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Dynamic Impacts of Climate Change on Cereal Yield in Egypt: An ARDL Model

التأثيرات الديناميكية للتغير المناخي على محصول الحبوب في مصر: نموذج ARDL

Walaa Mahrous
Lecturer of Economics, Department of Political Science and Economics, Institute of African Research and Studies, Cairo University, Cairo, Egypt
Walaa.mahrous@cu.edu.eg

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Abstract:

This study tries to examine the relationship between global climate change and cereal production in Egypt. An autoregressive distributed lag (ARDL) model is applied to estimate the long and short-run impacts of carbon dioxide emissions, rainfall, temperature and rural population on cereal yield in Egypt. Annual data for the variables included in the model, covering the period from 1961 till 2013, are used in the estimation process. Results indicate that cereal production in Egypt is adversely affected in the short run by rainfall and temperature. However, in the long-run, the increase of CO2 concentration in the atmosphere will be beneficial to some cereal crops. Furthermore, attaining sustainable environment is an aspect worth considering in developing countries like Egypt. Such a goal requires the Egyptian Government to increase the awareness of its importance among people and encourage the integration of pro-environmental measures into agricultural policies, practices, and planning.

Key words: Climate change, Cereal yield, Egypt, ARDL model.

الملخّص:

تسعى هذه الورقة البحثية إلى دراسة العلاقة بين تغير المناخ العالمي وإنتاج الحبوب في مصر، وذلك من خلال تقدير نموذج الانحدار الذاتي للفجوات الزمنية الموزعة المبطأة (ARDL). ويسعى هذا النموذج إلى تقدير التأثيرات طويلة وقصيرة الأجل لكلٍ من انبعاثات ثاني أكسيد الكربون، وهطول الأمطار، ودرجات الحرارة، وعدد سكانً الريف على حصيلة الحبوب في مصر. ويستخدم النموذج في عملية التقدير البيانات السنوية للمتغيرات السابق ذكرها، وذلك خلال الفترة (1961– 2013). وتشير النتائج إلى أن إنتاج الحبوب في مصر يتأثر سلًبا في الأجل القصير بهطول الأمطار ودرجات الحرارة. في حين تشير النتائج إلى أن زيادة تركز غاز ثاني أكسيد الكربون في الغلاف الجوي ستكون مفيدة لبعض الأنواع من محاصيل الحبوب في الأجل الطويل. كما تؤكد الدراسة على ضرورة اهتمام الدول النامية مثل مصر بتحقيق مفهوم "البيئة المستدامة". وقد يتحقق ذلك من خلال قيام الحكومة المصرية بزيادة الوعي بأهمية الحفاظ على البيئة بين أفراد المجتمع، وتشجيع تطبيق السياسات والممارسات الزراعية غير الملوثة للبيئة.

الكلمات المفتاحية: التغير المناخي، ناتج الحبوب، مصر، نموذح الانحدار الذاتي للفجوات الزمنية الموزعة المبطأة.

Introduction

According to the IPCC Fifth Assessment Report (2014), countries that lie in arid and semi-arid regions, like Egypt and many other developing countries, are highly vulnerable to climate change. The report predicts that, by the end of the 21st century, these countries may have faced huge decrease in precipitation, sharp increase in evaporation, shorter winters, drier and hotter summers, more frequent heat wave occurrences, and extreme weather events occurrences.

Also, many scientific studies have indicated that the agricultural sector is considered to be one of the most vulnerable sectors to climate change. This comes as a result for changes in temperature and precipitation that, by modifying land and water regimes, will adversely affect agricultural productivity. Consequently, developing countries are more likely to face severe reduction in food security and huge rise in poverty levels; as they are highly vulnerable to climate change and already suffer from technological, resource, and institutional constraints in the agricultural sector (Kurukulasuriya & Rosenthal 2003).

Although carbon dioxide (CO_2) is considered to be the greenhouse gas the most responsible for global climate change, some scientists argue that its increase is not necessarily bad for Earth. They claim that, in some regions of the world, crop yields may increase due to the positive (fertilizing) effect of CO_2; higher CO_2 concentrations in the atmosphere can boost plants growth by stimulating photosynthesis. In addition, experts find that this positive effect varies according to the plant type. For instance, experiments have showed that C3 plants (e.g. wheat, rice and soya bean) are more positively affected by CO_2 enrichment than C4 plants (such as maize, sorghum, sugar-cane, millet and pasture grasses). However, when taking other factors that influence plants growth into consideration (like water, temperature, nutrient availability), this positive impact may turn to be substantially less than the ideal (Houghton 2004).

The Egyptian agriculture sector plays crucial role in GDP growth, employment, supplying food and inputs for many industries. Recently, the Egyptian economy has been suffering from large food gap in some strategic crops (such as wheat, yellow maize, sugar, and oil crops). Consequently, to attain reasonable stage of food security and self-sufficiency of these crops, it is important to maximize productivity of agricultural resources. Also, it is necessary to tackle a list of challenges faced by this sector; climate change comes at the top of this list (Dhehibi 2016).

Hence, this study tries to find an answer to the following **problematic question**: to what extent does the food production in Egypt get affected by the global climate change? Consequently, **the main hypothesis** of this paper is that there is a negative relationship between climate change factors and the Egyptian food production.

Last but not least, it is worth mentioning that there are some factors that contribute to the significance of this study. They can be summarized as follows:

1. Econometric research relating to climate issues and their impacts on food production in developing countries like Egypt is still limited.

2. Empirical studies are essentially needed by policy makers to help them at designing agricultural policies that can adapt to climate change and ensure food security simultaneously (Mendelsohn 2009).

3. This paper tries to fill this literature gap by modeling the long run and short run relationship between cereal yields and different climate-change factors (namely CO_2 emissions, precipitation, and temperature) in Egypt.

The remainder of this study is organized as follows. Section 2 reviews the literature on the various impacts of global warming on food security and food production in developing countries. Section 3 presents facts on the link between climate change and crop production in Egypt. Both section 4 and 5 demonstrate the methodology, data sources and the diagnostic tests used. Section 6 reports the empirical results. Finally, section 7 provides the conclusion.

1. Literature Review

By depending on the results of global climate models carried out during the 21st century, numerous studies have examined the sensitivity of some major crops- that occupy a large percent of the world's food supply- to climate change. They have estimated the effect of CO_2 fertilization, changes in temperature and precipitation on food production in different regions of the world. In general, these papers have shown mixed findings of the global warming effects on crop growth and yield. Additionally, some of them have modeled the possible effects of economic factors and modest levels of adaptation (De Salvo et al 2013). Consequently, as long as we're concerned with the countries the most vulnerable to global warming, this section reviews empirical studies carried out on developing countries; mainly in Africa and Asia. This is achieved by giving details on the main variables used, estimation methodologies and the main findings.

For empirical studies on African developing countries, Kabubo-Mariara & Kabara (2015) investigated the impact of climate change on food availability in Kenya as one of the dimensions of food security. The paper estimated fixed and random effects regression models for 4 main crops: maize, beans, sorghum, and millet, over the period (1975-2012). The results indicated that the climate variables have a non-linear relationship with food insecurity. For instance, increased seasonal precipitation was associated with reduced food insecurity while excessive precipitation would insecurity due to damage to crops. For Tunisia, Ben Zaied & Ben Cheikh (2015) investigated the long and short run impacts of climate change (proxied by annual rainfall and temperature) on cereal and date production, for the period 1979-2011. The paper used the full-modified ordinary least squares method to estimate its model. Results indicated that annual temperature decreased both cereals and date production while annual rainfall had a positive effect on their production. Also, findings indicated that the short run climate effect was smaller than the long run effect.

Additionally, in Ghana, Lawrence Amponsah et al (2015) examined the effect of the increasing concentration of CO_2 in the air on cereal yield, using ARDL approach, for the period of 1961-2010. The results indicated that there was a significant negative impact for CO_2 on cereal yield in Ghana. Besides, there was a significant positive long effect for real gross domestic product on the food security there. Also, Abu (2015) studied the long-run relationship between sorghum yield, rainfall, and producer price in Nigeria over the period (1970-2010), by applying the Johansen co- integration test and vector error correction model (VECM). The results showed that, in the long run, adverse impacts of climate change on rainfalls would negatively affect crop yield in Nigeria. Also, these results indicated that prices of agricultural commodities gave signals to producers over the type and quantity of commodity to produce.

Furthermore, in Togo, Boansi (2017) investigated the impacts of climatic (mean temperature and rainfall variability) and non-climatic (area planted with cassava, rural population, and nominal exchange rate) factors on cassava yields, using an ARDL approach, for the period 1978–2009. Results showed that cassava yield was positively affected by rainfall while negatively affected by average temperatures in both short and long run. Also, findings showed an inverse relationship between area harvested and yield of cassava, but a significant positive effect of labour availability on yield in the long run. Finally, in Guyana, the United Nations Economic Commission for Latin America and the Caribbean (2011) used an ARDL approach to estimate the effects of climate change (proxied by average rainfall and air temperature) on agricultural output; mainly sugarcane and rice. By controlling for price effects and typical agricultural inputs, estimation results showed that, in the long run, temperature had no significant effect on sugarcane output while it had an adverse effect on rice production. With respect to rainfall, it has a negative impact on each of rice and sugarcane.

With respect to the studies focusing on Asian countries, Maiadua et al (2016) applied an ARDL model to estimate the impact of some climate change variables (carbon dioxide, temperature and rainfall variables) on food production in India, from 1970 till 2015. The results showed that, in the long-run, each of carbon dioxide and rainfall had a significant positive impact on food production, while temperature had a significant negative effect. Also, Kazi & Siddique (2014) studied the impact of temperature, rainfall, humidity and sunshine, as proxies for climate change, on rice production in Bangladesh. The data on these variables were compiled for 23 regions in Bangladesh from 1975 till 2008. The study used fixed effects regression approach to control for regional and temporal differences. Results showed that long term changes the climatic variables have different impacts on the productivity of rice; while temperature and humidity had negative impacts on rice yield, sunshine and rain had positive ones.

In addition, Janjuaa et al (2014) tried to measure the impact of each of CO2 emissions, average temperature and average precipitation, as proxies for the global climate change, on wheat production in Pakistan. The study estimated an ARDL model by using annual data from 1960 to 2009. The estimation results showed no influence for the climate change variables on wheat crop in Pakistan. Lastly, Arshed & Abduqayumov (2016) estimated the short and long run impacts of climate change on the productivity of cotton and wheat in the districts of Punjab in Pakistan, for the period (1970-2010). The study used the variables of sale price, fertilizers, number of tube wells, and deviations from each of average maximum annual temperature and average rainfall as indicators for climate change. By applying panel ARDL approach, estimated results showed that deviations from average rainfall were harmful to cotton crop in the long run and cotton & wheat in the short run, while deviations in maximum temperature was only harmful for cotton crop in the short run.

2. Climate Change and Food Production in Egypt

Egypt lies in the northeastern part of the African continent and occupies about 3% of the total area of Africa. The country has an arid desert climate; it is hot and almost rainless. The River Nile is the only secured source for regular and voluminous water. Less than 3% of the total area of Egypt is covered with fertile lands where most of its population lives (Ibrahim & Ibrahim 2003).

During the last three decades, the CO_2 emissions in Egypt were observed to grow from about 1.6 metric tons per capita in 1990 to about 2.5 metric tons per capita in 2015 (Olivier et al 2016). This comes as a result for country's economic growth, expanding urban population, and fossil fuel subsidies that encourage inefficient energy use. Also, over 70% of Egypt's green house gas (GHG) emissions come from the energy sector; half of Egypt's primary energy supply is satisfied by oil and oil products. The power generation and transport sectors account for 42% and 21% of Egypt's total GHG emissions, respectively. Emissions from electricity generation in particular have grown rapidly in recent years (by 19.8% from 2012 to 2015) as oil filled the gap left by shortages in the supply of natural gas (World Bank 2016).

Regarding the agricultural sector, it is one of the largest sectors of the Egyptian economy; comprising 11.1% of GDP and providing 25.8% of all employment in 2015 (CAPMAS 2016). However, agriculture production is still concentrated in the Nile Valley zone and Delta. In addition, the quality of these lands has decreased and, consequently, average productivity per acre of major crop yields has declined (Handoussa 2010). For example, in 2014, average productivity per acre of wheat decreased by 31.5% and that of rice increased slightly by 12.4%, if compared with their values in 1997. Moreover, Egypt's self-sufficiency ratio of wheat decreased from about 62.5% in 2003 to about 54.8% in 2008 and 49.1% in 2015 (CAPMAS 2017). Also, there are other challenges that still face the agricultural sector in Egypt, such as fragmentation of agricultural lands, rural poverty, food security, and improving irrigation efficiency (Handoussa 2010).

Although Egypt's contribution to the global CO_2 emissions is considered to be very limited (about 0.6% in 2015), global climate change is threatening it (Olivier et al 2016). These threats can be represented in: rising sea level, drowning of the Nile Delta (about 10–12% of the total area), scarce water resources, low agricultural productivity, desertification, and land degradation. Also, all these effects can lead to many social and economic disruptions. For instance, Egyptian population, especially those living in rural areas, may face basic food items shortage as a result of expected lower agricultural productivity. Besides, due to the increase in the number of small farms, this may lead to a decrease in the capacity of agricultural sector in Egypt to adapt to climate change[1] (Smith et al 2014).

3. Methodology and Data

3.1 ARDL Approach

According to Janjuaa et al (2014), wheat production's response to both climatic and non-climatic variables is expressed in a Cobb–Douglas functional form. Emissions of carbon dioxide, average temperature, and average precipitation are used as proxies for climate change while water, area under wheat production, agriculture credit, fertilizers, and technology are adopted as the non-climatic factors. Our paper has applied the same model with some modifications in the explanatory variables due to some data limitations[2]. Thus, the following single multivariate equation is used to examine the relationship between cereal yields in Egypt and both climatic and non-climatic factors:

$$CY_t = \theta_0 + \theta_1 CO_{2t} + \theta_2 \Pr ecip_t + \theta_3 Temp_t + \theta_4 Rulpop_{tt} + \mu_t \tag{1}$$

[1] It is generally thought that larger, well-capitalized farms will have a higher capacity to adapt to climate change than smaller, less well-capitalized farms.

[2] Due to the limited availability of data in our case on water, agriculture credit, fertilizers, and technology, as non-climatic factors, rural population has been used instead as a proxy for the number of labors in the agricultural sector.

Where CY_t is cereal yield (kilogram per hectare), CO_{2t} is per capita carbon dioxide emissions (metric tons), $\Pr ecip_t$ is average precipitation (millimeter), $Temp_t$ is average temperature (Celsius degree centigrade)[3], $Rulpop$ is Rural population (millions), and μ_t is the regression error term.

All these variables are converted into natural logarithms to facilitate the estimation procedure. Also, annual data for these variables from 1961 till 2013 are obtained from Climate Change Knowledge Portal and the World Development Indicators Database; both provided by the World Bank (World Bank 2017). The descriptive statistics, mean value, standard deviation and coefficient of variation of different variables are given in Table (1) in Appendix.

The ARDL technique is adopted to estimate our model. This single cointegration approach has been developed by Pesaran and others in 2001 (Pesaran et al 2001). This method has a lot of advantages which can be stated as follows (Narayan 2005):

- ✓ It gives unbiased estimates of the long-run coefficients even if there is an endogeneity problem among the regressors.
- ✓ It can estimate the long and short-run parameters simultaneously.
- ✓ It can test for the existence of a long-run relationship between the variables in levels irrespective of whether they are I (0), I (1), or a combination of both.
- ✓ In small samples, it gives estimates with properties more superior to that of Gregory and Hansen cointegration procedures.

Thus, the ARDL representation of equation (1) can be put as follows:

[3] Time series data of precipitation and temperature were collected on monthly basis from the World Bank (climate change knowledge portal: http://sdwebx.worldbank.org/climateportal) and then converted to annual values for the period (1961-2013).

$$\Delta CY_t = \alpha_0 + \alpha_1 CY_{t-1} + \alpha_2 CO_{2t-1} + \alpha_3 \Pr ecip_{t-1} + \alpha_4 Temp_{t-1} + \alpha_5 Rulpop_{t-1} + \sum_{i=1}^{m} \alpha_{6i} \Delta CY_{t-i} + \sum_{i=1}^{m} \alpha_{7i} \Delta CO_{2t-i} + \sum_{i=1}^{m} \alpha_{8i} \Delta \Pr ecip_{t-i} + \sum_{i=1}^{m} \alpha_{9i} \Delta Temp_{t-i} + \sum_{i=1}^{m} \alpha_{10i} \Delta Rulpop_{t-i} + \varepsilon_t \qquad (2)$$

3.2 Estimation Procedure

To estimate equation (2) by using Pesaran's technique, **two steps** should be involved. **The first one** is to examine each variable series included in equation (1) for its integration order. This has been done by the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests. Results indicate that CY_t ,CO_{2t} , and *Rulpop* are I (1) while $\Pr ecip_t$ and $Temp_t$ are I (0), at the 5% level of significance [refer to Table (2) in Appendix]. Thus, this validates applying bounds testing approach.

The second step is to apply the specialized estimator[4], which has been recently included in **EViews 9** for handling ARDL models, to estimate equation (2). Based upon the estimation results of the equation – as displayed in Table (3) in Appendix – the ARDL bounds test is carried out. As it shows from Table (1), the F-statistic (4) is bigger than the critical value of the upper bound at 5% significance level (3.49). Thus, we reject the null hypothesis of $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = 0$ (i.e. there exists a long-run relationship between CY and its determinants).

[4] This estimator offers built-in lag-length selection methods, critical values for the bounds test, as well as other post-estimation tests. For further details, refer to: IHS Global Inc.: **EViews 9 User's Guide II**, 2015.

Table (1): ARDL Bounds Test

Sample: 1964 2013 Included observations: 50 Null Hypothesis: No long-run relationships exist		
Test Statistic	Value	k
F-statistic	4.007672	4
Critical Value Bounds		
Significance	I(0) Bound	I(1) Bound
10%	2.2	3.09
5%	2.56	3.49
2.5%	2.88	3.87
1%	3.29	4.37

Diagnostic Tests

After confirming long-run relationship among the variables, cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) tests are carried out to check the stability of the estimated coefficients. Figures 1 and 2 validate the stability of our model; as the line for each of CUSUM and CUSUMSQ test lies inside the 5% critical bands. Furthermore, the robustness of the model has been validated by **three** diagnostic tests. **First**, Breusch-Godfrey serial correlation LM test, in Table (4) in Appendix, indicates that there is no serial correlation between the estimated model errors (F-statistic = 0.389 and P = 0.679). **Second**, Jarque-Bera normality test assures the normality of errors at 5% significance level (see figure 3). **Third**, Breusch-Pagan-Godfrey heteroskedasticity test, in Table (5) in Appendix, shows that the residuals don't suffer from heteroskedasticity (Obs*R^2 = 14.42, P= 0.0714). Hence, the reported long and short-run estimated coefficients are valid for reliable interpretations.

Figure (1): Results of CUSUM Test

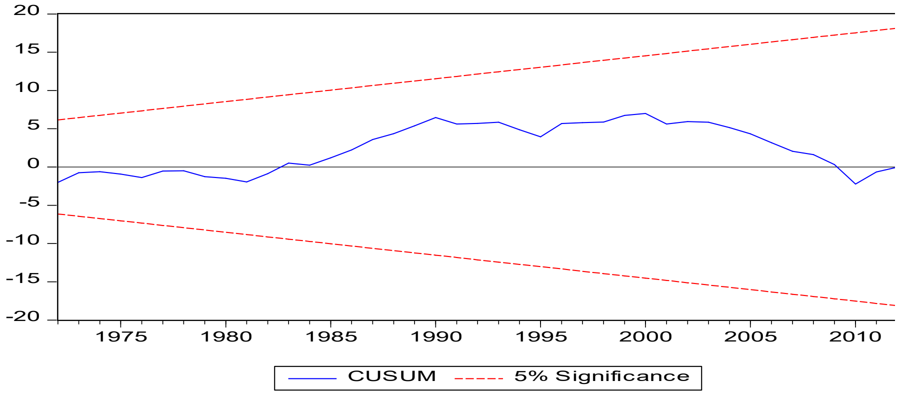


Figure (2): Results of CUSUMSQ Test

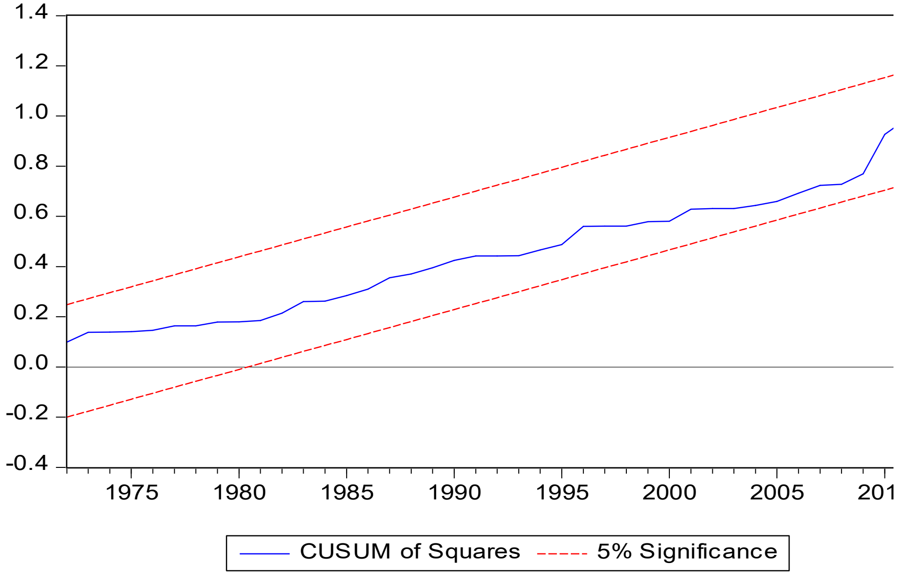
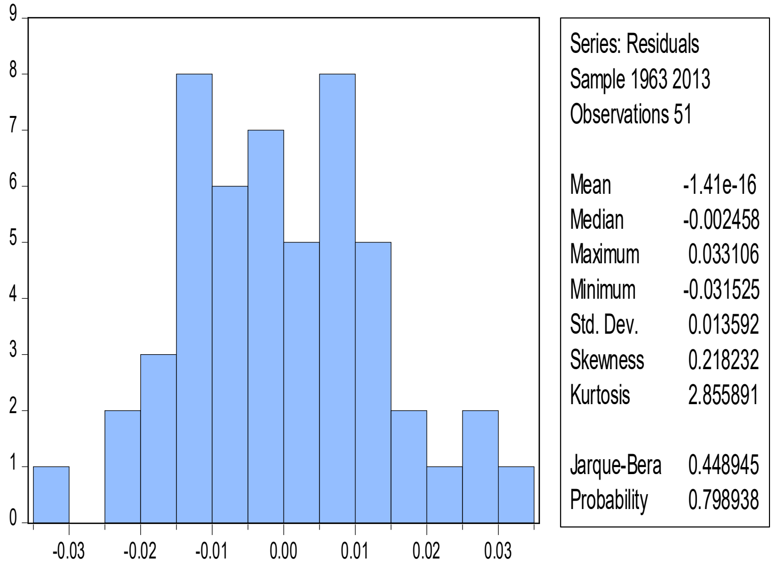


Figure (3): Results of Normality Test



4. Empirical Results

To capture the long and short-run relationships among the variables of our model, ARDL cointegrating form has been estimated. Results of the long-run estimated coefficients are shown in table (2). It is found that the only variable that has a long-run impact on cereal yield in Egypt is CO_2 emissions; its estimated coefficient is positive and significant at 5% level. The estimated long run coefficient of CO_2 shows that one percent increase in CO2 emission raises cereal yield by 0.7 percent. This matches the findings of both Hundal & Kaur (1996) and Maiadua et al (2016) for India. Thus, in the long-run, Egypt may witness shifts in cereal production due to climate change. Though the extent of this effect is still questionable, it agrees with those scientific studies revealing the positive impact of CO_2 on cereal cultivation (Houghton 2004).

Also, findings indicate that the probable change in rainfall pattern and temperature in consequence of the climate change may have insignificant impact on the overall level of cereal production. Additionally, the insignificance of the rural population coefficient points to the ineffectiveness of excessive labor force in the agriculture sector in Egypt. Due to lack of education and prevalence of poverty, Egyptian farmers still depend on old methods of cultivation and are not very well equipped with new technology. These results are in accord with the findings of Janjuaa et al (2014) for Pakistan.

Table (2): Estimated Long-Run Coefficients

Variable	Coefficient	Standard Error	t-Statistic	Probability
LNCO2	0.704051	0.386165	1.823188	0.0754*
LNPRECIP	-1.608571	2.588016	-0.621546	0.5376
LNTEMP	-12.429644	19.425376	-0.639866	0.5257
LNRULPOP	1.074691	2.127579	0.505124	0.6161
C	20.993987	26.968111	0.778475	0.4407

* indicates significance at the 5% level.

Concerning the estimated short-run effects of our variables, they are demonstrated in table (3). The short-run coefficients of precipitation, temperature and rural population, except that of carbon dioxide emissions, are statistically significant at 5% level. The table shows that an increase of one percent in each of precipitation and temperature may decrease food production by approximately 0.03% and 0.6% respectively. This is in line with the empirical findings reached by Aravind et al (2012) that both rising rainfall and temperature have adverse impacts on Indian agriculture. Also, there is an inverse relationship between the number of labour in the agricultural sector (proxied by the rural population) and food production in the short-term. This can be justified by the law of diminishing marginal productivity (increasing labour used on a fixed area of land may first increase output only up to a point and decline thereafter).

Furthermore, the estimated coefficient of the error correction mechanism (ECM) is negative and statistically significant at 5%[5]. This

[5] To make sure that the model variables are adjusting themselves till they reach their steady-state values in the long-run, ECM (-1) should be negative and significant (Enns et al 2014).

confirms the existence of a stable long-run relationship between the variables of our model. As it shows from table (3), ECM (-1) value is -0.0448. This suggests that when CO_2 emissions and the other regressors are above or below their equilibrium level, they adjust by almost 4.48% within the first year. The estimated ECM (-1) equation can be represented as follows:

$$ECM(-1) = LNCY - (0.7041*LNCO2 - 1.6086*LNPRECIP - 12.4296*LNTEMP + 1.0747*LNRULPOP + 20.9940)$$

Table (3): Estimated Short-Run Coefficients

Variable	Coefficient	Standard Error	t-Statistic	Probability
D(LNCY(-1))	-0.272667	0.134936	-2.020713	0.0497*
D(LNCO2)	0.052217	0.053557	0.974985	0.3351
D(LNPRECIP)	-0.037091	0.015550	-2.385325	0.0217*
D(LNTEMP)	-0.643568	0.189571	-3.394872	0.0015*
D(LNRULPOP)	-0.190541	0.087520	-2.177110	0.0351*
ECM(-1)	-0.044893	0.009391	-4.780593	0.0000*

* indicates significance at the 5% level.

5. Conclusion

In this paper, the relationship between climate-change, non climate-change factors and cereal yield is investigated in Egypt by an ARDL model for the period (1961 till 2013). The bounds test shows evidence of a long-run relationship between the annual percentage change of cereal yield, carbon dioxide emissions, precipitation, temperature, and rural population. Also, empirical findings show that food production is adversely affected in the short-run by some climate-change variables; rainfall and temperature. Besides, increasing the number of labors employed in the agricultural sector will have detrimental impacts on cereal production and agricultural productivity.

Thus, in the short-run, equipping farmers with new machines and technology can play an important role to offset any kind of negative shock to food production resulting from climate change. Whereas, the long-run results reveal that cultivating crops that benefit from the increase of CO2 concentration in the atmosphere will be the only remedy to counter any deficiency of food production in Egypt. In addition, it is important that the Egyptian Government institutes agricultural policies that focus on promoting a sustainable agriculture using environmental friendly agricultural practices, to ensure people (especially the poor and children under-5 years) have access to safe and nutritious food. Finally, it is recommended to increase the awareness of sustainable environment in Egypt by integrating climate change measures into agricultural policies, practices, and planning by the Government.

Appendix

Table (1): Descriptive Statistics

	CY	CO_2	Precip	Temp	Rulpop
Mean	3.705020	0.103549	0.423609	1.352925	0.303958
Median	3.689451	0.129233	0.422628	1.351938	0.301641
Maximum	3.878303	0.413607	0.673101	1.394392	0.472239
Minimum	3.463251	- 0.237600	0.234128	1.332392	0.146284
Standard Deviation	0.128675	0.204018	0.104407	0.012354	0.085372
Skewness	0.024091	- 0.104203	0.319008	0.583345	0.128475
Kurtosis	1.522750	1.798935	2.425229	3.729169	2.198743
Jarque-Bera	4.824298	3.281563	1.628484	4.180057	1.563580
Probability	0.089622	0.193829	0.442975	0.123684	0.457586
Sum	196.3661	5.488120	22.45127	71.70501	16.10979
Sum Square Deviation	0.860971	2.164418	0.566846	0.007936	0.378993
Observations	53	53	53	53	53

Table (2): Unit Root Tests

Series	Level		1st Difference	
	ADF	PP	ADF	PP
Cereal Yield	-1.574844	-1.615321	-8.925433*	-8.872252*
CO_2	-0.849497	-0.816891	-8.064926*	-8.058710*
Precipitation	-7.241230*	-7.277239*	-6.447509*	-24.22547*
Temperature	-2.298702	-4.289164*	-10.40710*	-18.55226*
Rural Population	-2.492716	-1.704868	-3.046919*	-3.046919*

* The null hypothesis of a unit root is rejected by the Mackinnon critical values at 5%.

Table (3): ARDL Model Estimation Results

Dependent Variable: CY
Method: ARDL
Date: 10/14/17 Time: 13:42
Sample (adjusted): 1963 2013
Included observations: 51 after adjustments
Maximum dependent lags: 2 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): CO2 PRECIP TEMP RULPOP
Fixed regressors: C
Number of models evaluated: 162
Selected Model: ARDL (2, 0, 1, 0, 1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
LNCY(-1)	0.661862	0.148624	4.453254	0.0001
LNCY(-2)	0.290647	0.135948	2.137928	0.0384
LNCO2	0.033436	0.044894	0.744774	0.4606
LNPRECIP	-0.039594	0.022965	-1.724144	0.0920
LNPRECIP(-1)	-0.036798	0.023966	-1.535425	0.1322
LNTEMP	-0.590291	0.268725	-2.196634	0.0336
LNRULPOP	-0.195595	0.109290	-1.789691	0.0807
C	0.997016	0.407796	2.444890	0.0188
R-squared	0.987877	Mean dependent variable		3.713523
Adjusted R-squared	0.985568	S.D. dependent variable		0.123452
S.E. of regression	0.014831	Akaike info criterion		-5.425475
Sum squared residuals	0.009238	Schwarz criterion		-5.084565
Log likelihood	147.3496	Hannan-Quinn criterion		-5.295203
F-statistic	427.8275	Durbin-Watson statistic		2.129491
Probability (F-statistic)	0.000000			

*Note: p-values and any subsequent tests do not account for model

Table (4): Breusch-Godfrey Serial Correlation LM Test

F-statistic	0.389568	Prob. F(4,37)		0.6799
Observations*R-squared	0.974418	Prob. Chi-Square(4)		0.6143
Test Equation: Dependent Variable: RESID Method: ARDL Sample: 1963 2013 Included observations: 51 Presample missing value lagged residuals set to zero.				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNCY(-1)	0.204215	0.294995	0.692268	0.4928
LNCY(-2)	-0.178258	0.271868	-0.655679	0.5158
LNCO2	-0.011151	0.048580	-0.229544	0.8196
LNPRECIP	-0.000188	0.023415	-0.008048	0.9936
LNPRECIP(-1)	0.007499	0.026098	0.287334	0.7753
LNTEMP	-0.032329	0.275167	-0.117490	0.9071
LNRULPOP	0.034071	0.117854	0.289095	0.7740
LNRULPOP(-1)	-0.037009	0.112859	-0.327922	0.7447
C	-0.054753	0.422143	-0.129703	0.8975
RESID(-1)	-0.263286	0.310888	-0.846886	0.4021
RESID(-2)	-0.004484	0.186748	-0.024009	0.9810
R-squared	0.019106	Mean dependent variable		-1.41E-16
Adjusted R-squared	-0.226117	S.D. dependent variable		0.013592
S.E. of regression	0.015051	Akaike info criterion		-5.366335
Sum squared residuals	0.009061	Schwarz criterion		-4.949666
Log likelihood	147.8415	Hannan-Quinn criterion		-5.207113
F-statistic	0.077914	Durbin-Watson statistic		1.938493
Probability (F-statistic)	0.999920			

Table (5): Heteroskedasticity Test (Breusch-Pagan-Godfrey)

Heteroskedasticity Test: Breusch-Pagan-Godfrey				
F-statistic	2.069829	Prob. F(8,41)		0.0609
Obs*R-squared	14.42128	Prob. Chi-Square(8)		0.0714
Scaled explained SS	9.075787	Prob. Chi-Square(8)		0.3359
Test Equation: Dependent Variable: RESID^2 Method: Least Squares Sample: 1963 2013 Included observations: 51				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.002985	0.006332	-0.471389	0.6398
LNCY(-1)	-0.006433	0.002308	-2.787410	0.0079
LNCY(-2)	0.003967	0.002111	1.879493	0.0671
LNCO2	0.001019	0.000697	1.461744	0.1513
LNPRECIP	-0.000428	0.000357	-1.200317	0.2367
LNPRECIP(-1)	-0.000321	0.000372	-0.861844	0.3937
LNTEMP	0.009315	0.004173	2.232441	0.0310
LNRULPOP	-0.003073	0.001697	-1.810751	0.0773
LNRULPOP(-1)	0.002842	0.001577	1.802064	0.0787
R-squared	0.282770	Mean dependent variable		0.000181
Adjusted R-squared	0.146155	S.D. dependent variable		0.000249
S.E. of regression	0.000230	Akaike info criterion		-13.75576
Sum squared residuals	2.23E-06	Schwarz criterion		-13.41485
Log likelihood	359.7719	Hannan-Quinn criterion		-13.62549
F-statistic	2.069829	Durbin-Watson statistic		1.826306
Probability (F-statistic)	0.060918			

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