprehensive to totally eliminate the error term. These variables are grouped into four major categories: i) household characteristics, corresponding to human dimension of the five "capitals", ii) farm characteristics (physical capital), iii) climate-related variables (natural capital), and iv) institutional variables (social and financial) (here and below I am partly inspired by Gbetibouo (2009)). Further, these variables are listed by category, and also some of the variables are elaborated when needed.

Household characteristics

Family size, age, education and gender of the household head are standard variables used in most adaptation studies, though there is no firm theoretical consensus on the direction of their impact on adaptation. In most cases, this is a matter of empirical analysis and can differ from one context to other. Income status of the household (whether rich or poor) may have an effect on adaptation as richer households have more resources and relatively greater adaptive capacities making them more likely to adapt. To capture the income status of the households the **value of total household assets and daily food consumption per household member** are used. Better knowledge of available agricultural technologies could become a facilitating factor for adaptation. The model uses **number of technologies known** by the farmer to capture this effect. **Availability of family farm labor** could have a positive effect on adaptation as more family labor could enable to undertake labor-demanding adaptation practices more conveniently.

Farm characteristics

Total farm size is expected to have a positive effect on adaptation as economies of scale could allow undertaking adaptation measures with scale-sensitive costs. It is expected that **soil fertility** will have a negative association with adaptation hence the producers with lower quality soils are more likely to be affected more strongly by climate change, so are more likely to adapt earlier. The availability and value of productive assets**,** in this case the **value of agricultural machinery owned**, **number of crops grown** (diversity of crop portfolio), could positively influence decisions on adaptation. Many rural households in Central Asia keep livestock as one of the key saving and investment strategies, hence **the value of the livestock owned** (different from income status) by the household can be a good indicator of the level of adaptive capacity.

Climatic characteristics

Higher **frequency, number and strength of climatic shocks** can provide with more incentives for adaptation. Relative strength of these variables would also corroborate the intuition that unless Governments encourage farmers for *ex ante* adaptation most of adaptation to climate change could be *ex post*. It is believed that many impacts of climate change would be felt along the **agro-ecological zones and farming system typologies**, hence the estimation controls for these variables. It is also thought that **availability of irrigation** could be an important factor influencing adaptation decisions. Higher long-term climate variability (30 years, 1980-2010) in terms of more **variable temperature and precipitation** could necessitate a more adaptive behavior. Finally, the estimation also takes into account **long-term average precipitation and temperature** (30 years, 1980-2010). The climate variables have been compiled for about 400 weather stations across Central Asia. The data come from national meteorological agencies, Williams and Konovalov (2008), NASA´s Global Summary of the Day, and other sources. Climate variables from individual weather stations were spatially projected to the digital map of Central Asia using spatial interpolation technique of inverse weighted distance. Following this, corresponding weather variables were extracted for each household using the GPS location of the household.

Institutional characteristics

Land tenure is a potentially important factor influencing farmers´ decisions, including those on adapting to climate change (Quan and Dyer, 2008). Adaptation to climate change may lead to increased production costs and/or necessitate long-term farm investments. Quan and Dyer (2008) note that secure land tenure arrangements are needed for better climate change adaptation. Farmers in Central Asia may operate several parcels with different tenure arrangements ranging from privately owned to those leased from the State. To instrumentalize this in one variable, taking into account different levels of incentives for long-term investments inherent to different land tenure arrangements, the share of privately owned land area in the total farm size is used in the model, even though, admittedly, this variable may not perfectly capture the tenure security. **Access to weather information and to extension,** higher **market access** should normally lead to more adaptation. The **country dummies** are included to implicitly account for other country-specific characteristics that are not included in the models explicitly. A proxy variable on **household's net position in terms of selling and buying agricultural products** is also included. The **intensity of night-time lighting** (DMSP-OLS Nighttime Lights Time Series. NOAA's National Geophysical Data Center, using the data collected by US Air Force Weather Agency) is used **as a proxy for availability of electricity.** More lighting could indicate at economic dynamism of the region and availability of non-farm job opportunities.

6.6. Results and Discussion

The descriptive analysis shows that majority of surveyed households have noticed changes in the climate, as manifested by changing temperature and precipitation amounts and patterns, even though the levels of adaptation in response to these changes remains relatively low. The results of the Pearson chi2 test also reject the null hypothesis that adaptation and perception are independent of each other (Table 6.1.). Among the respondents, 57% perceived changes in the climate but did not adapt, implying that either they saw no need in adapting or were constrained in their adaptive actions, including by such factors as insecure land tenure, administrative limits to certain adaptive actions, lack of access to credit, etc.

Table 6.1. Descriptive analysis of perception and adaptation to climate change

Indicators	Perceived change	Did not perceive any change	Total
Adapted	26%	0	26%
Did not adapt	57%	17%	74%
Total	83%	17%	100%

Pearson chi2(1) = 114.3239   Pr = 0.000

Further descriptive analysis validates both of these points. It seems for many households, the impacts of climate change were so far trivial, for some slightly negative and for some others slightly positive (Figure 6.1). On average, positive perceived impacts were reported for wheat yields and cattle productivity, while negative perceived impacts for cotton, vegetables and potato.

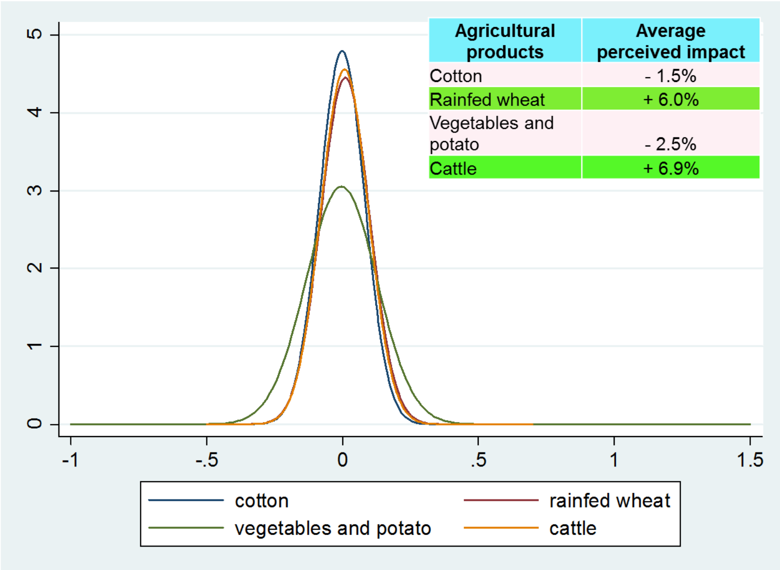


Figure 6.1 Perceived impacts of climate change in crop and livestock productivity

On the other hand, many households, especially poor households and those located in semiarid and arid areas, reported to be constrained in their adaptive actions by lack of credit, inputs, water, information and others (Figures 6.2 and 6.3). Major constraints to adaptation that are faced by poor farmers came out to be lack of access to credit and inputs. Whereas, in semiarid areas, several factors such as access to credit and inputs, but also to information, irrigation water, and even relative lack of labor seem to be hindering adaptive actions. Access to markets seems to be equally problematic in all agro-ecological zones.

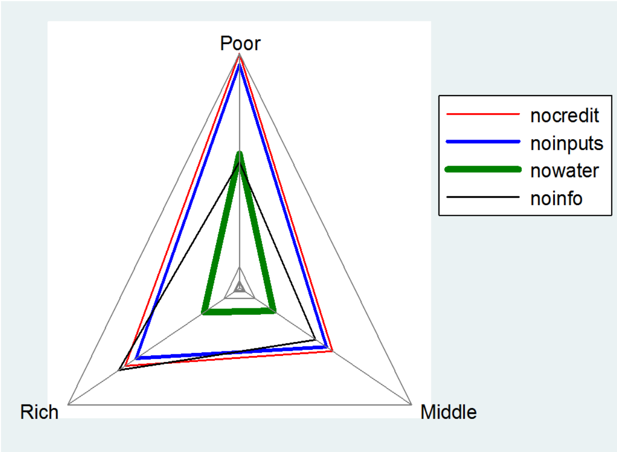


Figure 6.2. Constraints to adaptation by household's economic status

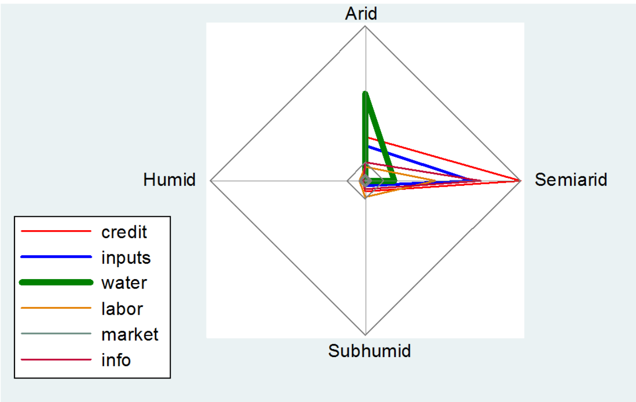


Figure 6.3. Constraints to adaptation by AEZ

Following this exploratory analysis, the tests are conducted leading to the choice of the estimation method. The validity of ordinal and multinomial models is tested using tests for independence of irrelevant alternatives and "proportional odds". Proportional odds hypothesis is rejected at 1% by likelihood ratio test(Table 6.2), hence, ordinal models would not be suitable as estimation choice. However, the results on testing the Independence of Irrelevant Alternatives

(IIA) are more ambiguous: the Small-Hsiao test rejects IIA assumption at 1%, whereas the Hausman test cannot reject.

The validity of assumptions of stereotype logit model (SLM) is also tested. Both assumptions of SLM: distinguishability and ordinality of categories of the dependent variable cannot be rejected. Separately conducted Wald test for combining alternatives after multinomial logit regressions also rejected at 1% that categories of the dependent variable are indistinguishable and can be combined.

Table 6.2. Tests for appropriate model choice

Tests	**Proportional odds**	**Independence of irrelevant alternatives**	**Distinguishability in SLM**	**Ordinality in SLM**
Likelihood-ratio test	rejected at 1%		cannot reject	
Small-Hsiao test		rejected at 1%		
Hausman test		cannot reject		
Specification comparison				cannot reject

Note: Long and Freese (2006) provide detailed information on these tests.

Given the somewhat inconclusive results from the IIA tests, both multinomial logit model and stereotype logit model are triangulated in the final estimation. The results of both models are broadly similar. For this reason and because of the fact that IIA assumption was rejected at least by Small-Hsiao test, and also because stereotype logit model is more efficient in its parameter estimates than multinomial logit model, the preferred model estimates are those from the stereotype logit model (Table 6.3.). So while interpreting the results, those by the SLM are preferred, whereas the results of the multinomial model are given in the Annex 1, Table A1.3.

Table 6.3. The results of the Stereotype Logit Model

Variables	Coefficients	e^b	e^bStdX
Gender (female - 0, male-1)	-0.0477	0.9534	0.9843
Age	0.00431	1.0043	1.0505
Family size	0.0470	1.0481	1.1521
Number of work age family members	0.0612*	1.0631	1.2842
Education	0.0211	1.0213	1.0255
Household daily per capita food expenses	0.393**	1.4822	1.3297
Household total assets	2.34e-05***	1	2.9707
Value of machinery owned	-2.89e-05**	1	0.5665
Number of SLM technologies known	0.137***	1.1464	2.8355
Total farm size	0.0246***	1.0249	2.2766
Soil fertility (log)	-0.237***	0.7892	0.57
Livestock value	-2.66e-05**	1	0.524
Number of weather shocks experienced	1.328***	3.7725	2.371
Frequency of weather shocks	-0.130***	0.8783	0.6895
Spread of weather shock impacts	1.284***	3.6117	7.1383
Share of private land in total	-0.923***	0.3975	0.664
Long-term temperature variability	1.291***	3.6373	7.4806
Long-term precipitation variability	0.00582*	1.0058	1.6207
Long-term mean annual precipitation	-0.00412**	0.9959	0.5402
Long-term mean annual temperature	0.552***	1.737	16.3622
Availability of irrigation in arid areas	2.126***	8.3846	1.6092
Access to extension	-0.513*	0.5988	0.7753
Access to weather information	-0.0719	0.9306	0.9796
Light intensity	0.00724	1.0073	1.0708
Crop portfolio diversity	0.165*	1.1788	1.2802
Market access	0.000520	1.0005	1.0557
Net agricultural position	-9.60e-06***	1	0.6897

gamma1_1	gamma1_2	gamma1_3	gamma1_4	theta1	theta2	theta3	theta4
1	0.659***	0.237***	Base (0)	11.71***	9.642***	2.728***	Base (0)

Categories of the dependent variable:

1. Did not perceive climate change, did not adapt
2. Perceived climate change, but saw no need to adapt
3. Perceived climate change, saw the need to adapt, but was constrained, so did not adapt
4. Perceived climate change and adapted

Note: Also controlled for agro-ecological zones, farming systems, and country-specific effects. The full model is given in the Supplement.

The base category in the SLM estimation in Table 6.3 is “category 3: perceived climate change and adapted” – gamma1_4, being compared with “category 0: did not perceive climate change and did not adapt”, gamma1_1. Positive values mean higher odds of being in category 3 compared with category 0 for a unit change in the explanatory variable. Similar coefficients comparing categories 1 and 2 with category 3 could be obtained by multiplying the given coefficients by the corresponding gammas for these categories given below Table 6.3.

Household demographic characteristics are generally non-significant. Only higher availability of family labor for on-farm activities seems to positively influence the odds of adaptation. Richer households (more specifically, those spending more on food per household member) seem to be perceiving and adapting more to climate change. For example, 1 USD increase in daily per capita household food consumption is increasing the odds of perceiving and adapting to climate change versus not perceiving and not adapting by a factor of 1.48 (under column e^b). Other indicators of household resource endowments such as household total assets, value of livestock owned, the value of agricultural machinery owned, total farm size were statistically significant, however, with little magnitudes of impact. As expected, higher number and spread of weather shocks is positively associated with higher likelihood of adapting to climate change. Interestingly, households seem to be adapting more when previous weather shocks are covariate than when their idiosyncratic. Contrary to expectations, higher frequency of weather shocks seems to decrease the odds of adaptation. This may be due to lower adaptive capacities as a result of repeated weather shocks. Better knowledge of sustainable land management technologies seem to increase the odds of adaptation, whereas higher soil fertility is negatively associated with adaptation as the farmers operating in more fertile soils may be less impacted by weather shocks than those cultivating more degraded areas. Higher temperature and precipitation variability are shown to increase the odds of adaptation, so do the higher mean temperatures. On the contrary, higher mean precipitation is slightly negatively associated with adaptation, which may be plausible given the aridity of the region's climate. The positive association of access to irrigation with odds of adaptation also corroborates this conclusion. Better access to more water could lessen the negative impacts of weather shocks in the arid environments of Central Asia, thus making adaptation relatively more costly. More diversified cropping portfolios are found to increase the odds of adapting. There is also a very surprising finding: it seems the higher share of private land tenure is strongly associated with lower odds of adaptation. This is most likely the result of imperfect representation of tenure security in our variable. Access to weather information, market access and night time lighting intensity, were found to be either non-significant, whereas surprisingly higher access to extension seems to be negatively associated with odds of adaptation. However, it should be noted that, as explained in the conceptual framework, more access to extension would not necessarily lead to adaptation if the household does not see the economic need to adapt.

6.7. Conclusions and policy implications

A noticeable share of farming households in Central Asia are already engaged in *ex post* adaptation to the changing climate. This is corroborated by the finding in this study that the number and intensity of weather shocks experienced in the past seems to significantly influence households' adaptation decisions.

However, many of the surveyed farming households do not perceive changes in the climate as a possible threat to their farming activities, because they have either not felt any negative impacts of climate change, or, in fact, feel that some of the on-going changes are positively influencing their crop and livestock productivity.

As climate change is a “low signal” risk, raising public awareness and Government support could be necessary for any *ex ante* pro-active actions. However, given the uncertainties of climate change, an important criterion in selecting *ex ante* adaptation measures should be that these measures need to enable farmers to better cope both with current and future climate-related challenges, i.e. be so-called no-regret options. Fortunately, the present study reveals that several of the most important factors positively influencing adaptation decisions have effects which would be strongly beneficial even now irrespective of climate change. Needless to say, the major role in promoting, supporting and implementing *ex ante* adaptation measures needs to be played by the Governments in the region.

There are several key areas where public action is needed for adaptation. One of these areas is improving farmers’ knowledge about sustainable land management practices, which would necessitate improving the quality and spread of extension services, also by making them more demand-driven. Many of the constraints on adaptation cited by the farmers involved lack of access to financial resources, hence there is a need for enabling policy environment to strengthen the role of rural financial institutions and of access to financial intermediation in the rural areas. The results also show that poorer farmers are less likely to adapt to climate change and take coping actions against weather shocks than richer farmers. This may be especially worrisome since poorer farmers depend more on climate-sensitive agriculture for their livelihoods. Future policy intervention on improving adaptive capacities in the region should take into account these differences in adaptive capacities among farmers and institute pro-poor measures.

Chapter 7. General Conclusions

The key objectives of this dissertation work have been to estimate the potential economic impacts of climate change on Central Asia's agriculture and rural livelihoods, as well as to identify factors catalyzing or constraining adaptation to climate change.

The analysis of the past climatic trends in the region has shown that the temperatures and precipitation have been increasing in most of the region over the last 50 years. So far, there has been no marked trend in the volumes of irrigation water run-off. The climate change forecasts for Central Asia indicate that temperatures are very likely to continue rising. However, there is no consensus in precipitation and irrigation water run-off predictions.

One of the consequences of climate change could be through increasing weather volatility. Higher weather volatility may be reflected in higher incidences of weather shocks. The effects of weather shocks on agricultural commodity prices in Central Asia have been studied through looking into the effects of specific weather variables such as temperature and precipitation, and availability of irrigation water, using an innovative, yet straightforward, method exploiting the idiosyncratic components of variables in a long panel setting. The results showed that weather volatility and fluctuations in the availability of irrigation water have statistically significant effects on wheat and potato prices in Central Asia. Negative shocks in irrigation water availability and precipitation could create conditions for higher wheat prices. In fact, the results show that wheat prices in the region are very sensitive to the availability of irrigation water, implying that hydrologic drought years have a strong potential to cause wheat price spikes in the region.

The assessment of climate change impacts on agriculture employed three distinct impact assessment methodologies using rich datasets at different scales and frequencies for more comprehensive and robust results. The estimates of the aggregate impacts of climate change on Central Asian agriculture range between +1.21% to -1.43% of net crop production revenues by 2040. The absolute monetary impact is not negligible, ranging from + 180 mln USD annually in the optimistic scenario, to – 210 mln USD annually in the pessimistic scenario relative to 2010 levels, where optimistic and pessimistic scenarios are defined to correspond to B1 (lowest future emission trajectory) and A1FI (highest future emission trajectory) scenarios by IPCC (2007), respectively. Central Asia is already subjected to a sharply continental climate with extreme temperatures and erratic rainfall. In most of the region, agricultural production occurs under sub-optimal climatic conditions with important year-to-year variations. As a result, agricultural producers operating in such inherently stressed environments may have more experience in dynamically adapting to erratic and changing environment.

The potential impacts of climate change and weather shocks on rural poverty and food security in the region have been analyzed using nationally representative household surveys within the framework of agricultural household model, accounting for agricultural households' potentially interlinked decision making on production, consumption and labor supply. The results confirm that poorer households are more vulnerable to the impacts of weather volatility and climate change, as every 1% decrease in the level of their farming profits is likely to lead to 0.52% decrease in their food expenses. A similar decrease for the richest 10% of households would translate to only 0.39% decrease in food consumption.

Factors facilitating or hindering adaptation to climate change in the region have been analyzed by duly accounting for various behavioral characteristics shaping households' decision making process. An innovation by this study has been its differentiation between households who did not adapt because of constraining factors and those who did not adapt because they did not see an economic benefit in adapting. It was found that many farmers in Central Asia are already engaged in *ex post* adaptation to the changing climate; however, further Government support is needed for pro-active *ex ante* actions. Lack of access to financial resources has been found as a major constraining factor, hence there is a need for enabling policy environment to strengthen the role of rural financial institutions and of access to financial intermediation in the rural areas. Most of the adaptation actions usually recommended in the literature for the region (Gupta *et al*. 2009, Christmann *et al*. 2009), such as for example, more efficient water use, development of drought-resistant cultivars, the adoption of sustainable land management practices and institutional reforms are highly useful for agricultural development in the region with or without climate change, thus could be implemented as no-regret options for adapting to climate change while reaping the benefits of these measures in terms of improved agricultural development in the region even in the case of perfect mitigation.

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Annex 1. Alternative model estimates in Chapters 5 and 6

Table A1.1. Chapter 5, Model estimation with instrumental variable only for households with non- separable decision making

Variables	Quantiles				
	10^{th}	30^{th}	50^{th}	70^{th}	90^{th}
Farming profits (log, instrumented)	0.306	0.421**	0.396*	0.502*	0.211
Age of household head	0.022	0.0365**	0.0242	0.00772	0.000419
Age of household head, squared	-0.00022	-0.000373**	-0.00026	-4.59E-05	3.86E-05
Education of household head	0.151	0.0169	-0.274	0.0471	-0.00431
Education of household head, squared	-0.0294	-0.00477	0.0600*	0.00583	0.00953
Gender of household head (0-female, 1-male)	-0.00329	-0.115	-0.0459	0.011	0.0917
Number of family members working:					
Non-farm work	0.05	0.0113	0.0281	0.0790**	-0.0283
On-farm work	-0.0363	-0.0254	-0.0425	-0.0871***	-0.0429
Distance to markets (log)	-0.0188	-0.0937**	-0.043	-0.0579	-0.0783
Livestock value (USD)	4.29E-06	4.77E-07	-2.13E-06	-1.66E-06	-4.66E-06
Value of total assets (log)	0.0868	0.0621**	0.0731**	0.0498	0.0726**
Market integration	0.151	0.0281	-0.0611	-0.312	-0.791**
Cooperation	0.00551	0.00249	0.0221	0.0184	0.0266
Net agricultural trade position (0-net buyer, 1-net seller)	-0.122	-0.0729	-0.0967	-0.190*	-0.212
Number of crops grown	0.0351	0.0203	-0.0205	-0.0257	0.0232
Subsistence farmer (0-yes, 1-no)	0.382	0.177	0.251	0.436	-0.00986
Vegetable price (log)	-0.0815	-0.0673	-0.0741	-0.0224	-0.00931
Potato price (log)	0.563	0.412	0.564*	0.298	-0.602
Wheat price (log)	-0.0499	-0.204	-0.144	0.04	-0.49
Maize price (log)	-0.247**	-0.198**	-0.141**	-0.193***	-0.0885
Share of privately owned land	-0.464**	-0.116	-0.00058	-0.0374	-0.0374
Farm size (log)	-0.0373	0.00812	0.0184	0.0527*	0.0345
Constant	-4.375**	-4.322**	-3.358**	-3.031	-1.421
Pseudo R2	18%	18%	17%	18%	20%

Table A1.2. Chapter 5, Model estimation without instrumental variable only for households with separable decision making

Variables	Quantiles				
	10th	**30th**	**50th**	**70th**	**90th**
Farming profits (log)	0.0619*	0.0482**	0.0539**	0.0548**	0.0863**
Age of household head	0.0185	0.00106	-0.0202	-0.0194	-0.0173
Age of household head, squared	-0.00025	-4.33E-05	0.000189	0.000167	0.000171
Education of household head	0.191	-0.0614	-0.11	-0.0913	0.0533
Education of household head, squared	-0.0392	0.0139	0.0231	0.0185	-0.0133
Gender of household head (0-female, 1-male)	0.0106	0.0663	0.0237	-0.0147	-0.181
Non-farm work	-0.00657	0.106***	0.0851**	0.0585	0.0682**
On-farm work	-0.00274	-0.0687***	-0.0640**	-0.0512**	-0.0645***
Distance to markets (log)	-0.078	-0.112***	-0.0521*	-0.0211	-0.0111
Livestock value (USD)	5.75E-07	2.02E-07	4.06E-08	-5.33E-08	-3.18E-07
Value of total assets (log)	0.0492***	0.0397*	0.0396*	0.0435*	0.00305
Market integration	-0.609**	-0.530***	-0.534***	-0.541***	-0.560***
Cooperation	0.0508	0.0468*	0.0521*	0.0456	0.0934**
Net agricultural trade position (0-net buyer, 1-net seller)	-0.477***	-0.415***	-0.330***	-0.267***	-0.229***
Number of crops grown	0.107***	0.0362	0.0382	0.0223	0.0342
Subsistence farmer (0-yes, 1-no)	0.289	0.152	0.411*	0.35	0.161
Vegetable price (log)	-0.0638	-0.00552	-0.0372	-0.0345	-0.0145
Potato price (log)	0.425	0.494**	0.415*	0.146	0.0787
Wheat price (log)	-0.277	-0.314	-0.327	-0.234	-0.232
Maize price (log)	-0.206	-0.203***	-0.138**	-0.0962	-0.0713
Share of privately owned land	-0.290***	-0.242***	-0.186*	-0.0931	-0.0258
Farm size (log)	0.00816	0.023	0.0182	0.0137	0.0466**
Constant	-1.003	0.607	0.725	0.729	1.377**
Pseudo R2	21%	22%	22%	22%	22%

Table A1.3. Chapter 6, Model estimation using multinomial logistic regression

```
Multinomial logistic regression                 Number of obs     =       1511
                                                LR chi2(105)      =    1774.43
                                                Prob > chi2       =     0.0000
Log likelihood =   -989.9953                    Pseudo R2         =     0.4726
```

depvar	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
0						
gender	-.2826271	.3994931	-0.71	0.479	-1.065619	.500365
age	-.0003606	.0118161	-0.03	0.976	-.0235198	.0227986
hhsize	-.0521168	.0599382	-0.87	0.385	-.1695934	.0653599
farm	-.0587533	.0413671	-1.42	0.156	-.1398313	.0223246
edu	.0326617	.1161595	0.28	0.779	-.1950067	.2603302
foodcapday	-.5143821	.2639155	-1.95	0.051	-1.031647	.0028828
totalassets	-.0000144	9.01e-06	-1.60	0.110	-.0000321	3.25e-06
machineryval	.0000247	.0000145	1.71	0.087	-3.58e-06	.0000531
knowtechnbr	-.1177361	.0374089	-3.15	0.002	-.1910562	-.044416
totalfarmsize	-.0257184	.0090996	-2.83	0.005	-.0435532	-.0078836
logsoilfer	.283289	.1084289	2.61	0.009	.0707723	.4958057
livestockvalue	.0000193	.0000107	1.80	0.072	-1.76e-06	.0000404
shocknbr	-1.072323	.3133904	-3.42	0.001	-1.686557	-.4580886
shockfreq	-.235615	.197117	-1.20	0.232	-.6219572	.1507273
shockspread	-1.054056	.1349076	-7.81	0.000	-1.31847	-.7896415
shareownedland	1.027239	.4217552	2.44	0.015	.2006139	1.853864
sdt	-1.185324	.3213851	-3.69	0.000	-1.815227	-.5554204
sdr	-.0077649	.0041752	-1.86	0.063	-.0159481	.0004183
prpann	-.0005972	.002494	-0.24	0.811	-.0054852	.0042909
tmean	-.6316447	.0948005	-6.66	0.000	-.8174502	-.4458392
irrigaridty	2.245686	.9185192	2.44	0.014	.4454215	4.04595
extension	.2139884	.3529061	0.61	0.544	-.4776949	.9056717
weatherinfo	.7252303	.5950082	1.22	0.223	-.4409643	1.891425
lights	-.0275488	.0216009	-1.28	0.202	-.0698857	.0147881
cropnbr	-.0991252	.126456	-0.78	0.433	-.3469744	.1487239
maccess	.0008089	.0017802	0.45	0.650	-.0026803	.0042981
netposition	8.71e-06	4.65e-06	1.87	0.061	-3.96e-07	.0000178
country1	-16.71186	1866.53	-0.01	0.993	-3675.043	3641.62
country2	1.384057	2418.505	0.00	1.000	-4738.799	4741.567
country3	4.661804	1.159995	4.02	0.000	2.388256	6.935353
country4	0	(omitted)				
aez1	.7514301	1.452819	0.52	0.605	-2.096042	3.598902
aez2	-2.756047	1.294899	-2.13	0.033	-5.294002	-.2180917
aez3	-.1667743	1.330449	-0.13	0.900	-2.774406	2.440857
aez4	0	(omitted)				
farmsys1	-10.53197	1866.53	-0.01	0.995	-3668.864	3647.8
farmsys2	-10.83415	1537.931	-0.01	0.994	-3025.124	3003.456
farmsys3	0	(omitted)				
_cons	29.42745	1866.531	0.02	0.987	-3628.907	3687.761

1						
gender	-.0304047	.2827486	-0.11	0.914	-.5845819	.5237724
age	.0167975	.0086821	1.93	0.053	-.0002191	.0338141
hhsize	-.054703	.036503	-1.50	0.134	-.1262475	.0168415
farm	-.0439056	.0264623	-1.66	0.097	-.0957708	.0079596
edu	.0353941	.08442	0.42	0.675	-.1300661	.2008543
foodcapday	.0441774	.1866916	0.24	0.813	-.3217315	.4100863
totalassets	-.0000106	6.93e-06	-1.52	0.127	-.0000241	3.01e-06
machineryval	6.16e-06	.0000121	0.51	0.612	-.0000177	.00003
knowtechnbr	-.1262521	.022838	-5.53	0.000	-.1710137	-.0814905
totalfarmsize	-.01476	.0050524	-2.92	0.003	-.0246625	-.0048575
logsoilfer	.1040579	.0705662	1.47	0.140	-.0342494	.2423652
livestockvalue	-2.02e-06	.0000142	-0.14	0.886	-.0000298	.0000258
shocknbr	-.7220962	.1996139	-3.62	0.000	-1.113332	-.3308601
shockfreq	.0689354	.0321022	2.15	0.032	.0060162	.1318545
shockspread	-.9594928	.1114274	-8.61	0.000	-1.177887	-.7410992
shareownedland	.3872312	.2900819	1.33	0.182	-.1813189	.9557814
sdt	-1.469274	.2274493	-6.46	0.000	-1.915067	-1.023481
sdr	-.0010715	.0029091	-0.37	0.713	-.0067733	.0046304
prpann	-.0008218	.00158	-0.52	0.603	-.0039187	.002275
tmean	-.6061919	.0895829	-6.77	0.000	-.7817711	-.4306127
irrigaridty	2.504304	.8361104	3.00	0.003	.8655578	4.14305
extension	-.2907646	.2688314	-1.08	0.279	-.8176645	.2361353
weatherinfo	.0021117	.3804718	0.01	0.996	-.7435993	.7478226
lights	.0231282	.0127278	1.82	0.069	-.0018178	.0480742
cropnbr	-.1740522	.080405	-2.16	0.030	-.3316432	-.0164612
maccess	.002172	.0013974	1.55	0.120	-.0005668	.0049108
netposition	7.28e-06	2.35e-06	3.09	0.002	2.66e-06	.0000119
country1	-.8829009	.55766	-1.58	0.113	-1.975895	.2100927
country2	1.493558	.8676102	1.72	0.085	-.2069271	3.194042
country3	6.597955	.7681668	8.59	0.000	5.092376	8.103534
country4	0	(omitted)				
aez1	1.276121	1.239488	1.03	0.303	-1.15323	3.705473
aez2	-2.73388	1.183965	-2.31	0.021	-5.054408	-.4133521
aez3	-1.029637	1.22079	-0.84	0.399	-3.422342	1.363067
aez4	0	(omitted)				
farmsys1	4.895621	1.039925	4.71	0.000	2.857406	6.933837
farmsys2	4.802987	.9492366	5.06	0.000	2.942518	6.663457
farmsys3	0	(omitted)				
_cons	12.72078	1.893	6.72	0.000	9.010572	16.43099
2						
gender	-.1589791	.3484632	-0.46	0.648	-.8419543	.5239962
age	.0317266	.0117635	2.70	0.007	.0086705	.0547826
hhsize	-.0498988	.0468416	-1.07	0.287	-.1417067	.0419092
farm	-.0403912	.0407044	-0.99	0.321	-.1201703	.0393879
edu	-.0037233	.1156709	-0.03	0.974	-.2304341	.2229876

foodcapday	.1254831	.2257713	0.56	0.578	-.3170206	.5679868
totalassets	-.00002	9.43e-06	-2.12	0.034	-.0000384	-1.48e-06
machineryval	.0000251	.0000128	1.96	0.050	-1.34e-08	.0000502
knowtechnbr	-.1186936	.028875	-4.11	0.000	-.1752874	-.0620997
totalfarmsize	-.0217119	.0082627	-2.63	0.009	-.0379065	-.0055172
logsoilfer	.1550638	.1108913	1.40	0.162	-.0622791	.3724067
livestockvalue	-.0000832	.0000388	-2.15	0.032	-.0001592	-7.25e-06
shocknbr	-.13774	.233888	-0.59	0.556	-.5961521	.3206721
shockfreq	-.0524963	.0615564	-0.85	0.394	-.1731446	.068152
shockspread	-.1778852	.1653854	-1.08	0.282	-.5020345	.1462642
shareownedland	.2961467	.4249501	0.70	0.486	-.5367403	1.129034
sdt	-3.636563	.5228666	-6.96	0.000	-4.661363	-2.611763
sdr	.0255682	.0068754	3.72	0.000	.0120926	.0390438
prpann	-.0066248	.0024845	-2.67	0.008	-.0114943	-.0017554
tmean	-.5804457	.1389035	-4.18	0.000	-.8526916	-.3081997
irrigaridty	5.246596	1.636138	3.21	0.001	2.039823	8.453368
extension	-.0100034	.4274896	-0.02	0.981	-.8478676	.8278609
weatherinfo	-.2421966	.4639024	-0.52	0.602	-1.151429	.6670354
lights	-.029051	.0196862	-1.48	0.140	-.0676352	.0095331
cropnbr	-.0743355	.1265902	-0.59	0.557	-.3224477	.1737768
maccess	-.0010976	.001891	-0.58	0.562	-.0048039	.0026087
netposition	3.75e-06	4.01e-06	0.93	0.350	-4.11e-06	.0000116
country1	-2.021051	.7352707	-2.75	0.006	-3.462155	-.579947
country2	5.547465	1.471915	3.77	0.000	2.662564	8.432366
country3	-10.9808	816.4949	-0.01	0.989	-1611.281	1589.32
country4	0	(omitted)				
aez1	-18.36058	832.3429	-0.02	0.982	-1649.723	1613.001
aez2	-3.804456	2.18663	-1.74	0.082	-8.090171	.4812594
aez3	-2.918403	2.141748	-1.36	0.173	-7.116152	1.279346
aez4	0	(omitted)				
farmsys1	1.099798	1.671479	0.66	0.511	-2.176239	4.375836
farmsys2	2.666624	1.384311	1.93	0.054	-.0465749	5.379823
farmsys3	0	(omitted)				
_cons	14.25949	3.452079	4.13	0.000	7.493542	21.02544
3	(base outcome)					