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The Impact of Climate Change on Grain Yield and Yield Variability in Iran

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Abstract

In this paper, we have examined the effect of climate variables on the yield average and variability of major grain crops (rice, maize, and wheat) in Iran from 1983 to 2014. For this purpose, we made use of the Just and Pope Production Function crop yields panel data. The results revealed that the influences of climate variables were different in the crops. The time trend positively influenced the average crop yield and yield variability, but increasing in the maximum temperature had a negative impact on the grain yields. While the maximum temperature increased the risk of wheat production, this variable reduced the risk of maize and rice production. Minimum temperature and rainfall had positive influences on the average yields of the crops. Furthermore, minimum temperature decreased the production risk of maize and wheat. Finally, the influences of rainfall on the yield variability were positive for whole crops. Regional dummies were statistically significant for certain climate zones. It is expected that future climate changes reduce the mean yield of the crops, all the more showing the significance of crop insurance schemes and policies that mitigate insecurity of food in the light of expected climate variations in the coming years.

Keywords: Climate Change, Grain Yields, Iran, Just and Pope Production Function.

JEL Classification: O13, Q51, Q54.

1. Introduction

According to the synthesis report (SYR) of climate change in 2014, as the final part of the Intergovernmental Panel on Climate Change

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(IPCC)'s Fifth Assessment Report (AR5), warming of the climate system is incontrovertible and since the 1950s, many of the observed changes are unexampled comparisons with the preceding decades and centuries (IPCC, 2014). The Middle East is a highly vulnerable region to climate change impacts due to its water scarcity that is the greatest in the globe (Elasha, 2010). The predicted climate changes in this area are more severe compared to other parts of the world. Whenever 21st century ends, this region may experience 3°C to 5°C rise in mean temperatures and a 20% decline in precipitation (IPCC, 2007). Because of the low precipitation, water run-off may drop by 20% to 30% in most Middle East regions by 2050 (Elasha, 2010). Iran, as a Middle Eastern country, is highly susceptible to the negative influences of climate variation. Based on the national climate change project, Iran is expected to undergo an augmentation of nearly 2.6°C in mean temperatures and a 35% decline in precipitation (NCCOI, 2014). Simulations of future climate change in Iran imply that the changes in the rainfall amount and its distribution, and temporal and spatial changes of temperature of the air, will increase the odds of flooding and drought events (Mansouri Daneshvar, 2016). Cereals, particularly wheat, are crucial annual crops generated in the country. In arid and semiarid areas, if crop water requirement increases due to change of climate under inadequate water supplies, the generation of irrigated crops, especially cereals, will suffer (Mansouri Daneshvar, 2016). Accordingly, cereals' vulnerability to climate change is of particular interest to both researchers and policymakers.

1.1 A Brief Overview of the Literature

Many researchers have measured the effects of climate variables on crop fertility via simulation models for example CERES-rice, CERES-maize, and EPIC models (Phillips et al., 1996; Rosenzweig et al., 2002; Tan and Shibasaki, 2003) or regression models (Mendelsohn et al., 1994; Chang, 2002; Haim et al., 2008). Previous studies have generally employed two major approaches to evaluating the effect of climate on agriculture: the approach of production function, agronomic model or crop modeling (Mearns et al., 1997), and the Ricardian approach (Mendelsohn et al., 1994). Employing controlled researches, the first approach simulates data on crop yields and climate variables in a laboratory. Employing a precise control and randomized usage of environmental circumstances, this method can anticipate the climatic influences on agriculture yields. However, it does not consider farmers' attitudes towards climate change adaptation, hence the fact that negative effects are overestimated while positive impacts are underestimated (Adams et al., 1990, 1999; Haim et al., 2008; Mendelsohn et al., 1994). On the contrary, the Ricardian model estimates the association among values of land and agro-climatic variables through cross-sectional information (Kumar and Parikh, 1998; Mendelsohn et al., 1994). The major power of the Ricardian model is that it considers farmers' adaptations which influence land values as measured by farm earnings or net revenue. The model has been used in different countries, namely the USA (Mendelsohn and Dinar, 2003; Mendelsohn et al., 1994), England and Wales (Maddison, 2000); Kenya (Mariara and Karanja, 2007), Taiwan (Chang, 2002), South Africa (Gbetibouo and Hassan, 2005), Cameroon (Moula, 2009), China (Wang et al., 2009), and India and Brazil (Sanghi and Mendelsohn, 2008). Nevertheless, the approach, in its main form, may not be used for most developing countries since there are no influential land markets and reasonable land expenses in these countries. The main shortcoming of the Ricardian approach is its potential omitted-variable bias pertaining to variables correlated with climate (Deschênes and Greenstone, 2007). In some researches, the yield variability was influenced because of climate variables (Chen et al., 2004; Chen and Chang, 2005; Kim and Pang, 2009); a Ricardian model, however, cannot examine the influence of climatic variation on variability of yield (Mearns et al., 1997), which has made certain economy experts apply a panel data method to consider the eliminated variables via inclusion of regional or district dummies in the model (Chen et al., 2004; Schlenker and Roberts, 2008; Deschenes and Greenstone, 2007; Guiteras, 2007; McCarl et al., 2008; Kim and Pang, 2009; Barnwal and Kotani, 2010; Cabas et al., 2010). Its weakness is that it only allows for a short-term conformity to fluctuations of climate by farmers and ignoring the long-term one (Deschênes and Greenstone, 2007), hence underestimating adaptation while overestimating the negative impacts of climate change.

Analyses of the global influences of climate change on fertility of crop have basically focused on average crop yields. The preponderance of these studies has employed either a crop simulation model or regression methods. Only a few studies have analyzed the impact of climate variation on fertility of yield (Chen et al., 2004; Isik and Devadoss, 2006; Finger and Schmid, 2007, Baubacar, 2010). Following a comprehensive literature search, a low number of researches have applied the panel data method in Iran: Vaseghi & Esmaeili (2008a), Vaseghi & Esmaeili (2008b), Ashktorab et al. (2015), Alijani et al. (2011), Salehnia & Falahi (2010), Shahraki et al. (2017), Norouzian et al. (2013). The present is probably the first study in Iran which has used maximum and minimum temperatures as temperature-based climate variables in a framework of panel data. This inquiry set to evaluate the influences of climate variation on the productions of major grain crops of Iran (wheat, maize, and rice) using panel data. Accordingly, we aimed at eliciting the reaction of crop variability and yield to climate variation in Iran. In this regard, a stochastic production function along with multiplicative heteroscedasticity was employed.

2. Materials and Methods

2.1 Data Sources

This research used cross-sectional time-series data for major grain crops (wheat, maize, and rice) from selected provinces in Iran. Five provinces were selected to study the rice, 15 for wheat and 9 for maize. Based on Gangi (2003), the provinces were categorized into four different climate regions (Table 1).

Table 1: Climate Zones in Iran

Name of Zone	Province
Cold	East Azarbaijan, West Azarbaijan, Ardebil, Alborz, Ilam, Tehran, Chaharmahal and Bakhtiari, Khorasan Razavi, North Khorasan, Zanjan, Qazvin, Kurdistan, Kermanshah, Kohgiluyeh and Boyer Ahmad, Lorestan, Hamedan
Warm and Dry	Isfahan, South Khorasan, Semnan, Sistan and Baluchestan, Fars, Qom, Kerman, Markazi, Yazd
Warm and Wet	Bushehr, Khuzestan, Hormozgan
Moderate and Humid	Golestan, Gilan, Mazandaran

Source: Based on Gangi (2003).

The data on crop yield, measured in kilograms per hectare (kg/ha), were gathered from the Ministry of Agricultural Jihad. Province-level climate data for monthly maximum temperature, monthly minimum temperature, and monthly total rainfall were gathered from the Iran meteorological department from 1983 to 2014. The monthly data were subsequently used to group the climate variables into annual averages for temperature and annual totals for rainfall concerning the crops. Crop yields are more often than reported based on their production year which is not on the basis of the calendar year; therefore, for simplicity in our analysis, the years were merged; for instance, the data of rice yield from 1982 to 1983 was taken into consideration as the yield for the year 1983. Accordingly, climate variables were in line with the yield data. Although yields are affected by numerous factors, only climate variables were taken into account, specifically temperature and precipitation. Other input factors such as fertilizer, seed, and herbicides may have been considered, but they were not accessible on a crop by crop basis. Table 2 shows the data description.

Table 2: Statistics Summary of Crop Yields and Climate Variables

Crops	Variables	Unit	N	Mean	S.D.	Min.	Max.
Wheat	Yield	(Kg/ha)	480	2919.52	888.55	902.4	5732.81
	T_{max}	(°C)	480	28.21	3.67	21.3	39.42
	T_{min}	(°C)	480	2.46	4.72	-6.69	15.7
	R	(mm)	480	316.66	130.11	40.8	771.1
Rice	Yield	(Kg/ha)	160	3826.19	763.82	2001	5699.97
	T_{max}	(°C)	160	31.18	3.91	24.83	39.42
	T_{min}	(°C)	160	8.75	3.06	4.01	15.7
	R	(mm)	160	661.02	439.66	76.8	1895.3
Maize	Yield	(Kg/ha)	288	5175.57	2251.49	259.81	11250
	T_{max}	(°C)	288	30.88	3.06	24.5	39.42
	T_{min}	(°C)	288	4.42	4.31	-5.13	15.7
	R	(mm)	288	298.97	178.22	18.3	771.1

Source: Research findings.

2.2 Empirical Model

The stochastic production function method was developed by Just and Pope (1978; 1979). The basic idea underlying this method is that the production function can be divided into two parts, the first one connected to the average yield level and the second one to the yield variability (Cabas et al., 2010; Kim & Pang, 2009). The common format of the Just and Pope Production Function is (Just & Pope, 1978):

$$y = f(X) + h(X)\epsilon, \qquad (1)$$

y is yield, and X involves explanatory variables. Estimating (X) gives the mean influence of the descriptive variables on yield; h(X) specifies their impact on the yield variability (Chen & Chang, 2005). Based on Saha et al. (1997) and Chen et al. (2004) a production function of the form below is obtained:

$$y = f(X) + u = f(X, \beta) + h(X, \alpha)\epsilon, \qquad (2)$$

y is crop yield (wheat, maize, and rice); X is descriptive variables (location, rainfall, temperature, and time period), and ϵ is the exogenous production shock with (ϵ)=0 and $Var(\epsilon) = \delta_\epsilon^2$. Using this formula, descriptive variables influence the variability and mean of crop yield because $E(y) = f(X) \quad Var(y) = Var(u) = h(.)$. The parameter estimation of $f(.)$ provides the mean impacts of the descriptive variables on yield, but h(.) reveals the impacts of the covariates on the variability of yield. A positive sign on any h(.) parameter implies a rise in the variable, indicating a rise in the yield variability. Also, a negative signal on the same function shows that climate variables are risk-decreasing. Three functional forms, namely quadratic, Cobb-Douglas, and translog forms, were employed for the Just and Pope Production Function (Tveteras, 1999; Chen et al., 2004; Isik & Devadoss, 2006; Kim & Pang, 2009). Since a translog would violate the Just and Pope assumptions (Koundouri & Nauges, 2005; Tveteras, 1999; Tveteras & Wan, 2000), the Cobb-Douglas and linear-quadratic forms, both compatible with the Just and Pope assumptions

(Kim & Pang, 2009), were chosen for the estimation of average crop yield function.

2.3 Mean Function

The mean function is defined as:
Cobb-Douglas form:

$$y = \alpha_0 + \alpha_t T + \prod_j {x_j}^{\alpha_j} \qquad (3)$$

Linear- Quadratic Form:

$$y = \alpha_0 + \alpha_t T + \sum_j \alpha_{1j} x_j + \sum_j \alpha_{2j} x_j^2 + \sum_j \sum_{k(k \neq j)} \alpha_{jk} x_j x_k \qquad (4)$$

where x_j and x_k are descriptive variables that involve weather variables, T represents trend of time and $\alpha's$ implies coefficients. The justification for including time trend is the fact that it considers technological progress in agriculture across the assumed time period.

2.4 Variance Function

The variability function's linear functional (Cobb–Douglas) form was the only one considered since the variance function is non-linear, and including quadratic terms for descriptive variables renders the analysis troublesome, resulting in more insights. Based on Just and Pope (1978, 1979), Kumbhakar and Tveteras (2003) and Koundouri and Nauges (2005), the variability function $h(.)$ was modeled in a Cobb–Douglas form as follows:

$$h\,(x) = \beta_0 T \prod_j x_j^{\beta_j} \qquad (5)$$

The maximum likelihood estimation (MLE) and the three-step feasible generalized least squares (FGLS) were proposed in Just and Pope (1978, 1979) so as to estimate functional forms. Nevertheless, estimation of FGLS has been used in many empirical researches though MLE is more effective and impartial compared with FGLS for small size samples (Saha et al., 1997). Assuming the great sample size, FGLS was utilized as proposed in Judge et al. (1988), so as to estimate a fixed effects panel. Additionally, MLE and FGLS were employed in the initial analyses with the former producing better results, which is yet another cause for the selection of FGLS as an estimation technique. Also, panel model estimation including time series and cross-section data can face heteroscedasticity and auto-correlation problems (Gujarati, 2004; Cameroon & Trivedi, 2009). Because FGLS assumes that panels are homoscedastic, and no auto-correlation exists, these problems are better dealt with (Wooldridge, 2002). Panel data models take two alternative forms: Random effects and fixed effects (Baltagi, 1995). The correct panel data model is defined by examining the random effects model against the fixed effects model employing the Hausman test statistics. The Hausman test statistics rejects the null hypothesis that the random effects estimator is fixed and effective for crop estimations. Accordingly, the fixed effects approach is better relevant than the random effects model regarding the two estimated yield equations.

2.5. Panel Unit Roots and Stationary

It is essential to examine the presence of unit roots for each potential variable estimating the model by either the FGLS method or MLE method. A crucial presumption of the Just and Pope Production Function is that the variables under investigation are static (Chen et al., 2004). Thus, variables having the features of I(1) have to be differenced prior to panel estimation (McCarl et al., 2008). Otherwise, the use of non-stationary data may directly lead to spurious results (Chen & Chang, 2005; Granger & Newbold, 1974). Several types of the panel unit root assessment exist in the literature. The present research employed the Fisher-type test used in Maddala and Wu (1999). The Fisher test entails more accurate findings in comparison with tests like LLC (Levin, Lin, Chu) (Barnwal & Kotani, 2010). To indicate the influences of climate variables on the crop variability and yield, the stochastic production function method by Just and Pope was applied.

3. Results

3.1 Results of the Panel Unit Root Test

The Fisher-type test studies the stationary attributes of the variables in a panel data model. Two types of the Fisher-type test exist: ADF and

PP (Philips and Perron) tests. This study obtained similar findings from these two types and reproduced the results via ADF only in Table 3. The obtained test data shows that cereal grain yields and climatic variables show identical outcomes with and without time trend, indicating that the unit roots' null hypothesis (non-stationary) is not accepted at the significance level of 1% for all variables, hence the fact that all the model variables are stationary. These findings are consistent with McCarl et al. (2008) and Kim and Pang (2009) results. Therefore, the three-stage FGLS can be used to data analysis without differencing.

Table 3: Results of Panel Unit Root Tests

Crops	Variables	ADF Test Statistics (P-value)	
		Without trend	**With trend**
Wheat	Yield	228.96(0.0000)	196.05 (0.0000)
	T_{max}	177.20 (0.0000)	290.14(0.0000)
	T_{min}	173.84 (0.0000)	212.94 (0.0000)
	R	347.17(0.0000)	308.34 (0.0000)
Rice	Yield	45.06(0.0000)	91.47(0.0000)
	T_{max}	69.25(0.0000)	67.20(0.0000)
	T_{min}	48.42(0.0000)	63.63(0.0000)
	R	115.00(0.0000)	98.21(0.0000)
Maize	Yield	59.66(0.0000)	85.81(0.0000)
	T_{max}	111.91(0.0000)	169.68(0.0000)
	T_{min}	95.51(0.0000)	116.09(0.0000)
	R	178.67(0.0000)	173.51(0.0000)

Notes: Hypothesis in ADF Test: Ho: All panels contain unit roots; Ha: At least one panel is stationary.

3.2 Results of the Empirical Model

The Cobb-Douglas and quadratic functional forms of the average crop yield and linear functional forms pertaining to crop yield variability were estimated through the use of FGLS model. Regional dummies were considered in the average crop yield function not in the variability function, considering the fact that mean yields are different across zones but variances are almost identical. Three regional dummies were considered for climate zones to prevent dummy variable trap (Gujarati, 2004). Estimated outcomes are given in Table 4. Three crop models have, therefore, an overall utility as overall significance is concerned. The independent variables of the wheat model are jointly statistically significant because the Wald statistic of the Cobb–Douglas linear form is 267.91 and has a p-value of 0.000 and that of 283.01 under the quadratic functional form also has a p-value of 0.000. Since the Wald statistic of 486.04 has a p-value of 0.000 regarding the rice linear functional form, the p-value of Wald statistic for the quadratic functional form of rice is also 0.000; the regressors under both functional forms are statistically significant as a whole. Furthermore, the p-values of maize functional forms corroborate the fact that both are meaningful. Nevertheless, the BIC and AIC values cause the linear form become slightly more significant. The estimated coefficients of the quadratic and linear functional forms in the mean yield function have different signs and significance among the three crop models. Both rainfall and minimum temperature have a positive relationship with mean wheat yield in the linear form, while the former has a negative and the latter has a positive impact on yield under linear–quadratic form. These two factors are meaningful only in a linear functional form. The highest amount of temperature is negatively related to average yield in the linear form, whereas it has a positive impact on yield under linear–quadratic form and it is meaningful only in the linear form. The quadratic or interaction expressions of the climatic variables in the quadratic function are statistically insignificant. Regional dummies are meaningful in both functional forms. Moreover, the time trend has a notable positive association with the mean yield in the linear form. Regarding the yield variability function of wheat, the coefficients reveal that the rise in the least temperature reduces the wheat yield variability, meaning the minimum temperature, in contrast to maximum temperature and rainfall, is risk-reducing. The trend of time is correlated to the variability function and is meaningful in the quadratic approach; consistent with the results of Anderson and Hazell (1989), Isik and Devadoss (2006), and Kim and Pang (2009), revealing that yields of crop rises with time as a result of improvement in irrigation equipment, development of high yielding varieties (HYVs) and augmented usage of fertilizers.

Table 4: Estimation Results Associated with Wheat, Rice and Maize Yields

Variables	Wheat		Rice		Maize	
	LCD	LQ	LCD	LQ	LCD	LQ
Mean yield						
Trend	9.90***	-5.36	92.36***	218.6***	202.63***	721.97***
T_{max}	-37.52**	23.11	-233.68***	-289.05***	-581.49***	-5869.13***
T_{min}	15.99***	-87.25	142.06***	39.74***	286.47***	3565.5***
R	1.42**	2.74	0.46	2.35**	3.42	20.02***
T_{max}^2		-510.82*		667.13**		11680.4***
T_{min}^2		-7.85		2968.80**		11935.31
R^2		-0. 85		0.04		-8.83***
T_{max}*T_{min}		447.47		-2293.24**		-18323.82***
T_{max}*R		-31.38*		-21.85***		46.38
T_{min}*R		24.06		58.14***		393.59**
Cold	-1167.02***	-1253.97***	(omitted)	(omitted)	996.87**	1385.46***
Warm and dry	-1187.13***	-1257.93***	470.91***	363.91***	1824.38***	1978.67***
Warm and humid	-974.87***	-855.94***	-110.99	-439.47	2842.51***	2276.88***
Moderate and humid (omitted to avoid dummy variable trap)						
Constant	-0.58	-5.88	-7.90***	-27.15***	-2.85	-33.87***
Yield variability						
Trend	0.0099	0.02**	0.041**	0.047***	0.03**	0.028***
T_{max}	0.10*	0.139**	-0.08	-0.037	-0.047	-0.23***
T_{min}	-0.01	-0.1**	0.046	-0.0050	-0.0063	0.146***
R	0.0042***	0.00096	0.00065	0.00051	0.0011	0.00075
Constant	6.054***	5. 69***	12.16***	11.17***	14.16***	19.29***
Model summary						
Log Likelihood	-919.65	-914.856	-306.7179	-306.07	-573.43	-569.96
Wald Chi-square	267.91	283.01	486.04	419.52	235.83	283.95
Prob. > Chi-square	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
AIC	1857.304	1859.712	629.4358	640.15	1164.87	1169.92
BIC	1894.868	1922.319	654.0372	683.21	1197.84	1224.86

LCD = Linear Cobb–Douglas; LQ = Linear–Quadratic

*, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

Source: Research findings

The maximum temperature imposes a negative impact on average rice and maize yields both in quadratic and linear functional forms, while minimum temperature and rainfall exert positive influences on the two yields in both functions. Both temperatures are meaningful in the two functional forms, yet the rainfall is meaningful only in the quadratic form where the quadratic aspects for minimum and maximum temperature are notable with positive impacts on rice production. In the case of maize, the quadratic terms related to maximum temperature and rainfall rates are considerable with positive and negative influences on yield, respectively. The three interaction aspects are meaningful. The rainfall and minimum temperature interaction term exerts a positive impact on the yield of rice, while the other two interaction aspects have a negative influence. Additionally, the rainfall and minimum temperature interaction exerts a positive influence on maize production; however, the minimum and maximum temperature association has a negative influence. Both interaction terms are statistically significant. The regional dummy for the warm and dry zone is meaningful in both functional forms with a positive influence on rice production. As far as maize is concerned, all regional dummies are meaningful in both functional forms. The trend of time is associated positively with the average yield and meaningful in both functional forms. From the viewpoint of the yield variability function, the trend is meaningful for rice and maize. Moreover, the impact of rainfall on rice and variability of maize yield is insignificantly positive. On the contrary, in both functional forms, the influence of maximum temperature on the variability of rice and maize yield is negative, indicating that the maximum temperature is risk-decreasing while the overall rainfall is risk-increasing regarding the production of maize and rice. The minimum and maximum temperatures are meaningful only in the linear-quadratic functional form of the maize. The BIC and AIC values specified the superior functional form which was the linear Cobb–Douglas since it has the smallest positive value.

3.3. Climate Elasticities of Wheat and Rice Yields

Because the quadratic approaches have interaction and quadratic terms, the extent and signs of the obtained coefficients in the quadratic function cannot be compared to those in the linear function. The elasticity’s estimation, giving a common denominator, was assessed and compared the influence of climatic variables in the linear Cobb-Douglas and linear-quadratic functional approaches (Isik & Devadoss, 2006). The elasticities can be calculated through multiplying the coefficients of weather variables, like minimum temperature, maximum temperature, and rainfall, by the mean climate variable and breaking up the result into the average yield (Chen et al., 2004). Table 5 shows these elasticities. Concerning the average yield and the function of variance, the obtained elasticities of quadratic and linear approaches are a little different.

Table 5: Elasticities of Climate Variables

Yield function	Climate Variables	Crops	Linear Cobb-Douglas	Quadratic Model
Mean Yield	T_{max}	wheat	-1.33	-5.56
		rice	-1.48	-2.30
		maize	-4.03	-39.33
	T_{min}	wheat	0.04	0.05
		rice	0.21	0.26
		maize	0.26	3.40
	R	wheat	0.52	-1.48
		rice	0.20	0.32
		maize	0.22	1.23
Yield Variability	T_{max}	wheat	0.27	0.38
		rice	-0.22	-0.1
		maize	-0.1	-0.54
	T_{min}	wheat	-0.002	-0.02
		rice	0.036	-0.0039
		maize	-0.002	0.048
	R	wheat	0.12	0.03
		rice	0.038	0.03
		maize	0.024	0.016

Source: Research findings

As is observed, the maximum temperature elasticities differ from -39.33 to -1.33 in the average yield function of the three crops. As far as these amounts are more than unity, the reaction of crops mean yields to the alterations in the maximum temperature is elastic, showing that the maximum temperature is yield-decreasing for wheat and rice in quadratic and linear forms. Nevertheless, the obtained elasticities range from 0.27 to 0.38, -0.22 to -0.1, and -0.54 to -0.1 in the variance functions of wheat, rice, and maize, respectively. Hence, the reaction of three crops variance to the alterations in maximum temperature is not elastic. The rise in the maximum temperature reduces the rice and maize yields' variance while augmenting the wheat variability. The minimum temperature elasticities vary from 0.04 to 0.05 regarding the mean yield function of wheat, from 0.21 to 0.26 concerning the mean rice function and from 0.26 to 3.4 for the mean maize function, hence inelastic for the three crops. Increasing the minimum temperature decreases the wheat yield variability in both functional forms. The variance response to the alterations in minimum temperature is not elastic.

The rainfall elasticities varied from -1.48 to 0.52 in the mean wheat function, 0.2 to 0.32 in the mean rice function and from 0.22 to 1.23 in the average maize function. Therefore, the response of the average yields of the crops is mixed to the variations in rainfall. That is, the average yield of wheat is not elastic in the linear function, but elastic in the quadratic function. Nevertheless, the average yields of maize and rice are not elastic in quadratic and linear functional forms. Also, the obtained elasticities are lower than one in the variance function, showing that the crop yields variance is inelastic to variations in rainfall. The elasticities' signs show that rainfall is risk-increasing for the three crop yields.

In general, the obtained elasticities of the maximum temperature were much larger than the rainfall and minimum temperature. These results indicated that the influence of climate variations on Iranian agriculture is largely driven by the utmost temperature change.

3.4. Effects of Future Climate Change

Via the obtained elasticities, the influences of future scenarios of climate variation on crop variability and yield can be estimated (IPCC, 2013). The IPCC predicted the variations in climate for three time-slices viz. 2035, 2065 and 2100 (Table 5). Accordingly, by 2100, the annual temperature may rise by 1.3 °C to 3.5 °C and changes in precipitation by this year are expected to be within the range of -3% to 27%. By 2065, the increase in the annual temperature is expected to vary from 0.8 °C to 2.5 °C and the yearly rainfall is predicted to range from -2% to 26%. The variations in rainfall and temperature towards 2035 are not so significant. The annual temperature is predicted to augment by 0.2°C to 1.3°C and the annual rainfall range is expected to be between -2% and 7%. The crop yields at the maximum and minimum temperature changes were projected using Equation (6).

$$\Delta Y = \left[\left(\frac{\partial Y}{\partial R}\right) * \Delta R + \left(\frac{\partial Y}{\partial T}\right) * \Delta T\right] * 100 \qquad (6)$$

where Y is the yield, R is the rainfall, and T is the temperature; ($\partial Y/\partial R$) and ($\partial Y/\partial T$) were identified by the equations of the model. The predicted impacts of climate change on crop yields are given in Table 6.

Table 6: Predicted Changes in Temperature and Rainfall by 2035, 2065 and 2100

Time slice	Temperature (ºC)		Rainfall (%)	
	Minimum Δ	Maximum Δ	Minimum Δ	Maximum Δ
2035	0.2	1.3	-2	7
2065	0.8	2.5	-2	26
2100	1.3	3.5	-3	27

The climate variation will affect the production of maize more than any other crop. By the year 2100, with a significant change in climate, the yield of maize and rice will be about 40% and 11% which is lower in comparison with the current yield. By the year 2065, the rice and maize yield will also decrease, but the wheat gain would show a marginal value. If no considerable alteration is detected in the climate, yield losses will be less. The influences of weather will not be so notable in the short-run, that is, towards 2035. Owing to the continuous adaptation by farmers, the climate impacts cannot also be so severe in a long period of time. One caveat to these findings is that they differ depending on climate change scenarios, which might vary from model to model. Accordingly, the future climate variations may also change and any adaptation strategy should take this into account.

Table 7: Projected Change in Mean Yield and Yield Variability by 2100 (in percent)

Crop	2035		2065		2100	
	Minimum ΔT and ΔR	Maximum ΔT and ΔR	Minimum ΔT and ΔR	Maximum ΔT and ΔR	Minimum ΔT and ΔR	Maximum ΔT and ΔR
Wheat						
Mean	-0.715	-2.489	0.26	1.74	0.55	-2.46
Variance	-0.256	2.08	0.3	5.51	-0.465	6.588
Rice						
Mean	0.08	-4.77	1.52	-6.66	2.52	-11.21
Variance	0.004	-0.65	0.253	-0.775	0.42	-0.442
Maize						
Mean	0.73	-15.4	4.26	-26.9	6.987	-39.73
Variance	-0.057	-0.253	-0.08	-0.185	-0.13	-0.485

Source: Research findings

3. Discussion

The main aim of this study was to examine the influences of climate variations on the variability and yield of three main grain crops (wheat, rice, and maize) employing disaggregated data. The Just–Pope Production Function was applied as the hypothetical framework. A balanced panel data approach accomplished the objective. The results showed that the influences of climatic variables differ in different crops. In contrast to the rainfall and minimum temperature, the maximum temperature was associated negatively to the wheat, rice, and maize average yield. The values of elasticity under the variance function indicated that the maximum temperature was risk-increasing for wheat while risk-decreasing for rice and maize production. However, the minimum temperature influences over the variability of yield were different. The rise in the minimum temperature probably reduced the maize and wheat yields' variability. Therefore, the minimum temperature was risk-reducing as concerns these two crops. For all crops, the influences of rainfall on the variability of yield were positive, confirming that rainfall was risk-increasing. The obtained elasticities were further employed to measure the influences of future scenarios of climate variation on crop production and variability for three time-slices viz. 2035, 2065 and 2100. The variations in crop production for every scenario were calculated applying the percentage alterations in minimum temperature, maximum temperature, and rainfall in an aggregate form. Climate change scenarios forecasted that by 2100, crop yield levels will drop from their 1960-2005 average. Moreover, the results revealed that future variation of climate may decrease the maize yield variability. However, the variability would be different for rice and wheat at maximum and minimum changes in rainfall and temperature. It will be positive for rice at minimum variations in rainfall and temperature and negative at maximum changes in temperature and rainfall. Moreover, most regional dummy variables were meaningful with different impacts on crop production proving that various climate regions are influenced differently by the climate change. Accordingly, the impacts of climate variation on crop yields will be different in the climate regions. Adaptation strategies which are region-specific or climate zone specific should be implemented which further highlights the necessity of further location-specific studies regarding climate variation and agricultural productivity. This will develop micro-level adaptation practices to reduce yield variability, improve food security, and reduce rural poverty in climate variation.

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