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Impact of Climate Change on Cereal Production: Evidence from Lower-Middle-Income Countries

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Abstract

This study empirically examines the impact of climate change on cereal production in selected lower-middle-income countries with a balanced panel dataset spanning the period 1971-2016. The study uses average annual temperature, average annual rainfall, and CO 2 emissions to measure climate change. Besides this, cultivated land under cereal production, and rural population are also used as the control variables. Second generation unit root tests, i.e., CIPS, and CADF, are used to test the stationarity of the variables. Feasible Generalized Least Square (FGLS) model is used to overcome the issues of cross-sectional dependence, serial correlation, and group-wise heteroscedasticity. The findings show that a rise in the temperature reduces the cereal production in lower-middle-income countries. While other climate variables, i.e., rainfall and CO 2, affect cereal production positively. The sensitivity of long run elasticity has been checked with the help of Driscoll-Kraay standard regression. The adverse effects of temperature on cereal production are likely to pose severe implications for food security. In conclusion, the paper recommends that governments and cereal producers should carry out adaptation activities and programmes to cope with the negative effects of temperature on cereal production.

1. Introduction

Agriculture is one of the most sensitive and extremely vulnerable sectors to climate change (Kotir, 2011). It is vital for any nation's economic development, especially in developing countries like India, where agriculture significantly contributes to employment and food security. Climate change affects productivity and production patterns in the agriculture sector (Bosello and Zhang, 2005). The variability in weather and climate is a critical factor that influences the productivity of agriculture and the cropping pattern. This variability in weather becomes a severe problem to sustainability in countries where agriculture sector plays a vital role in sustaining livelihood and food security (Howden et al., 2007). The change of climate affects the livelihoods of the people, who occupy around 40% land and consume 70% water resources globally (Masters et al. 2010). Moreover, the variability in the climate has severe implications on agriculture in terms of the increased crop damages, low productivity and high production/operational costs. This leads to a decrease in farmers' income resulting in poverty and inequality level that would reduce the farmers' active involvement in agriculture (Alam et al., 2012). Climate factors such as temperature, precipitation (rain, snow, hail and ice pellets etc.), and frequency of occurring uncertainty events, like increasing CO_2 concentration in the atmosphere and rising sea level, directly affect livestock and agricultural produce. (Adams et al., 1998). The climate change can have both negative and positive effects on agriculture that can emerge depending on the geographical location or the types of crops produced in that area (Mishra and Sahu, 2014). Tropical and sub-tropical regions are more vulnerable due to higher temperature leading to the damage of crops and more water requirement. It not only leads to floods and famines but also causes socio-economic backwardness in a country (Ali et al., 2017) and affects the maturity period of a crop (Hatfield and Prueger, 2015). Moreover, soil fertility can degrade by erosion, pesticides, change in cropping pattern, harvest period, and water availability (Bhardwaj et al., 2018). Adams et al. (1998) also argued that climatic variability and extreme events such as floods, droughts, and windstorms affect crop and livestock productivity.

In response to climate change, the frequency and intensity of rainfall can alter the availability of direct water to crops, drought stress on crops, animals' production conditions, forage supply for animals, and irrigation facilities (Shankar and Shikha, 2017). It is also expected that the impact of CO_2 will be higher on C_3 species which include wheat, rice, and soybeans as compared to C_4 species which include corn and sorghum. Extreme events of climate change lead to harming trees, crops, livestock, water-borne transport and ports, which has a severe effect on agricultural productivity. According to the World Economic Forum (2015), 9 out of 10 countries affected by climate change in the lower-middle-income category between 1995 to 2014. Lower-middle-income countries are defined by World Bank (2018) as "those with a Gross National Income (GNI) per capita lying between $1,006 and $3,955. In these income countries, the share of the agriculture sector to Gross Domestic Product (GDP) is 14.9% in comparison to 5.7%, 7.8% in upper middle-and middle-income countries respectively in 2018 (World Bank, 2019). Therefore, it would be imperative to assess the impact of climate change on cereal production in lower-middle-income countries and design suitable policy on the nexus between climate change and cereal production in addressing these issues in the direction to boost agricultural production in these regions.

In the literature, most of the studies have used a time-series approach to study the impact of climate change on agricultural crops production (Rahim and Puay, 2017; Zaied and Zouabi, 2015; Dumrul and Kilicarslan, 2017; Onour, 2019). Some researchers have used the panel data approach to analyze the effect of climate change variables on agriculture (Loum and Fogarassy, 2015; Sarker et al., 2014; Ali et al., 2017; Amin et al. 2015). The paper contributes in terms of focusing on cereals production in lower-middle-income

(LMI) countries. This study takes into account the impact of climate change on cereals production firstly on a panel of 11 LMI countries. Then, a time series analysis is conducted to analyse the country-specific effects. We have adopted the feasible generalized least square (FGLS) and Driscoll-Kraay standard regression model which resolves the problems of serial correlation, panel group-wise heteroskedasticity, cross-sectional dependence, and heterogeneity during 1971–2016. We have taken a sample of 11 countries of the lower-middle-income category. As per our knowledge, no study has assessed the impact of climate change on cereal production in lower-middle-income countries. Cereal crop production is more vulnerable to climate change in lower-middle-income countries (Praveen and Sharma, 2019a). Besides this, other significant control variables are used, i.e., land under cereal production, rural population, which indirectly affect cereal crops production. Moreover, to better appreciate the effect of climate change at the country level, the study also analysed the effects of climate change on cereal production country-wise to infer the implication closest to the reality in terms of climate variability-economic nexus policy.

The remaining part of the paper proceeds as follows. Review of literature related to the impact of climate change on agriculture is presented in Section 2. Section 3 explains the theoretical framework, model specification and data, and econometric methods. Empirical results are presented and discussed in Section 4. Finally, Section 5 presents the conclusion and policy implications of the study.

2. Review Of Literature

This section presents an overview of the literature related to climate change and agricultural production in the below table.

S. No.	Author(s)	Time	Country(ies)/State(s)	Econometric model(s)	Results
1	Dumrul and Kilicarslan (2017)	1961–2013	Turkey	ARDL	Temperature, Rainfall => + Agriculture Production
2	Loum and Fogarassy (2015)	1960–2013	Gambia	Multiple Regression	Rainfall, Temperature => - Cereals Production CO_2 => + Cereals Production
3	Sarker et al. (2014)	1972–2009	Bangladesh	FGLS	Varying effects of temperature and rainfall on different rice crops
4	Dasgupta (2013)	1971–2002	66 Countries	Quantile Regression	Rainfall, Temperature => - Maize and Rice Production
5	Barnwal and Kotani (2013)	1971–2004	Andhra Pradesh	Quantile Regression	Monsoon crops are more sensitive to climate change than winter crops
6	Mishra and Sahu (2014)	1993–2009	Odisha	Multiple Regression	Temperature => - Agriculture Production
7	Dell et al. (2012)	1950–2003	125 Countries	Quantile Regression	Varying effects of temperature and rainfall on different country groups based on income
8	Brown et al. (2010)	1961-2003	137 Countries	FE	Rainfall => + Agriculture Production Temperature => - Agriculture Production
9	Akram (2012)	1972-2009	8 Asian Countries	FE and Seemingly Unrelated Regression	Temperature, Rainfall => - Agriculture Production

S. No.	Author(s)	Time	Country(ies)/State(s)	Econometric model(s)	Results
10	Rahim and Puay (2017)	1983–2013	Malaysia	VECM	one-way causality from temperature, rainfall and agriculture land to GDP
11	Zaied and Zouabi (2015)	1980-2012	Tunisia	Panel Cointegration	Temperature => - Olive Production
12	Praveen and Sharma (2019b)	1967–2016	India	Multiple Regression	Temperature, Rainfall => - Agriculture Production
13	Guntukula (2020)	1961-2017	India	Multiple Regression	Rainfall => + Non-food Crop Production Rainfall => - Food Crop Production
14	Attiaoui and Boufateh (2019)	1975–2014	Tunisia	PMG	Rainfall => + Cereals Production Temperature => - Cereals Production
15	Singh et al. (2019)	1966–2011	India	FGLS	Climate change => - Agriculture Production
16	Ali et al. (2017)	1989-2015	Pakistan	FGLS	Rainfall => - Crop yield except Wheat Temperature => - Crop yield
17	Ali et al. (2020)	2004–2018	USA	FGLS	Human Needs positively correlated with extreme weather
18	Susanto et al. (2020)	2008–2018	Indonesia	FGLS	Temperature, Relative Humidity => - No. of International Tourists
19	Amin et al. (2015)	1972–2010	Bangladesh	FGLS	Rainfall => - Rice Production Max. Temperature => - Crop Yield and Cropping Area
20	Onour (2019)	1961–2016	Sudan	ARDL	CO_2 => + Cereals Production
21	Chandio et. al (2020a)	1982-2014	China	ARDL	CO_2 => + Cereals Production Climate Change => - Cereals Production
22	Ahsan et. al (2020)	1971-2014	Pakistan	ARDL	CO_2, Cultivated land => + Cereals Production
23	Demirhan (2020)	1960-2017	World	–	Temperature => - Wheat Production CO_2=> + Wheat Production
24	Dogan (2018)	1993-2016	Turkey and Some Eurasian Countries	ARDL	Agricultural Land => - CO_2 Level
25	Chandio et al. (2020b)	1968-2014	Turkey	ARDL	Varying effects of CO_2 and temperature on cereal yield in the short and long run
26	Janjua et al. (2020)	1960-2009	Pakistan	ARDL	Global climate change does not affect wheat production in Pakistan
27	Zhai et al. (2017)	1970-2014	China	ARDL	Rainfall => - Wheat Yield, Temperature has no effect on Wheat Yield
28	Baig et al. (2020)	1990-2017	India	ARDL	CO_2 => + Wheat and Pulse Productivity

Note: = >: unidirectional relationship, +: positive effect and - : negative effect, PMG: pool mean group, VECM: vector error correction model, FE: fixed effects, FGLS: feasible generalized least square, ARDL: autoregressive distributed lag

The above-discussed studies confirm that climate variables affect agricultural production. Most of the researchers have used temperature and rainfall as a proxy for climate change. Many of the studies are country-specific (Dumrul and Kilicarslan, 2017; Zaied and Zouabi, 2015; Praveen and Sharma, 2019b; Attiaoui and Boufateh, 2019; Onour, 2019; Chandio et al., 2020a; Chandio et al., 2020b Ahsan et al., 2019). It is also found that there is a limited number of studies on the relationship between climate change and cereal production. The use and impact of introducing control variables to capture the unbiased effects of climate change on cereal

crop are missing in the existing literature. Lower-middle-income (LMI) countries are agriculture-based economies. Thus it is crucial to explore the effects of climate change variables on cereal production. In the literature, no study has been undertaken concerning LMI countries. When it comes to methodological aspects, it is found that many studies have not used appropriate econometric methods in estimating the impact of climate change on cereal production. The issues of serial correlation, panel group-wise heteroscedasticity, cross-sectional dependence and heterogeneity have not been taken into consideration in the literature (Mishra and Sahu, 2014; Loum and Fogarassy, 2015; Dumrul and Kilicarslan, 2017; Akram, 2012; Ansari et al., 2019; Praveen and Sharma, 2019b; Guntukula, 2020; Ansari et al., 2020). Only a few studies have considered these issues in their papers (Susanto et al., 2020; Ali et al., 2020). In this empirical work, we have added the other important variables that indirectly affect cereal production. We have used the FGLS model that is free from the issues of serial correlation, panel group-wise heteroscedasticity and cross-sectional dependence. Moreover, the sensitivity of the long-run estimates has been checked with the help of Driscoll-Kraay regression approach

3. Theoretical Framework, Model Specification, And Data

3.1 Theoretical Framework and Model Specification

After reviewing the literature, it is found that temperature, rainfall and CO_2 emissions are considered as significant factors behind the cereal production. Temperature variability has a varying impact on cereal production. There are a different optimum minimum and maximum temperature for different crops. A higher temperature may result in a higher yield for some crops while it can reduce the yield for other crops. From the existing literature, it is evident that rainfall also has mixed effects on various crop yields in different parts of the world. The impact of CO_2 on cereal production is found to be positive in some studies (Ahsan et al., 2019). However, other studies have shown that greenhouse gases like CO_2 increases cereal yield in the short run. But, an environment with a higher concentration of such gases leads to deterioration in soil quality and nutritional value of the food produced there (Ebi and Ziska, 2018). Apart from these, the rural population has also affected cereal production. If the rural population is high, then it is expected that cereal production will be increased and vice-versa. Besides, land under cereal crop is another control variable used in our study. The following empirical Equation 1 describes the impact of climate change on cereal production (Chandio et al., 2020b and Attiaoui and Boufateh, 2019).

$$CP_{it} = f\left(AAT_{it},\ AAR_{it},\ CO_{2_{it}},\ LCP_{it},\ RPOP_{it}\right) \quad (1)$$

Where, CP represents cereal production; *AAT* denotes the average annual temperature; *AAR* shows average annual rainfall; CO_2 symbolizes carbon dioxide emissions; *LCP* means land under cereal production; *RPOP* defines the rural population (% of the total population); subscript *t* shows the time (1971–2016), and the subscript *i* denotes the cross-sections (11 countries). For intuitive and appropriate results, the variables have been converted into natural logarithmic form. Thus, Equation (1) becomes:

$$lnCP_{it} = \beta_0 + \beta_1 lnAAT_{it} + \beta_2 \ln AAR_{it} + \beta_3 lnCO_{2it} + \beta_4 lnLCP_{it} + \beta_5 lnRPOP_{it} + u_{it} \quad (2)$$

where β_0 shows the constant term; the symbols β_1, β_2, β_3, β_4, and β_5 represent the coefficients of explanatory variables; u denotes the error term.

This paper uses panel data of 11 LMI countries from 1971 to 2016 (see Table 3). These countries are selected based on their continuous engagement in the agriculture sector in their economy. On average, during 1990-2016, the agriculture sector in these countries has engaged 49% of the total working population in the selected countries. The selected variables are average annual temperature, average annual rainfall, CO_2 emissions, cultivated land, rural population, and cereal production for empirical analysis. The trends of these climate variables and cereal production in the sample countries are presented in Figure 1–4. The detailed description of the variables is discussed in Table 1.

3.2 Econometric Methods

3.2.1 Cross-Sectional Dependence

The testing of the presence of cross-sectional dependence (CSD) among panels is the first step in the panel data analysis (Kappa, 2020; Ansari et al., 2020a). The CSD among the panels reflects the existence of a common unobserved shock among cross-sectional variables over a time period. Presence of CSD removes the mean values during correlation computation (Khan et al., 2019; Ansari et al., 2020b). In the literature, there are many tests for identifying CSD among the panels. We have used Pesaran (2004), Friedman (1937), and Frees (1995) tests.

3.2.2 Second Generation Unit Root Tests

In any regression analysis, testing of stationarity is a necessary step. If the variables are stationary at level, then simple level analysis can be performed. On the other hand, if the variables are stationary at the first difference, then the level analysis cannot be performed. We have to differentiate the variables for level analysis. We have used the second-generation unit root tests developed by Pesaran (2007), i.e. Cross-section Augmented Dickey-Fuller (CADF) and Cross-section Augmented Im, Pesaran and Shin (CIPS). These tests control CSD among cross-sections.

3.2.3 Serial Correlation and Group-Wise Heteroscedasticity

Serial correlation is a disturbance term correlated with any variable of the model that has not been influenced by the disturbance term associated with other variables in this model (Khan et al., 2019; Attari et al., 2016; Ansari et al., 2020b). On the other hand, the problem of heteroskedasticity in panel data emerges when the variance of the error terms differs across observations (Simpson, 2012). The serial correlation and heteroskedasticity can be resolved by the FGLS model (Khan et al., 2019; Maddala and Lahiri, 2006; Judge et al., 1985).

3.2.4 Feasible Generalized Least Square (FGLS) Model

This paper employs a Feasible Generalized Least Square (FGLS) model proposed by Parks (1967). This model is suitable in two cases: firstly, when we have large data sets and secondly, to overcome the problems associated with the presence of heteroscedasticity, serial correlation, and cross-sectional dependence (Gujarati, 2004; Wooldridge, 2010). A lot of attention has been paid to FGLS in the recent years, many researchers have used this method to analyze the impact of climate change on agricultural output (Susanto et al., 2020; Singh et al., 2019; Ali et al., 2017; Amin et al., 2015). Reed and Ye (2011) suggested two models to deal with the large datasets and issues of the presence of heteroscedasticity, serial correlation, and cross-sectional dependence. These are feasible generalized least square (FGLS) method and panel corrected standard errors (PCSE) method. There is one condition in selecting one method out of FGLS and PCSE. If the time period (*t*) is greater than the number of cross-sections (*i*), FGLS model is a better option; otherwise, PCSE method is preferred. In our study time-period (t=46) is greater than the number of cross-sections (i=11), FGLS is the better option available (Reed, 2011).

The mathematical form of the FGLS model is expressed as:

$$\hat{\beta} = (X'\hat{\Omega}^{-1}X)^{-1} X'\hat{\Omega}^{-1}y$$

$$Var(\hat{\beta}) = (X'\hat{\Omega}^{-1}X)^{-1}$$

Where $\hat{\Omega}$: assumptions of CSD, autocorrelation, and heteroscedasticity. The FGLS model requires that the number of cross-sections (*i*) should be less than or equal to the time period (*t*) (Reed and Ye, 2011). This condition is satisfied in this study.

4. Results And Discussion

The aggregate summary statistics of the variables are reported in Table 2. Cereal production has a higher mean value with 16.50, followed by the land under cereal production, rainfall, rural population, CO_2, and temperature. In terms of variance, highest variance is for CO_2 (1.42%), followed by cereal production (1.42%), land under cereal production (1.28%), average rainfall (0.64%), rural population (0.15%), and temperature (0.08%). The country-wise descriptive statistics of the variables are presented in Table 3.

Before doing regression analysis, it is mandatory to check whether variables are stationary or non-stationary. Suppose the variables are stationary at level. It implies that one can apply level type analysis. Otherwise, data will have to be converted into the level form by differentiating the variables. We have used second-generation unit root tests, i.e. CADF, and CIPS. The results of unit root tests are

reported in Table 4. The variables *CP, AAT, AAR,* CO_2, and *LCP* are found as stationary at level at 1% of significance. Also, the variable *RPOP* is found as stationary at level but on a 5% level of significance. The results of unit root tests indicate that level panel data analysis can be performed as all the variables are found to be stationary at level.

After performing unit root tests, we have applied panel data models for preliminary analysis, i.e. fixed effects (FE) and random effects (RE). However, before this, one should check the multicollinearity problem among the independent variables. If explanatory variables are correlated, then the panel data model estimation will be overfitted; consequently, results will be biased. So, we have reported a correlation matrix in Table 5. Result of correlation matrix indicates that the variables are free from the multicollinearity problem. The results of the panel models are shown in Table 6.

According to the FE model, climate change variables, i.e. *AAT, AAR*, and CO_2, are found to have a significant positive impact on *CP* in LMI countries. At the same time, *RPOP* is found to have a significant negative effect on *CP*. It is also found that *LCP* has a significant positive impact on *CP*. This finding implies that a large land area under cereal production leads to an increase in cereal crops production. Further RE model reports that *AAT* and *RPOP* have a significant adverse effect on CP in sample countries.

Hausman (1978) specification test is applied to choose the between FE and RE models. In Hausman test, the null hypothesis states that the RE model is appropriate against the alternative hypothesis. The null hypothesis is rejected at one percent level of significance, and the test results indicate that the FE model is suitable for the present study (Table 6).

Most of the scholars directly interpreted the FE and RE model results without conducting the diagnostic tests in the literature. However, interpreting the results without diagnostic tests may give erroneous estimates. In our analysis, coefficients of *AAT* differ in FE and RE models (Table 6). The reason for this might be that FE and RE models are suffering from the issues of CSD, serial correlation, and group-wise heteroscedasticity. So, it is necessary to conduct the diagnostic tests to ensure that the model is robust. So, the results of various diagnostic tests are reported in Table 7.

Pesaran (2004), Friedman (1937) and Frees (1995) tests are employed to test the CSD among cross-sections. In all CSD tests, the null hypothesis is rejected at 1% level of significance. It implies that there is a presence of CSD among the panels. Wooldridge (2010) test is applied for serial correlation. The null hypothesis of the absence of first-order serial correlation is rejected at 1% level of significance. It reveals that the fixed effect model is suffering from the serial correlation problem. Lastly, for panel group-wise heteroskedasticity, modified Wald test by Boum (2000) is applied. The null hypothesis of panel group-wise homoskedasticity is rejected at 1% level of significance. The result of the Wald test indicates the presence of group-wise heteroscedasticity in the model. Thus, the diagnostic tests conclude that the FE model has serial correlation, CSD and group-wise heteroscedasticity problems. In order to resolve these problems, the FGLS and Driscoll-Kraay standard model is used.

The FGLS results are presented in Table 8, and the summary of the long-run estimates between the considered variables are reported in Fig. 5. The coefficient of average temperature is statistically significant and negative, with one percent level of significance. In terms of magnitude, the value of the coefficient of average temperature reveals that a one percent increase in *AAT* leads to a fall in total cereal production by 0.70 percent in LMI countries, keeping other variables constant. It implies that when the temperature rises, cereal production will decrease. This finding can be supported for several reasons. First, numerous researchers have found that increasing global warming could affect cereal production around the globe. Over the last few decades, rise in global average temperature by 0.5 to 0.6°C (Hansen et al., 2010) has resulted in increased carbon metabolism, respiration in the plant and a decline in the production of paddy (Zhao and Fitzgerald, 2013). Climate change could lower cereal production by 10 to 15 percent, leading to a rise in market price (Nelson et al., 2009). Moreover, the increased average temperature has adversely impacted the rice cultivation in various parts of Asia such as India, Thailand, Bangladesh, Indonesia, Vietnam, Sri Lanka, and Pakistan, which resulted in reduced average yields by 4 percent (Mathews et al., 1997). There is a cold climate in other parts of the Asian region where the increased global temperature positively affects cereal production, but this would not be enough to compensate for the overall loss. Hence, it is suggested for policymakers that using shorter ripening periods with faster-maturing varieties to balance the agricultural production. This finding is similar to those of Loum and Fogarassy (2015), Dasgupta (2013), Mishra and Sahu (2014), Brown et al. (2010), Akram (2012), Praveen and Sharma (2019b), and Attiaoui and Boufateh, 2019).

The coefficient of climate variable, i.e. rainfall, is found to be positive, with one percent level of significance. This finding reveals that rainfall has a significant positive effect on cereal production. The value of *AAR* shows that the value of *CP* rises by 0.184 percent,

with a one percent increase in *AAR*. This connection indicates that agricultural productivity growth improves as rainfall increases. Rainfall is one of the most significant determinants considered in the agriculture sector. The finding is logical since it indicates that cereal farming strongly depends on rainfall. Hence, during the rainy season, these lower-middle-income countries received the best harvests, leading to an increase in agricultural growth productivity. This further implies that a decline in the precipitation in the long run would impact the cereal yields. This empirical result is in line with those of Attiaoui and Boufateh (2019), Guntukula (2019), Dumrul and Kilicarslan (2017), and Brown et al., 2010).

The coefficient of CO_2 is positive, with one percent level of significance. It implies that CO_2 emission has a positive effect on *CP*. The coefficient of CO_2 reveals that a one percent rise in the carbon emissions leads to a 0.12 percent increase in cereal production. This finding suggests that carbon emission plays a positive role in the growth of cereal crops. Sometimes the adverse effects of climate change can be beneficial for cereal production. This can be understood that carbon dioxide levels are expected to have a positive impact by cutting transpiration rates and increasing their growth rate. This is because the crop plants with increased CO_2 levels may use more water efficiently and effectively, thereby increasing the cereals production in lower-middle-income countries. This finding is consistent with studies in the literature (Loum and Fogarassy, 2015; Onour, 2019; Chandio et al., 2020a; Ahsan et al., 2019; Demirhan, 2020; Baig et al., 2020)

Similarly, the coefficient of the land under cereal production is found as positive, with one percent level of significance. This signifies that *LCP* has a positive effect on *CP* in LMI countries. The value of the coefficient of *LCP* justifies that the value of *LCP* increases by 0.785 percent with every one percent rise in *LCP*. Land under cereal production refers to the harvested area; this reflects that harvested areas increase cereal crop production in these income group countries. India is the second top country in terms of land under cereal production globally after China. According to the World Bank, the *LCP* in India was 99 million hectares that account for 13% of the world's land under cereal production in 2017. The other countries (Indonesia, Nigeria, Pakistan, Bangladesh, and Thailand) accounted for approximately 22% of it. According to the World Bank, the lower-middle-income countries under land cereal production were estimated at 724 million hectares in 2017. This rise in land under cereal crops will enhance the productivity of the agriculture sector in lower-middle-income countries. This finding is in line with the results reported by other researchers in the literature (Dogan, 2018; Ahsan et al., 2019). However, the estimated long-run coefficient of the rural population is (-0.184), and the p-value is (0.220), which shows that the association between the rural population and cereal production is negative and insignificant.

4.1 Robustness Analysis

Considering the similar issues of heterogeneity and the cross-sectional dependence, we have further included the Driscoll and Kraay (1998) panel regression model. This technique is robust in case of panel heterogeneity and cross-sectional dependence and has been used extensively in the literature (Liu et al., 2019; Khan et al., 2020; Ha et al., 2020). This technique is flexible and provides consistent and efficient results in a large sample size with missing values. Similarly, it is useful to overcome autocorrelation and heteroscedasticity in unbalanced and balanced panel data (Baloch et al., 2019; Ahmad et al., 2020; Dogan et al., 2020). Hence, we employed Driscoll-Kraay long-run estimates in Table 9 to examine the robustness of the outcomes given in Table 8. The empirical findings provided in Table 9 indicate that the signs are similar amongst all variables. This implies that the outcome documented in Table 9 highlights that FGLS approach is consistent with the regression results of Driscol-Kraay standard error estimator[1]. Though in terms of magnitude, the coefficients seem to be different among the variables.

4.2 Country-Wise Analysis

Table 10 reports the results of long-run elasticity for cereal production indicator with respect to *AAT, AAR,* CO_2, *LCP,* and *RPOP* variables for LMI countries. FGLS test is used to examine the long-run elasticity of the *CP* model. This country-wise analysis indicates closer outcomes with each other and showed the almost same level of significance. According to the empirical findings, cereal production *(CP)* is reduced by -0.830% due to a 1 percent increase in average temperature *(AAT)* in India. Thus, the positive effect of *AAT* on CP by 1.991% exists in Sri Lanka. The impact of *AAR* on *CP* in Ghana is found to be statistically significant and positive, resulting in a 0.381% increase in CP. Carbon dioxide is also considered a major determinant of cereal production. The estimated coefficient are 0.228%, 0.742%, 0.176%, 0.378, and 0.202% in *CP* model for Bangladesh, India, Indonesia, Philippines, and Sri Lanka, respectively. It implies that CO_2 contribute to *CP* in these countries. On the contrary, CO_2 is adversely associated with CP in the case of Kenya and Pakistan. The country-wise analysis also indicates that a 1% hike in land under cereal production (LCP) stimulates cereal crops production in the countries under lower-middle-income countries. According to the World Bank, the land

under cereals production was estimated at 724 million hectares in 2017. So, a rise in the land under cereals production will enhance the agricultural productivity in lower-middle-income countries. Regarding the impact of the rural population (RPOP) on CP, the empirical findings confirm that there is a decrease of 1.935%, 0.652%, 3.697%, 5.457%, 1.964%, and 2.105% in CP due to 1 percent expansion in *RPOP* for Ghana, Indonesia, Kenya, Myanmar, Nigeria, and the Philippines respectively. However, there is a positive coefficient value of 4.433% of RPOP for India.

[1] Except for AAT with an impact of 0.65 (negative) but statistically insignificant, and RPOP which is negative and statistically significant.

5. Conclusion And Policy Implication

This paper sets out to explore the effects of climate change variables on cereal production in 11 lower-middle-income countries of the world during 1971–2016. This study has resolved serial correlation problems, panel group-wise heteroscedasticity, cross-sectional dependence and heterogeneity by adopting the FGLS and Driscoll Kraay standard error technique. The average annual temperature and the average annual rainfall and CO_2 emissions have been used to measure climate change. FGLS panel model is used to examine the effects of climate change on cereal production.

The findings of the study reveal that climate change variables significantly affect the cereal crop production in the sample countries. Cereal crops are negatively affected by the rise in temperature. In contrast, rainfall and CO_2 emissions have a positive impact on the production of cereal crops. Besides this, it is found that cultivated land plays a vital role in the rise of cereal crops. A surge in land under cereal crops raise the production of cereal crops. Moreover, the results of the country-wise analysis are similar to LMI countries, but a few countries explored the different outcomes due to different strategies, development level, policy formulation, ability to work, population size, and some other aspects that were not taken in the estimation process.

The study results would help the policymakers focus on mitigating the ill effects of temperature and chalk out the strategies to enhance the adaptive capacity of the farmers to increase cereal production in the low-income countries where a large number of people consume the cereal crops. It is a staple food for millions of the household. The respective governments of 11 countries should implement policies and programmes to raise cereals production to ensure food security for many poor people in the light of climate variability. When we concern the policy implication at the country level, we recommend the government of these countries to enhance the cereal yields. As carbon emissions are one of the major challenges globally, every nation is trying their best to lower greenhouse gas emissions to expand economic growth and the agricultural sector. This causes bad influence on the environment and the adverse effect on climate change. In this respect, the government of these countries should design well-targeted policies on agriculture sector to reduce the harmful effects of climate on the cereal yield. Moreover, the country-wise analysis also reveals that rural population have negative influence of cereal production. It may be because when more labour force is working on the same land, the agricultural productivity decreases as land cannot produce beyond its capacity (Zakaria et al., 2019). Hence the government should focuses on some agriculture related awareness programmes to check this negative influence on cereal production.

Declarations

Ethics approval and conset to participate: Not applicable

Conset for publication: Not applicable

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Tables

Table 1. Description of Variables

Variable	Symbol	Unit	Source
Cereal Production	CP	metric tons	World Development Indicators (WDI)
CO_2 emissions	CO_2	kt	World Development Indicators (WDI)
Rainfall	AAR	millimeter (mm)	Climate Change Knowledge Portal of World Bank
Temperature	AAT	Degree celsius	Climate Change Knowledge Portal of World Bank
Land under cereal production	LCP	hectares	World Development Indicators (WDI)
Rural Population	RPOP	% of total population	World Development Indicators (WDI)

Table 2. Descriptive Statistics

Variables	Observations	Mean	Std. Dev.	Minimum	Maximum
lnCP	506	16.500	1.427	12.976	19.512
lnAAT	506	3.218	0.085	2.962	3.341
lnAAR	506	4.718	0.640	2.772	5.698
lnCO2	506	3.463	1.633	0.829	7.771
lnLCP	506	15.731	1.283	13.377	18.485
lnRPOP	506	4.257	0.152	3.812	4.523

Table 3. Country Wise Descriptive Statistics

Variables	Statistics	Bangladesh	Ghana	India	Indonesia	Kenya	Myanmar	Nigeria	Pakistan	Philippines	Sri Lanka	Vietnam
lnCP	Mean	17.221	14.104	19.080	17.739	14.925	16.680	16.570	16.963	16.503	14.747	16.973
	Std. dev.	0.388	0.536	0.305	0.425	0.220	0.437	0.506	0.381	0.376	0.331	0.548
	Minimum	16.529	12.976	18.486	16.890	14.369	15.829	15.575	16.244	15.681	14.007	16.140
	Maximum	17.831	14.883	19.512	18.450	15.366	17.343	17.286	17.566	17.102	15.392	17.735
lnAAT	Mean	3.228	3.313	3.194	3.261	3.213	3.139	3.298	3.008	3.249	3.298	3.194
	Std. dev.	0.015	0.015	0.014	0.011	0.017	0.014	0.015	0.025	0.011	0.012	0.017
	Minimum	3.198	3.277	3.160	3.237	3.177	3.105	3.266	2.962	3.219	3.267	3.156
	Maximum	3.267	3.341	3.228	3.287	3.249	3.172	3.327	3.064	3.276	3.322	3.232
lnAAR	Mean	5.273	4.556	4.464	5.472	3.995	5.094	4.534	3.247	5.316	4.923	5.023
	Std. dev.	0.133	0.099	0.091	0.108	0.177	0.105	0.087	0.198	0.132	0.135	0.102
	Minimum	4.966	4.232	4.230	5.194	3.590	4.846	4.278	2.772	5.061	4.601	4.845
	Maximum	5.554	4.737	4.614	5.698	4.385	5.332	4.721	3.563	5.604	5.173	5.186
$lnCO_2$	Mean	2.865	1.621	6.546	5.206	1.937	2.009	4.177	4.239	3.945	1.866	3.687
	Std. dev.	0.903	0.591	0.744	0.751	0.428	0.470	0.419	0.742	0.433	0.630	0.841
	Minimum	1.254	0.829	5.325	3.662	1.303	1.408	3.474	2.939	3.274	1.029	2.632
	Maximum	4.331	2.786	7.771	6.329	2.842	3.217	4.869	5.281	4.782	3.137	5.212
lnLCP	Mean	16.220	13.965	18.430	16.449	14.489	15.655	16.389	16.280	15.719	13.678	15.769
	Std. dev.	0.060	0.253	0.024	0.167	0.172	0.215	0.405	0.115	0.063	0.144	0.190
	Minimum	16.070	13.377	18.364	16.124	14.074	15.395	15.397	16.034	15.525	13.434	15.410
	Maximum	16.314	14.312	18.485	16.791	14.850	16.013	16.857	16.461	15.810	14.048	16.021
lnRPOP	Mean	4.363	4.086	4.297	4.158	4.400	4.302	4.214	4.230	4.039	4.402	4.335
	Std. dev.	0.097	0.143	0.050	0.189	0.050	0.028	0.138	0.047	0.076	0.003	0.067
	Minimum	4.173	3.812	4.202	3.829	4.303	4.247	3.938	4.155	3.971	4.398	4.182
	Maximum	4.523	4.260	4.382	4.415	4.491	4.341	4.405	4.316	4.197	4.410	4.402

Table 4. Unit Root Test Results

Variables	CADF Test		CIPS Test	
	Statistics	Order of Integration	Statistics	Order of Integration
lnCP	-3.3***	I(0)	-3.3***	I(0)
lnAAT	-4.874***	I(0)	-4.874***	I(0)
lnAAR	-6.203***	I(0)	-6.203***	I(0)
$lnCO_2$	-3.038***	I(0)	-3.038***	I(0)
lnLCP	-3.352***	I(0)	-3.352***	I(0)
lnRPOP	-2.304**	I(0)	-2.304***	I(0)

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 5. Correlation Matrix

Variables	lnAAT	lnAAR	$lnCO_2$	lnLCP	lnRPOP
lnAAT	1				
lnAAR	0.540	1			
$lnCO_2$	-0.141	-0.012	1		
lnLCP	-0.332	-0.003	0.846	1	
lnRPOP	-0.200	-0.116	-0.355	-0.121	1

Table 6. Panel Regression Results (*Dependent Variable is Cereal Production*)

Variables	Fixed Effect		Random Effect	
	Coefficient	P-Value	Coefficient	P-Value
lnAAT	0.938*	0.070	-0.829**	0.021
	(0.518)		(0.359)	
lnAAR	0.084*	0.090	0.271***	0.000
	(0.050)		(0.042)	
lnCO2	0.312***	0.000	0.306***	0.000
	(0.016)		(0.017)	
lnLCP	0.998***	0.000	0.766***	0.000
	(0.045)		(0.029)	
lnRPOP	-0.422***	0.000	-0.671***	0.000
	(0.112)		(0.109)	
Constant	-1.897	0.307	7.631***	0.000
	(1.856)		(1.473)	
Observations	506		506	
Number of ID	11		11	
Hausman Test		Statistics	P-Value	
		-1699.40***	0.005	

Note: Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7. Diagnostic Tests

Test	Problem	Test	Statistic	P-value	Results
Modified Wald test	Groupwise heteroscedasticity	Chi^2	1597.190***	0.000	Presence of inter-provincial homoscedasticity
Wooldridge test	Autocorrelation	F	17.967***	0.002	Presence of autocorrelation
Pesaran test	CSD	–	4.267***	0.000	Presence of group sectional dependence in Pesaran, Friedman and Frees tests
Friedman test	CSD	–	79.713***	0.000	
Frees test	CSD	–	1.347***	0.000	

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 8. Feasible Generalised Least Square (FGLS) Model Results (*Dependent Variable is Cereal Production)*

Variable	Coefficient	Standard Error	P-value
lnAAT	-0.702***	0.223	0.002
lnAAR	0.184***	0.022	0.000
$lnCO_2$	0.204***	0.023	0.000
lnLCP	0.785***	0.028	0.000
lnRPOP	-0.184	0.150	0.220
Constant	5.657***	1.036	0.000

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 9. Driscoll-Kraay Standard Model Results *(Dependent Variable is Cereal Production)*

Variable	Coefficient	Drisc/Kraay Standard Error	P-value
lnAAT	-0.938	0.650	0.156
lnAAR	0.084*	0.043	0.055
$lnCO_2$	0.312***	0.018	0.000
lnLCP	0.998***	0.090	0.000
lnRPOP	-0.422***	0.106	0.000
Constant	-1.897	2.763	0.496

Note: *** p<0.01, ** p<0.05, * p<0.

Table 10. Country Wise Results

Countries	lnAAT		lnAAR		$lnCO_2$		lnLCP		lnRPOP		Constant	
	Coef.	P-value	Coef.	P-value	Coef.	P-value	Coef.	P-value	Coef.	P-value	Coef.	P-value
Bangladesh	-0.581	0.239	0.025	0.503	0.228***	0.007	1.159***	0.000	-1.196	0.121	4.733	0.396
	0.493		0.037		0.085		0.257		0.771		5.575	
Ghana	-1.161	0.410	0.381**	0.011	-0.053	0.722	1.163***	0.000	-1.935***	0.007	7.966	0.209
	1.408		0.151		0.150		0.146		0.719		6.346	
India	-0.830*	0.075	0.078	0.153	0.742***	0.000	1.989***	0.000	4.433***	0.000	-39.183***	0.000
	0.467		0.055		0.064		0.271		0.949		7.694	
Indonesia	-0.183	0.805	-0.082	0.206	0.176***	0.000	1.008***	0.000	-0.652***	0.003	3.998	0.273
	0.741		0.065		0.049		0.187		0.221		3.644	
Kenya	-0.981	0.573	0.125	0.143	-0.333***	0.001	0.936***	0.000	-3.697***	0.000	20.929**	0.015
	1.740		0.085		0.099		0.151		0.953		8.566	
Myanmar	0.304	0.680	-0.041	0.529	-0.011	0.876	1.282***	0.000	-5.457***	0.004	19.344*	0.087
	0.736		0.065		0.070		0.194		1.905		11.302	
Nigeria	-1.265	0.378	0.190	0.219	-0.002	0.979	0.624***	0.000	-1.964***	0.000	17.933***	0.004
	1.436		0.155		0.080		0.096		0.401		6.163	
Pakistan	-0.136	0.665	-0.003	0.937	-0.300***	0.000	0.973***	0.000	-10.379***	0.000	46.713***	0.000
	0.314		0.032		0.085		0.232		1.296		7.376	
Philippines	-1.101	0.235	0.070	0.215	0.378***	0.000	1.161***	0.000	-2.105***	0.000	8.476	0.124
	0.928		0.056		0.070		0.163		0.445		5.504	
Sri Lanka	1.991*	0.083	-0.013	0.794	0.202***	0.000	1.067***	0.000	-23.253***	0.005	95.634**	0.012
	1.150		0.050		0.044		0.076		8.336		37.929	
Vietnam	-0.371	0.452	-0.045	0.444	0.091	0.154	1.885***	0.000	-1.447	0.144	-5.411	0.452
	0.493		0.059		0.064		0.208		0.990		7.193	

Note: *** p<0.01, ** p<0.05, * p<0

Figures

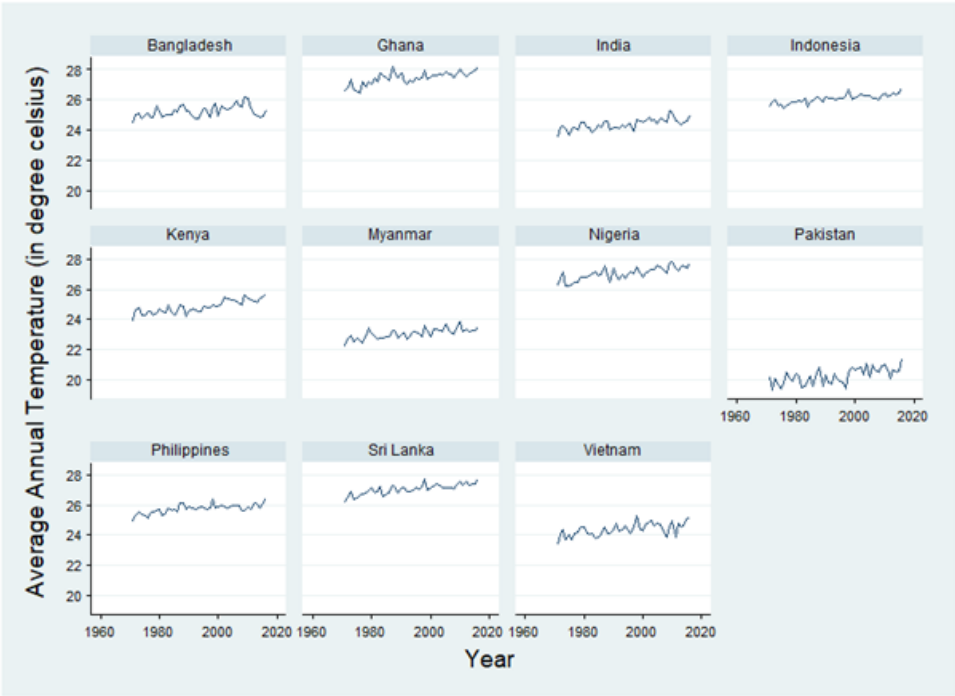

Figure 1

Trends in Average Annual Temperature in LMI Countries (1971–2016)

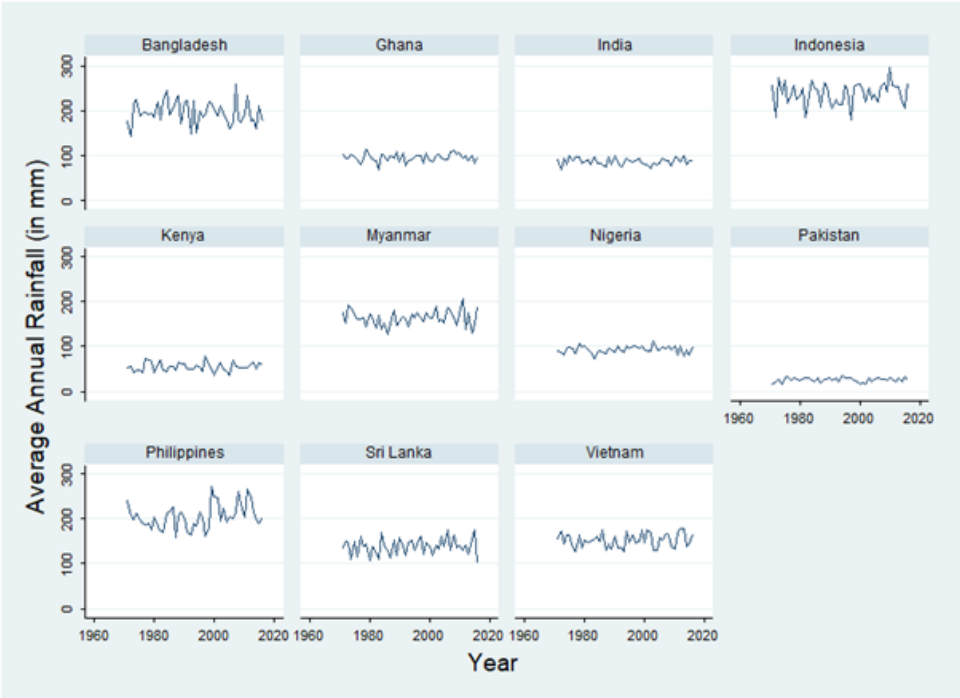

Figure 2

Trends in Average Annual Rainfall in LMI Countries (1971–2016)

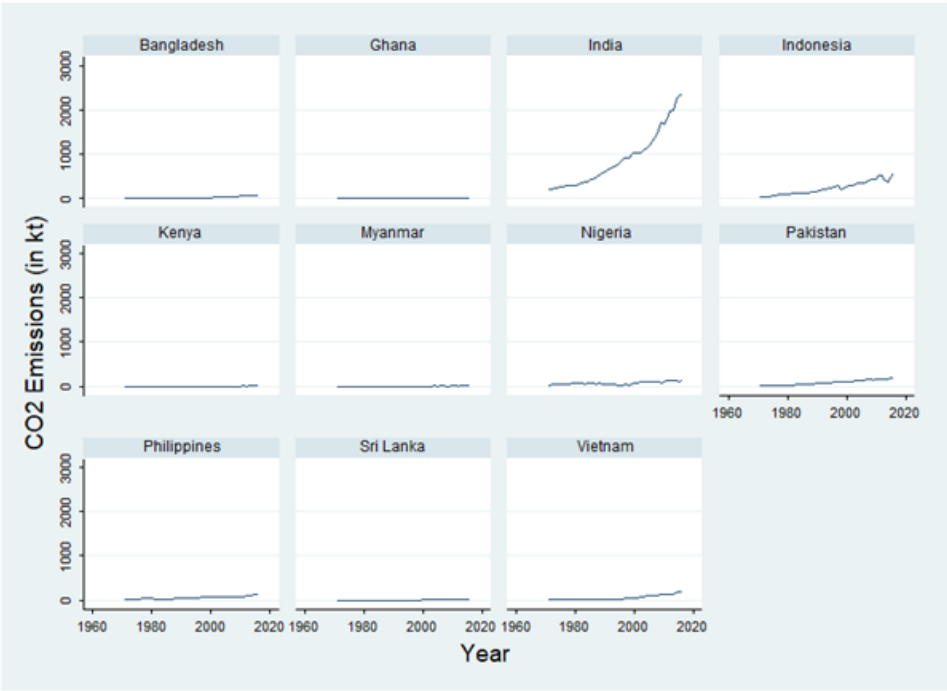

Figure 3

Trends in CO2 Emissions in LMI Countries (1971–2016)

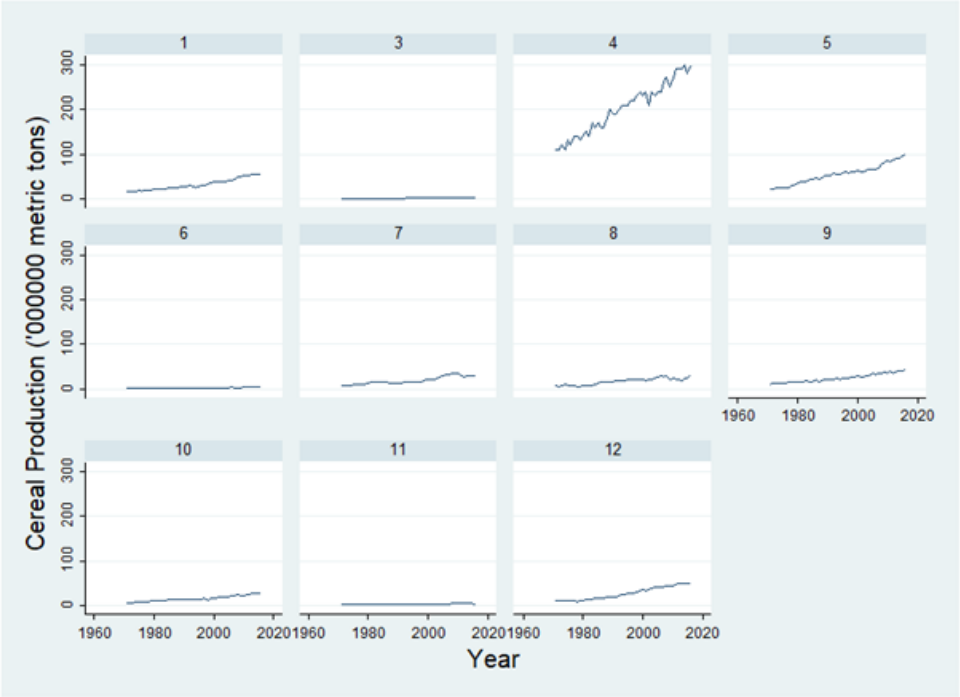

Figure 4

Trends in Cereal Production in LMI Countries (1971–2016)

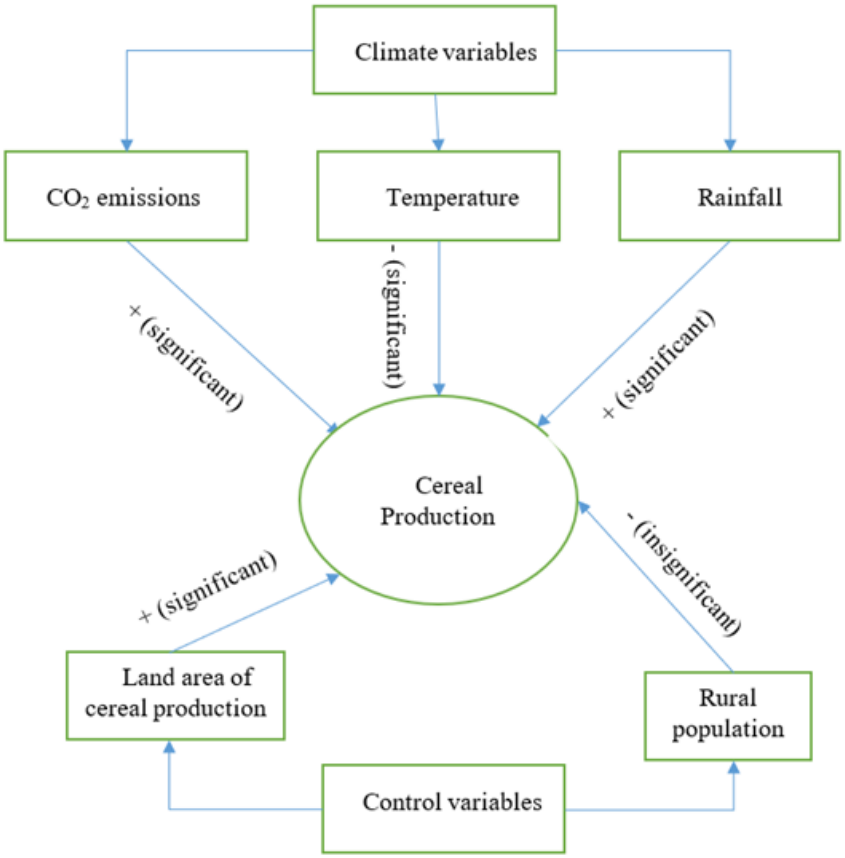

Figure 5

Summary of Findings