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Impacts of Weather Variability and Climate Change on Agricultural Revenues in Central Asia

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Abstract

The study evaluates the impact of weather variability on agricultural revenues in the four Central Asian countries using a panel data at the province level for the period of 1990-2010. The net average effects of weather variability are estimated to be less than 1% of total crop production revenues, with variations among the provinces in the region. This result is robust to numerous specification checks. It is believed that the main reason for such relatively low levels of impacts, in addition to good weather years, is evolving adaptive capacities and coping actions by farmers in the region. In most of Central Asia, important year-to-year weather variations are the norm rather than an exception. As a key conclusion, agricultural producers operating in such inherently stressed environments may have more experience to dynamically adapt to erratic and changing environment.

Keywords: weather variability, agricultural revenues, climate change, Central Asia
JEL: Q1, Q54

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 only 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 do certainly have an important impact on agricultural systems, however, individual and social adaptation are capable and likely to prevent any major damage to global food security, as long as climate change is not catastrophic. A key characteristic of climate change is defined by its distributional effects. Temperate areas are likely to gain from climate change, while tropical and arid areas are likely to lose (IPCC, 2007). After eighteen 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, 2008).

Central Asia, consisting of Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan and Uzbekistan, is located mainly 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 may likely be skewed against the poorer areas and poorer farmers with less financial resources and adaptive capacities. In this context, this study seeks to evaluate the impact of weather variability on agricultural revenues in the region using a relatively long panel data at the province level for the period of 1990-2010. The results of this analysis could also be indicative of the potential impacts of climate change in the region, as it is believed that, in fact, major negative shocks for agricultural production under the changing climate would come from higher weather variability, rather than gradual changes in climate means. The study also strives to fill an important geographic gap in the analysis of potential 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 positively contribute to global food security. The previous studies of climate change impacts in Central Asia, discussed in more detail in the next section, did not account comprehensively for adaptation, thus overestimating its negative impacts (NELSON et al., 2010; BOBOJONOV et al., 2012; KATO et al., 2012; SOMMER et al., 2012). This study, in contrast, seeks to implicitly account for a wider range of adaptation actions in the region, thus, providing more accurate estimates of the impacts of climate change.

2 Relevant Literature

The previous literature for assessing the impacts of climate change on agriculture was built around four major approaches. 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. Its major weakness is inability to comprehensively account for adaptation (MENDELSOHN and DINAR, 1999; MENDELSOHN, 2008), biasing its estimates: this approach exaggerates the negative impacts of climate change. The effects of weather on crop yields can, alternatively, be captured by statistical regression models (CABAS et al., 2010; YOU et al., 2009). The advantage of the statistical regression models over crop simulation models is that they can integrate not only biophysical variables such as soils, temperature and precipitation, but also socio-economic and institutional factors that crop models cannot capture directly. The third approach, so-called Ricardian method (MENDELSOHN et al., 1994), 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. Its strengths include capacity to capture efficient adaptation, albeit implicitly, and take the spatial heterogeneity into account. Its major weakness involves a potential bias resulting from omitted variables that are correlated with climate (MENDELSOHN and DINAR, 1999; MENDELSOHN, 2008; DESCHÊNES and GREENSTONE, 2007). The Ricardian method 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, 2008). Finally, the panel approach suggested by DESCHÊNES and GREENSTONE (2007) builds on the Ricardian method 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 weaknesses are that it allows only for the partial adaptation to weather fluctuations by farmers and miss the long-term adaptation to climate change (DESCHÊNES and GREENSTONE, 2007), thus it can be considered to underestimate adaptation and overestimate negative impacts of climate change.

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 (MIRZABAEV, 2013). 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 1,180 mm across different localities in the region (MIRZABAEV, 2013). 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). 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.

Adaptation can significantly reduce the negative impacts of climate change, but also enhance its potentially positive impacts in some parts of the region. The evidence gathered from household surveys in Central Asia indicates that majority of agricultural households (83% of the surveyed) have already perceived the ongoing climatic changes, but only a third of the same households have taken adaptation actions (MIRZABAEV, 2013). MIRZABAEV (2013) elaborates that not all of these non-adapting households were constrained by lack of capacities, but rather the costs of adapting for them were higher than costs of climate change. Among the key constraints to adaptation cited by respondents were lack of access to credit, high costs of inputs, but also lack of information and knowledge on adaptation actions. Changing planting dates, crop or variety switching, higher input use were cited among the more frequent adaptation actions. Most of these actions were funded through household savings (including in livestock) or borrowing from relatives (ibid.).

There have been only a few studies quantitatively assessing the impacts of climate change on Central Asian agriculture. Most of these previous studies were based on the integrated assessment method, involving mainly integration of climate and crop models and in some cases as in BOBOJONOV et al. (2012) and NELSON et al. (2010) also including economic 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 cotton yields may be impacted more negatively, especially in the long-term (2040-2070) (CHUB, 2007; NELSON et al., 2010; SOMMER et al., 2012; KATO et al., 2012). BOBOJONOV et al. (2012) estimate that a decline of 30% in irrigation water availability is likely to lead to 4%-17% reductions in expected gross agricultural incomes during 2010-2040, and to 35%-55% reductions during 2040-2070 in Uzbekistan. 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%) (ibid.). 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%) (NELSON et al., 2010). Somewhat differently, SOMMER et al. (2012) indicate that wheat yields may grow on average by +12% across Central Asia, ranging from -3% to +27%. CHUB (2007) also concludes that in most areas of Uzbekistan, the yields of cotton may increase by 10%-15%, and of cereals by 7%-15%. In contrast, KATO et al. (2012) indicate cotton yields may decrease by up to 40% across Central Asia. The key shortcoming of these studies listed above is that they model adaptation arbitrarily and cannot account for a full range of possible adaptation actions that agricultural producers in the region may undertake.

3 Conceptual Framework

The panel approach, also applied here, uses annual weather fluctuations as explanatory variables, and not long-term climate parameters used in the Ricardian models. Thus, if the Ricardian model can be said to represent equilibrium conditions and account for long-term adaptation to climate, the panel approach, as suggested by DESCHÊNES and GREENSTONE (2007), looks into short-term impacts of weather and implicitly accounts for short-term adjustments or coping strategies to weather events. 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 agricultural 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 used in this study also differs in some aspects from the panel model suggested by DESCHÊNES 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 (DESCHÊNES and GREENSTONE (2007) apply the latter approach on lower administrative scale of counties in a state, i.e. districts within a province).

The key conceptual reason underlying the evaluation of weather shocks as deviations from trend rather than deviations from the mean is based on the expectation 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.

4 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. The estimation also includes province and country by year fixed effects to control for unobserved time-invariant heterogeneity among countries and among provinces in each country, such as soils, other agro-ecological characteristics, etc. The estimation approach also seeks to implicitly account for unobserved time-variant covariate and idiosyncratic shocks among provinces, such as annual input application rates, commodity prices, policy changes, etc. The model specification also explicitly distinguishes between provinces with predominantly rainfed and irrigated agricultural production. Thus, the estimated coefficients of weather variables are thought to be purged of the potential biases resulting from these and other similar omitted variables. The model is formulated as follows:

$$y_{dt} = \alpha_d + \beta_d + \delta_t + \eta_d + \alpha_d*\delta_t + \beta_d*\delta_t + \sum\phi_i(W_{idt}) + \varepsilon_{dt} \tag{1}$$

where,

y_{dt} – agricultural revenues per hectare for province d at time t
α_d – province fixed effects
β_d – country fixed effects
δ_t – year indicator, specified as linear time trend, to control for annual differences in the dependent variable that are common across provinces
η_d – dummy differentiating irrigated and rainfed areas
$\alpha_d*\delta_t$ – interaction of province fixed effects with year indicator to control for other province-specific annual shocks
$\beta_d*\delta_t$ – interaction of country-fixed effects with year indicator to control for country-specific annual shocks
ϕ_i – effect of weather
W_{idt} – a vector of weather variables
ε_{dt} – the error terms

The dependent variable was transformed to logarithmic form and then first-differenced to avoid potential estimation biases emanating from its non-stationarity in the level form, and equally importantly, the differenced form would, arguably, better capture the effect of year-to-year weather variations on changes in agricultural revenues. Weather variables enter the regression as deviations from trend, filtered using Hodrick-Prescott approach (HODRICK and PRESCOTT, 1997). Given the relative length of the panel dataset (T-20 and N-38), using deviations around trend also allows for solving for potential non-stationarity of the variables, since random weather deviations around the trend are expected to be stationary. The weather variables enter the regression model both in level and quadratic forms.

There are strong reasons to believe that the cross-sections of the panel dataset could be inter-dependent, for example, the weather variables in the neighboring provinces could naturally be correlated. The Pesaran test for cross-sectional dependence (PESARAN, 2004) is used to test for such cross-sectional correlation. Furthermore, there may still remain several problems in the data series for which the estimation approach employed should account for. These problems are, in addition to dependence in the cross-sectional units, autocorrelation and heteroscedasticity. Feasible generalized least squares (FGLS) approach is the technique that is capable of adequately handling all these remaining problems, which motivates the choice of this technique for the empirical estimation. Wooldridge test for autocorrelation in panel data (WOOLDRIDGE, 2002) and the likelihood ratio test for heteroscedasticity after FGLS are used to test for autocorrelation and heteroscedasticity in the data series.

5 Data

The dependent variable is the annual per hectare provincial agricultural revenues from crop production, compiled from several dozens of statistical bulletins and publications on agriculture by the National Statistical Committees and Agencies in Kazakhstan, Kyrgyzstan, Tajikistan and Uzbekistan. The original values in national currencies were converted to US dollars using the average exchange rate during the corresponding year. The dependent variable aggregates the revenues from all crops grown in each province. It is then divided by the extent of cropped area in each province in the corresponding year to get the per hectare values. Both revenues from crop production and extent of cropped area are reported by the national statistical committees. There may be two limitations to this dependent variable. First, the statistical agencies have strong capacities to collect the statistics from bigger registered farms which have to report on their production activities and relatively weaker outreach to informal small semi-subsistence household kitchen gardens. The share of the latter is although very small in the overall cropped area, household kitchen gardens produce a significant proportion of vegetables and fruits. This may or may not lead to potential measurement errors, as usually the statistical agencies state that their data includes the kitchen gardens ("household plots"). Second, at this level of aggregation at province level, the dependent variable may miss out on stronger variability at finer scales. However, it is believed that the results still provide an accurate picture of aggregate effects. Moreover, relatively long time period and the number of observations also contribute to minimizing any potential biases emanating from these data limitations.

Among the independent variables, weather variables – seasonal mean temperature and accumulated precipitation – represent year-specific deviations from climatic trend in each province. They have been compiled and cross-checked from several sources, including 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. It is believed that there are no major concerns with the weather data quality. However, weather data comes from specific weather stations and is not available for every location. To address this limitation, the climate change studies use various spatial interpolation techniques. In this study, mean monthly temperature and total monthly rainfall data from about 400 individual weather stations were spatially projected to the digital administrative map of Central Asia using spatial interpolation technique of inverse-distance weighting[1]. Following this, the pixel-level weather variables were averaged for each province.

6 Results and Discussion

Following the empirical strategy outlined in the previous section, the variables in the model are tested for cross-sectional independence. Pesaran test for cross sectional independence strongly rejects the null hypothesis that the cross-sections in the model are not correlated (Table 1). The higher is the test statistic (CD-test), more strongly the panels are correlated. Similarly, the columns “corr” and “abs(corr)” show the estimated strength of the cross-sectional correlation. Moreover, the Wooldridge test for autocorrelation in panel data strongly rejects the null hypothesis of no first order autocorrelation (F (1, 37) = 65.898, Prob > F = 0.0000). Furthermore, the likelihood ratio test for heteroscedasticity after FGLS rejects the hypothesis of no heteroscedasticity at less than 1% (LR chi2(37) = 89.25, Prob > chi2 = 0.0000). Taking these results into account, the next step is to estimate the model using FGLS, thus, adequately accounting for cross-sectional dependence, autocorrelation and heteroscedasticity in the data series (Table 2).

In the resulting model, all seasonal weather variables and their squared terms are statistically significant. Temperature deviations from their trend values have convex relationship with crop production revenues in all seasons of the year. The model also indicates that upward precipitation deviations from their trend values are positively associated with higher crop revenues throughout the year, except in spring – when, probably excessive precipitation could subsequently lead to lower crop revenues through retarding planting and field operations, causing flooding events, creating favorable conditions for the development of plant diseases, such as yellow rust in Central Asia.

These results are then used for *ex post* estimation of the average effect of weather variations on changes in agricultural revenues over the last 20 years for the provinces of four Central Asian countries: Kazakhstan, Kyrgyzstan, Tajikistan and Uzbekistan. The results show that, even though there were bad and good years in terms of weather, on average, the weather variability has had a small net impact on crop production revenues during the last 20 years. Its mean economic effect during this entire period is

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[1] Inverse-distance weighting is a deterministic spatial interpolation technique where the values are assigned to pixels with absent data as the weighted average of values from pixels where data is available. The distance from pixels without data to those with data is used in the weighting. The closer pixel with data has a bigger weight in determining the value of the unknown pixel than a more remote pixel with available data (more discussion on benefits and limitations of this approach is given by LU and WONG (2008)).

estimated to be less than 1% of the total crop production revenues, with some variations in different provinces in the region (Figure 1).

Table 1. Pesaran test for cross-sectional independence

VARIABLES	CD-test	p-value	corr	abs(corr)
Crop revenues	82.2	0.000	0.69	0.70
Temperature				
Winter	81.2	0.000	0.67	0.67
Spring	81.5	0.000	0.67	0.68
Summer	54.5	0.000	0.45	0.46
Fall	88.9	0.000	0.73	0.73
Precipitation				
Winter	60.5	0.000	0.50	0.50
Spring	58.3	0.000	0.48	0.50
Summer	41.0	0.000	0.34	0.37
Fall	70.6	0.000	0.58	0.59
Temperature squared				
Winter	49.9	0.000	0.41	0.43
Spring	67.8	0.000	0.56	0.59
Summer	23.0	0.000	0.19	0.28
Fall	92.1	0.000	0.76	0.76
Precipitation squared				
Winter	35.6	0.000	0.29	0.37
Spring	40.0	0.000	0.33	0.37
Summer	25.2	0.000	0.21	0.28
Fall	41.3	0.000	0.34	0.38

Source: the author´s calculations

The provinces in the central transect in the region seem to have been more positively affected by the weather changes, whereas those in the western part – desertic areas around the drying Aral Sea, and those in the eastern part, seem to be less positively affected. However, the differences are negligible.

The sensitivity analyses of the impact of changes in temperature and precipitation on crop revenues are given in Figures 2 and 3, where uniform changes of given magnitudes in temperature and precipitation throughout the seasons of the year are analyzed with regard to their impact on crop production revenues. The results point at steeper slope of impacts for precipitation changes on crop revenues, compared to changes in temperature.

Table 2. The results of FGLS panel regression
(Dependent variable: crop revenues per ha, in log, 1st differenced)

VARIABLES	**Coefficient**	**Standard errors**	**Confidence interval -95%**	
Temperature				
Winter	-0.04916***	0.000408	-0.04996	-0.04836
Spring	-0.03019***	0.001176	-0.03249	-0.02788
Summer	-0.02498***	0.000856	-0.02666	-0.02331
Fall	-0.30138***	0.001012	-0.30336	-0.29939
Precipitation				
Winter	0.004502***	3.58E-05	0.004432	0.004572
Spring	-0.0011***	2.23E-05	-0.00114	-0.00106
Summer	0.003208***	2.28E-05	0.003163	0.003252
Fall	0.00506***	1.69E-05	0.005027	0.005093
Temperature squared				
Winter	0.001888***	0.000149	0.001597	0.002179
Spring	0.0074***	0.000155	0.007097	0.007703
Summer	-0.00621***	0.000114	-0.00643	-0.00599
Fall	0.025478***	8.98E-05	0.025302	0.025654
Precipitation squared				
Winter	4.54E-05***	9.50E-07	4.36E-05	4.73E-05
Spring	3.94E-06***	1.18E-07	3.71E-06	4.17E-06
Summer	-5.9E-05***	7.96E-07	-6E-05	-5.7E-05
Fall	0.000106***	4.37E-07	0.000106	0.000107
Province dummies	yes	yes	yes	yes
Country dummies	yes	yes	yes	yes
Year dummy	yes	yes	yes	yes
Province-Year interactions	yes	yes	yes	yes
Country-Year interactions	yes	yes	yes	yes
Irrigation dummy	yes	yes	yes	yes

*** $p<0.01$, ** $p<0.05$, * $p<0.1$, Prob > chi2 =0.0000
Number of observations =760, Number of panels = 38, Time periods= 20.
Source: the author´s calculations

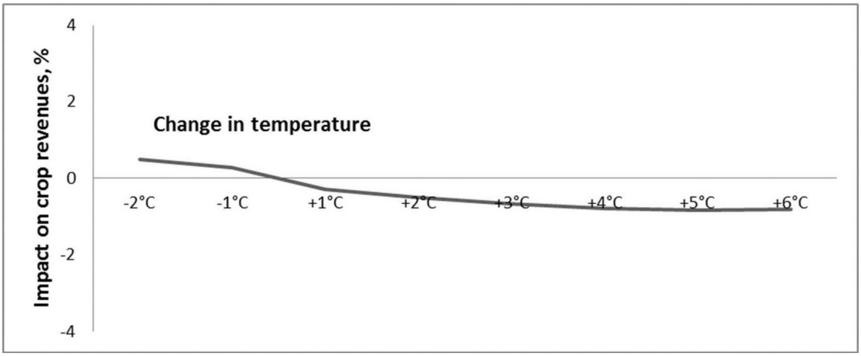
Figure 1. Mean impact of weather deviations from trend on revenues from crop production in the studied provinces of Central Asia

Source: the author´s calculations

In order to check for the robustness of the results, 13 different specification checks were run involving estimating the regression models separately for different time periods: before and after 2000, separately for different countries, with explicit inclusions of other potentially relevant variables – such as water and fertilizer application rates, soil quality variables, length of growing periods – to verify further for any omitted variables bias, using different regression methods, i.e. instead of FGLS, OLS, random and fixed-effects models. Even though the significance of coefficients may have changed depending on the specification chosen, the overall impact of less than 1% remained robust (Figure 4).

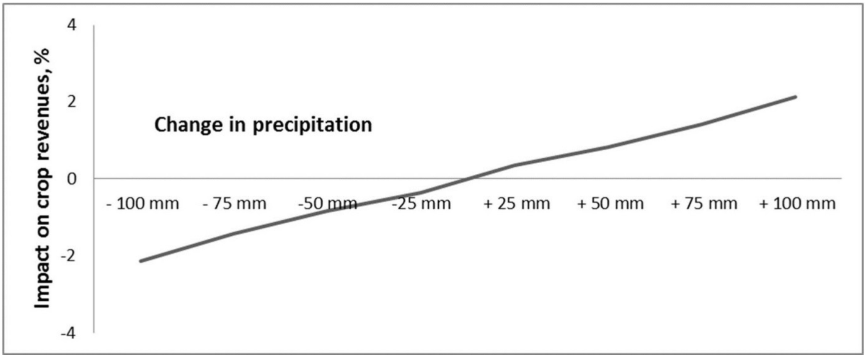
These relatively lower levels of weather impacts are also consistent with existing literature from other regions with similar agro-ecological conditions (for example, DESCHÊNES and GREENSTONE, 2007). It is believed that the main reason for this, in addition to good weather years, are evolving adaptive capacities and coping actions by farmers and other agricultural producers in the region. Moreover, several institutional and technological shifts during the last two decades 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 and Tajikistan, significant gains in wheat productivity due to development of new wheat varieties in Uzbekistan, etc. Finally, and importantly, Central Asia is already subjected to a sharply continental climate with extreme temperatures and erratic rainfall. In most of the region, important year-to-year weather variations are the norm rather than an exception. As a key conclusion, agricultural producers operating in such inherently stressed environments may have more experience to dynamically adapt to erratic and changing environment.

Figure 2. Sensitivity analysis of the impact of temperature changes from trend values on crop production revenues



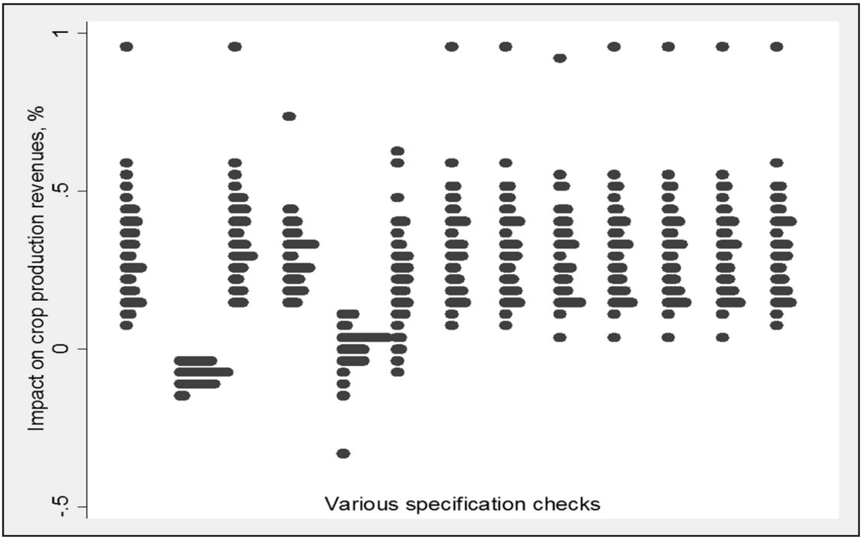
Source: the author´s calculations

Figure 3. Sensitivity analysis of the impact of precipitation changes from trend values on crop production revenues



Source: the author´s calculations

Figure 4. The results of specification checks (dots mean the values are for specific provinces)



Source: the author´s calculations

The results presented here represent aggregate impacts at province level for all crops taken together. If only one specific crop is considered, or if the analysis is conducted at village or household level the impact estimates could be different. Thus, for more comprehensive and multi-faceted analysis of climate change impacts in the region there is a need for continued research efforts from different aspects and angles.

7 Conclusions

Do these results mean that there is nothing to do in terms of policy action? The answer is certainly negative. The weather variability and the frequency of weather shocks may likely increase in the future (IPCC, 2011), straining the adaptive capacities of the farmers in the region. To facilitate successful adaptation to the changing climate, public policies could allocate additional investments into agricultural research with a view to enhance the potential positive effects and mitigate negative effects of climate change. It is even more obvious considering that 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 weather shocks, with or without climate change. Thus, these and other similar adaptive actions 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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