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

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Research Article

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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 CO2 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 CO2, 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 CO2 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 (Hattfield 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 CO2 will be higher on C3 species which include wheat, rice, and soybeans as compared to C4 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 CO₂ => + 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 |
### Results of Econometric Models

| S. No. | Author(s)           | Time          | Country(ies)/State(s)  | Econometric model(s) | Results                                                                 |
|--------|---------------------|---------------|------------------------|----------------------|-------------------------------------------------------------------------|
| 10     | Rahim and Puay      | 1983-2013     | Malaysia               | VECM                 | one-way causality from temperature, rainfall and agriculture land to GDP |
| 11     | Zaied and Zouabi    | 1980-2012     | Tunisia                | Panel Cointegration  | Temperature => - Olive Production                                      |
| 12     | Praveen and Sharma  | 1967-2016     | India                  | Multiple Regression  | Temperature, Rainfall => - Agriculture Production                      |
| 13     | Guntukula           | 1961-2017     | India                  | Multiple Regression  | Rainfall => + Non-food Crop Production Rainfall => - Food Crop Production|
| 14     | Attiaoui and Boufateh| 1975-2014    | Tunisia                | PMG                  | Rainfall => + Cereals Production Temperature => - Cereals Production    |
| 15     | Singh et al.        | 1966-2011     | India                  | FGLS                 | Climate change => - Agriculture Production                             |
| 16     | Ali et al.          | 1989-2015     | Pakistan               | FGLS                 | Rainfall => - Crop yield except Wheat Temperature => - Crop yield       |
| 17     | Ali et al.          | 2004-2018     | USA                    | FGLS                 | Human Needs positively correlated with extreme weather                  |
| 18     | Susanto et al.      | 2008-2018     | Indonesia              | FGLS                 | Temperature, Relative Humidity => - No. of International Tourists       |

| S. No. | Author(s)           | Time          | Country(ies)/State(s)  | Econometric model(s) | Results                                                                 |
|--------|---------------------|---------------|------------------------|----------------------|-------------------------------------------------------------------------|
| 19     | Amin et al.         | 1972-2010     | Bangladesh             | FGLS                 | Rainfall => - Rice Production Max. Temperature => - Crop Yield and Cropping Area |
| 20     | Onour               | 1961-2016     | Sudan                  | ARDL                 | CO₂ => + Cereals Production                                             |
| 21     | Chandio et al.      | 1982-2014     | China                  | ARDL                 | CO₂ => + Cereals Production Climate Change => - Cereals Production      |
| 22     | Ahsan et al.        | 1971-2014     | Pakistan               | ARDL                 | CO₂, Cultivated land => + Cereals Production                            |
| 23     | Demirhan            | 1960-2017     | World                  | -                    | Temperature => - Wheat Production CO₂=> + Wheat Production             |
| 24     | Dogan               | 1993-2016     | Turkey and Some Eurasian Countries | ARDL | Agricultural Land => - CO₂ Level                                      |
| 25     | Chandio et al.      | 1968-2014     | Turkey                 | ARDL                 | Varying effects of CO₂ and temperature on cereal yield in the short and long run |
| 26     | Janjua et al.       | 1960-2009     | Pakistan               | ARDL                 | Global climate change does not affect wheat production in Pakistan     |
| 27     | Zhai et al.         | 1970-2014     | China                  | ARDL                 | Rainfall => - Wheat Yield, Temperature has no effect on Wheat Yield     |
| 28     | Baig et al.         | 1990-2017     | India                  | ARDL                 | CO₂ => + 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 Kiliçarslan, 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 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).

$$CP_{it} = f(AAT_{it}, AAR_{it}, CO_2_{it}, LCP_{it}, RPOP_{it})$$ (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:

$$\ln CP_{it} = \beta_0 + \beta_1 \ln AAT_{it} + \beta_2 \ln AAR_{it} + \beta_3 \ln CO_2_{it} + \beta_4 \ln LCP_{it} + \beta_5 \ln RPOP_{it} + u_{it}$$ (2)

where $\beta_0$ shows the constant term; the symbols $\beta_1$, $\beta_2$, $\beta_3$, $\beta_4$, and $\beta_5$ 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:

$$\hat{\beta} = (x'\tilde{\nu}^{-1}x)^{-1}x'\tilde{\nu}^{-1}y$$

$$\text{var}(\hat{\beta}) = (x'\tilde{\nu}^{-1}x)^{-1}$$

Where $\tilde{\nu}$: assumptions of CSD, autocorrelation, and heteroskedasticity. 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
rainfall has a significant positive effect on cereal production. The value of climate variable, i.e. rainfall, is found to be positive, with one percent level of significance. This finding reveals 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), and Akram (2012), Praveen and Sharma (2019b), and Attiaoui and Boufateh, 2019).

According to the FE model, climate change variables, i.e. AAT, AAR, and CO₂, 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 CR 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 is 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

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Consent for publication: Not applicable

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**Tables**

**Table 1.** Description of Variables

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| Variable                          | Symbol | Unit            | Source                                                                 |
|----------------------------------|--------|-----------------|------------------------------------------------------------------------|
| Cereal Production                | CP     | metric tons     | World Development Indicators (WDI)                                    |
| CO₂ emissions                    | CO₂    | 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          | 4.718  | 0.640 | 2.772  | 5.698  |
| lnAAR     | 506          | 3.463  | 1.633 | 0.829  | 7.771  |
| lnCO₂     | 506          | 3.829  | 0.215 | 4.721  | 0.132  |
| lnLCP     | 506          | 9.317  | 0.132 | 7.771  | 0.087  |
| lnRPOP    | 506          | 3.971  | 0.024 | 0.063  | 0.024  |

### Table 3. Country Wise Descriptive Statistics

| Variables | Bangladesh | Ghana | India | Indonesia | Kenya | Myanmar | Nigeria | Pakistan | Philippines | Sri Lanka | Vietnam |
|-----------|------------|-------|-------|-----------|-------|---------|---------|----------|-------------|-----------|---------|
| lnCP      | 17.221     | 14.104| 19.080| 17.739    | 14.925| 16.680  | 16.570  | 16.963   | 16.503      | 14.747    | 16.973  |
|           | 0.388      | 0.536 | 0.305 | 0.425     | 0.220 | 0.437   | 0.506   | 0.381    | 0.376       | 0.331      | 0.548   |
| lnAAT     | 16.529     | 12.976| 18.486| 16.890    | 14.369| 15.829  | 15.575  | 16.244   | 15.681      | 14.007    | 16.140  |
|           | 17.831     | 14.883| 19.512| 18.450    | 15.366| 17.343  | 17.286  | 17.566   | 17.102      | 15.392    | 17.735  |
| lnAAR     | 3.228      | 3.313 | 3.194 | 3.261     | 3.213 | 3.139   | 3.298   | 3.008    | 3.249       | 3.298     | 3.194   |
|           | 0.015      | 0.015 | 0.014 | 0.011     | 0.017 | 0.014   | 0.015   | 0.025    | 0.011       | 0.012     | 0.017   |
| lnCO₂     | 5.198      | 4.556 | 4.464 | 5.472     | 3.995 | 5.094   | 4.534   | 3.247    | 5.316       | 4.923     | 5.023   |
|           | 0.133      | 0.099 | 0.091 | 0.108     | 0.177 | 0.105   | 0.087   | 0.198    | 0.132       | 0.135     | 0.102   |
| lnLCP     | 5.554      | 4.737 | 4.614 | 5.698     | 4.385 | 5.332   | 4.721   | 3.563    | 5.604       | 5.713     | 5.186   |
|           | 2.865      | 1.621 | 6.546 | 5.206     | 1.937 | 2.009   | 4.177   | 4.239    | 3.954       | 1.866     | 3.687   |
| lnRPOP    | 2.295      | 0.903 | 0.591 | 0.751     | 0.428 | 0.470   | 0.419   | 0.742    | 0.433       | 0.630     | 0.841   |
|           | 1.254      | 0.829 | 5.325 | 3.662     | 1.303 | 1.408   | 3.474   | 2.939    | 3.274       | 1.029     | 2.632   |
|           | 4.331      | 2.786 | 7.711 | 6.329     | 2.842 | 3.217   | 4.869   | 5.281    | 4.782       | 3.137     | 5.212   |
| lnCO₂     | 16.220     | 13.965| 18.430| 16.449    | 14.489| 15.655  | 16.389  | 16.280   | 15.719      | 13.678    | 15.769  |
|           | 0.060      | 0.253 | 0.024 | 0.167     | 0.172 | 0.215   | 0.405   | 0.115    | 0.063       | 0.144     | 0.190   |
| lnLCP     | 16.070     | 13.377| 18.364| 16.124    | 14.074| 15.395  | 15.397  | 16.034   | 15.525      | 13.434    | 15.410  |
| lnRPOP    | 16.314     | 14.312| 18.485| 16.791    | 14.850| 16.013  | 16.857  | 16.461   | 15.810      | 14.048    | 16.021  |

### Table 4. Unit Root Test Results
Note: *** p<0.01, ** p<0.05, * p<0.1

Table 5. Correlation Matrix

| Variables | lnAAT | lnAAR | lnCO₂ | lnLCP | lnRPOP |
|-----------|-------|-------|-------|-------|--------|
| lnAAT     | 1     | 0.540 | -0.141| -0.332| -0.200 |
| lnAAR     | 0.540 | 1     | -0.012| 0.846 | 0.116  |
| lnCO₂     | -0.141| -0.012| 1     | 0.000 | -0.355 |
| lnLCP     | -0.332| 0.846 | -0.355| 1     | 0.000  |
| lnRPOP    | -0.200| 0.116 | -0.355| 0.000 | 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 |       | -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            | Chi²   | 1597.190*** | 0.000   | Presence of inter-provincial homoscedasticity |
| Wooldridge test         | heteroscedasticity   |        |           |         |                                              |
|                         | Autocorrelation      |        |           |         |                                              |
| Pesaran test            | CSD                  | F      | 17.967***  | 0.002   | Presence of autocorrelation                 |
| Friedman test           | CSD                  | -      | 4.267***   | 0.000   | Presence of group sectional dependence in Pesaran, Friedman and Frees tests |
| Frees test              | CSD                  | -      | 79.713***  | 0.000   |                                              |
|                         |                      |        | 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   |
| lnCO²    | 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   |
| lnCO²    | 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 Coef. | P-value | lnAAR Coef. | P-value | lnCO² Coef. | P-value | lnLCP Coef. | P-value | lnRPOP Coef. | P-value | Constant Coef. | P-value |
|-----------|-------------|---------|-------------|---------|-------------|---------|-------------|---------|--------------|---------|----------------|---------|
| Bangladesh| -0.581      | 0.239   | 0.025       | 0.503   | 0.225***    | 0.007  | 1.159***    | 0.000  | -1.196       | 0.121  | 4.733          | 0.396   |
| 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   |
| 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   |
| 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   |
| 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   |
| Myanmar   | 0.304       | 0.680   | -0.041      | 0.529   | 0.099       | 0.143  | 0.788***    | 0.000  | 5.164*       | 0.004  | 19.343*        | 0.009   |
| 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   |
| 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   |
| Philippines| 0.314      | 0.032   | 0.085       | 0.232   | 0.232       | 0.126  | 1.964***    | 0.000  | 7.376        |        | 3.644          |        |
| Sri Lanka | -1.101      | 0.235   | 0.070       | 0.215   | 0.370***    | 0.000  | 1.161***    | 0.000  | -2.105***    | 0.000  | 8.476          | 0.124   |
| 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   |

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