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RESEARCH ARTICLE

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 1971–2016. The study uses average annual temperature and rainfall to measure climate change. Besides this, CO_2 emissions, cultivated land under cereal production, and rural population are 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) and fully modified ordinary least square (FMOLS) models are used to achieve the objective. Pedroni cointegration test confirms the presence of cointegration between cereal production and climate change variables. The findings show that a rise in the temperature reduces cereal production in lower-middle-income countries. In contrast, rainfall and CO_2 emissions have a positive effect on cereal production. For robustness purpose, the Driscoll-Kraay standard regression and dynamic ordinary least square (DOLS) models have also found similar results. Dumitrescu-Hurlin test has found the bidirectional causality of cereal production with temperature and CO_2 emissions. Also, unidirectional causality is running from rainfall and rural population to cereal production. The adverse effects of temperature on cereal production are likely to pose severe implications for food security. The paper recommends that governments of the sample countries should research and develop heat-resistant varieties of cereal crops to cope with the adverse effects of temperature on cereal production and ensure food security.

Keywords Cereal production · Climate change · Cross-sectional dependence · Heterogeneity · FGLS · Lower-middle-income countries · Driscoll-Kraay

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Introduction

Agriculture is one of the most sensitive and highly vulnerable sectors to climate change (Aryal et al. 2019). It is vital for any nation's economic development, especially in developing countries like India, where agriculture contributes to employment and food security. Climate change affects productivity and production patterns in the agriculture sector (Arora 2019). The variability in weather and climate is a critical factor that influences agricultural productivity and the cropping pattern. This variability in weather becomes a severe problem for sustainability in countries where the agriculture sector plays a vital role in sustaining livelihood and food security (Kogo et al. 2020). The change of climate affects the livelihoods of the people, who occupy around 40% of land and consume 70% of water resources globally (Masters et al. 2010; Alam 2017).

Moreover, climate variability has severe implications on agriculture in terms of the increased crop damages, low productivity and high production/operational costs. It leads to a decrease in farmers' income resulting in poverty and inequality that would reduce their active involvement in agriculture (Chuang 2019). 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; Agovino et al. 2019). 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; Kaye and Quemada 2017).

Tropical and sub-tropical regions are more vulnerable to higher temperature leading to the damage of crops and more water requirement. It causes floods and famines, resulting in socio-economic backwardness in a country (Ali et al. 2017) and affects the maturity period of a crop (Hatfield and Prueger 2015). Further, soil fertility can degrade due to erosion, pesticides, change in cropping pattern, harvest period, and water availability (Bhardwaj et al. 2018). Climatic variability and extreme events such as floods, droughts, and windstorms affect crop and livestock productivity (Quandt and Kimathi 2017).

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 climate change events lead to harming trees, crops, livestock, water-borne transport, and ports, which severely affects agricultural productivity. According to the World Economic Forum (2015), 9 out of 10 countries affected by climate change were from the lower-middle-income (LMI) category between 1995 and 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 countries, the share of the agriculture sector to Gross Domestic Product (GDP) is 14.9% compared 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, many studies have used a time-series approach to study the impact of climate change on agricultural crop production (Zaied and Zouabi 2015; Rahim and Puay 2017; Dumrul and Kilicarslan 2017; Onour 2019; Warsame et al. 2021). Some researchers have used the panel data approach to analyze the effect of climate change variables on agriculture (Sarker et al. 2014; Loum and Fogarassy 2015; Amin et al. 2015; Ali et al. 2017; Susanto et al. 2020). These panel studies have taken districts or states as panels for the analysis. However, no study has taken multiple countries as panel for the analysis. The paper contributes to focusing on the impact of climate change on cereal production firstly on a panel of 11 LMI countries. We have adopted the feasible generalized least square (FGLS), fully modified ordinary least square (FMOLS), dynamic ordinary least square (DOLS) and Driscoll-Kraay standard regression model, which resolves endogeneity, serial correlation, panel groupwise heteroskedasticity, cross-sectional dependence, and heterogeneity issues during 1971–2016. The selected 11 LMI countries are based on their population engagement in the agriculture sector. The growth of cereal production in the selected countries is presented in Fig. 1. An increasing trend in cereal production can be observed from the figure. As per our knowledge, this is the first study to analyze the effects of climate change on cereal production in a panel of 11 lower-middle-countries of the world in an econometrics framework. Cereal crop production is more vulnerable to climate change in lower-middle-income countries (Praveen and Sharma 2019a). Other significant control variables are used, i.e., CO_2 emissions, land under cereal production, rural population, which indirectly affect cereal crops production. The remaining part of the paper proceeds as follows. A review of literature related to the impact of climate change on agriculture is presented in the "Review of literature" section. The "Theoretical framework, model specification, and data" section explains the theoretical framework, model specification and data, and econometric methods. Empirical results are presented and discussed in the "Econometric methods" section. Finally, the "Results and discussion" section presents the conclusion and policy implications of the study.

Review of literature

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

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 (Zaied and Zouabi 2015; Dumrul and Kilicarslan 2017; Praveen and Sharma

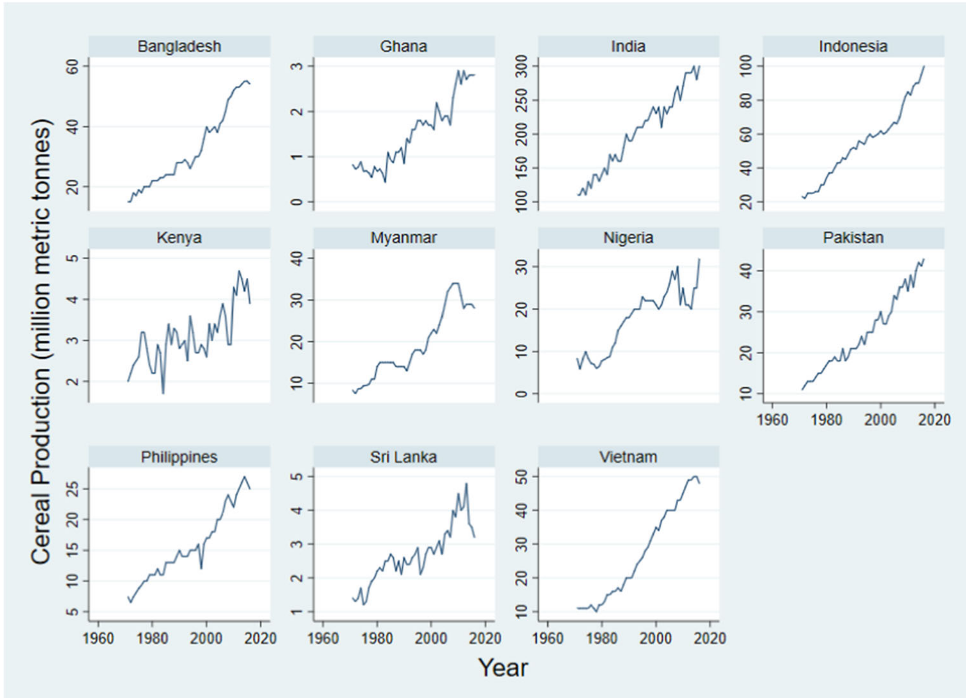

Fig. 1 Trends in cereal production in LMI countries (1971–2016)

2019b; Attiaoui and Boufateh 2019; Onour 2019; Ahsan et al. 2020; Chandio et al. 2020a; Chandio et al. 2020b). It is also found that there are 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. 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 groupwise heteroscedasticity, cross-sectional dependence and heterogeneity have not been taken into consideration in the literature (Akram 2012; Mishra and Sahu 2014; Loum and Fogarassy 2015; Dumrul and Kilicarslan 2017; Praveen and Sharma 2019b; Guntukula 2020). Only a few studies have considered these issues in their papers (Susanto et al. 2020; Ali et al. 2020).

Theoretical framework, model specification, and data

Theoretical framework and model specification

After reviewing the literature, it is found that temperature, rainfall, and CO_2 emissions are considered significant factors behind cereal production. Temperature variability has a varying impact on cereal production. There are different optimum minimum and maximum temperatures 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. 2020). 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 nutrition 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.

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

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 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:

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

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 (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 Figs. 1, 2, 3, and 4. The detailed description of the variables is discussed in Table 1.

Econometric methods

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). The CSD among the panels reflects the existence of a common unobserved shock among cross-sectional variables over a time period. The presence of CSD removes the mean values during correlation computation (Khan et al. 2019a, b). In the literature, there are many tests for identifying CSD among the panels. We have used Friedman (1937), Frees (1995), and Pesaran (2004) tests.

Second-generation unit root tests and cointegration test

In any regression analysis, testing the 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. Pedroni (2004) cointegration test is used to examine the long-run relationship between cereal production and selected variables. Pedroni proposed seven test statistics that confirm the long-run relationship between the variables. These seven test statistics are divided into panel cointegration tests and group mean panel cointegration tests. There are four test statistics in the first category: panel PP-statistic, panel v-statistic, panel rho-statistic, and panel ADF-statistic. On the other hand, the second category contains only three test statistics: ADF-statistic, Rho-statistic, and PP-statistic. These tests assume heterogeneity across the sample.

Serial correlation and groupwise 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 (Attari et al. 2016; Khan et al. 2019a, b). 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 (Maddala and Lahiri 2006; Khan et al. 2019a, b).

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 of heteroscedasticity, serial correlation, and cross-sectional dependence (Gujarati and Porter 2004; Wooldridge 2010). A lot of attention has been paid to

Table 1 Description of variables

Variable	Symbol	Unit	Source
Cereal production	CP	Metric tonnes	World Development Indicators (WDI)
CO_2 emissions	CO_2	Kilo tonnes	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	Percentage of total population	World Development Indicators (WDI)

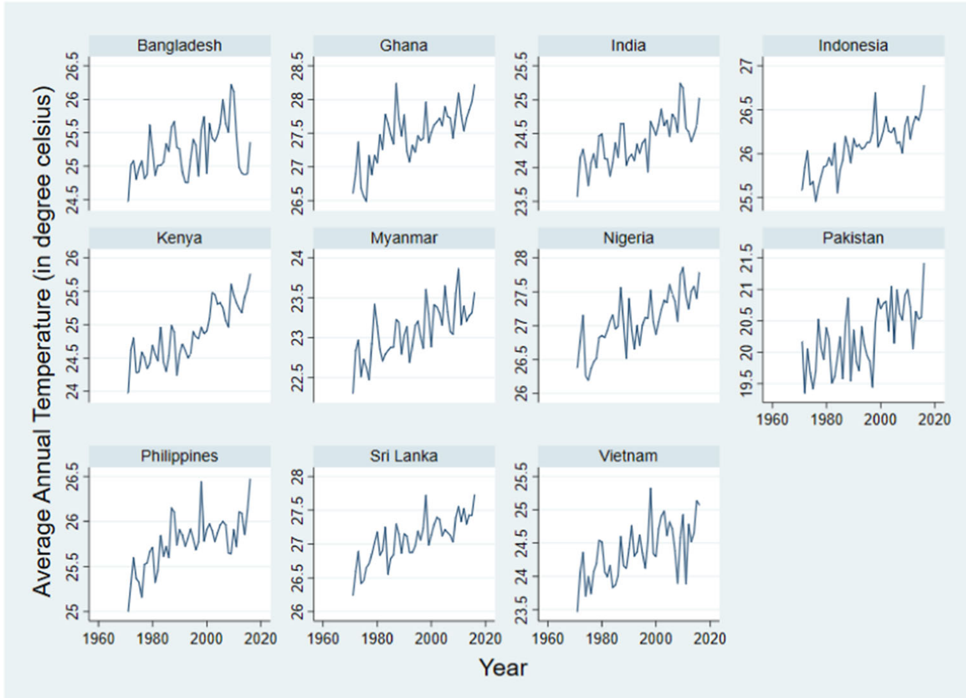

Fig. 2 Trends in average annual temperature in LMI countries (1971–2016)

FGLS in recent years; many researchers have used this method to analyze the impact of climate change on agricultural output (Amin et al. 2015; Ali et al. 2017; Singh et al. 2019; Susanto et al. 2020). Reed and Ye (2011) suggested two models to deal with 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*), the FGLS model is a better option; otherwise, the PCSE method is preferred (Reed and Ye 2011; Kumar et al. 2021). In our study time period

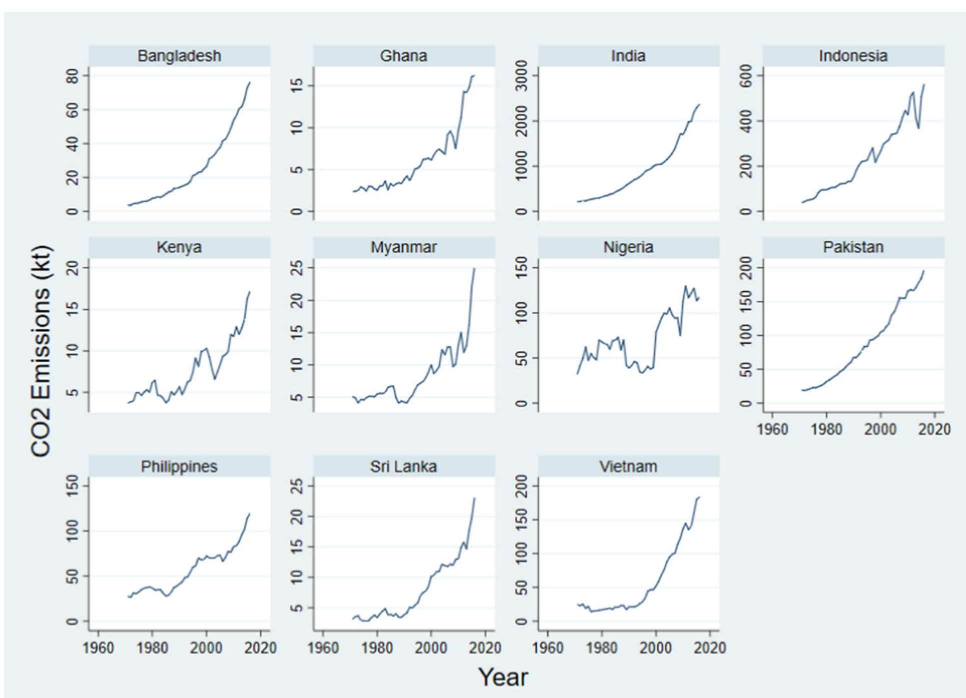

Fig. 3 Trends in CO_2 emissions in LMI countries (1971–2016)

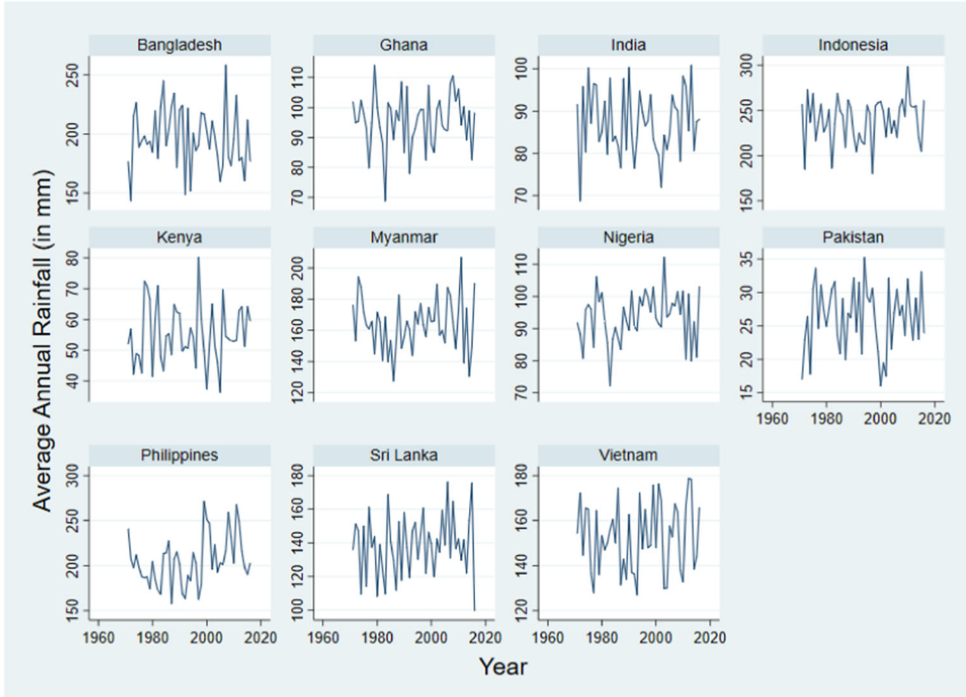

Fig. 4 Trends in average annual rainfall in LMI countries (1971–2016)

(t=46) is greater than the number of cross-sections (i=11), FGLS is the better option available (Reed and Ye 2011).

The mathematical form of the FGLS model is expressed as:

$$\widehat{\beta} = \left(X' \widehat{\Omega}^{-1} X\right)^{-1} X' \widehat{\Omega}^{-1} y \tag{3}$$

$$Var\left(\widehat{\beta}\right) = \left(X' \widehat{\Omega}^{-1} X\right)^{-1} \tag{4}$$

where $\widehat{\Omega}$: 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). This condition is satisfied in the present study.

FMOLS and DOLS econometric methods

Panel cointegration tests can only provide the long-run relationship among the variables. It cannot suggest the direction or signal for the coefficients of variables used in the study. Different panel models are available: pooled ordinary least square (POLS), generalized method of moment (GMM), fixed effect, random effect, pooled mean group (PMG), fully modified ordinary least square (FMOLS), dynamic ordinary least square (DOLS) that can provide the direction for coefficients of variables undertaken in the study. Kao and Chiang (2001) reviewed the OLS properties for panel data and proved that OLS has inconsistent characteristics with panel data. Kao and Chiang (2001) study suggested that FMOLS and DOLS are appropriate for panel cointegration. These techniques are superior because of their outperformance in a small sample, overcoming autocorrelation and endogeneity issues by introducing lags. So, in this study, FMOLS and DOLS methods are used. The functional forms of these tests are presented in the following Equation 5 and Equation 6.

$$\widehat{\beta}^{*}_{FMOLS} = N^{-1} \sum_{n=1}^{N} \widehat{\beta}^{*}_{FMOLS,n} \tag{5}$$

Here $\widehat{\beta}^{*}_{FMOLS}$ represents FMOLS regression parameter applied in n countries.

$$\widehat{\beta}^{*}_{DOLS} = N^{-1} \sum_{n=1}^{N} \widehat{\beta}^{*}_{DOLS,n} \tag{6}$$

Here $\widehat{\beta}^{*}_{DOLS}$ represents DOLS regression parameter applied to cross-sections n.

Dumitrescu-Hurlin causality test

Apart from FGLS, FMOLS, DOLS, and Driscoll-Kraay models, Dumitrescu-Hurlin (2012) panel causality test is used to detect the causality among the used variables in the study. Dumitrescu-Hurlin (2012) modified the Granger causality test to account for heterogeneity in the panel data. The null hypothesis states that there is no causality among the variables. On the other hand, the alternative hypothesis indicates that there is a causal relationship among the variables. The following equation represents the mathematical form of the test:

$$y_{it} = \alpha_i + \sum_{i=1}^{k} \gamma_i^{(k)} y_{i,t-k} + \sum_{i=1}^{k} \beta_i^{(k)} x_{i,t-k} + \varepsilon_{it} \quad (7)$$

where $\beta_i = \left(\beta_i^{(1)}, \beta_i^{(2)} \ldots, \beta_i^{(k)}\right)$ α_i represents individual effects which are supposed to be fixed in the time dimension, k denotes the lag orders and is assumed same for all cross-sectional units, and $\gamma_i^{(k)}$ and $\beta_i^{(k)}$, respectively, represent lag and slope parameters that differ across groups.

Results and discussion

The aggregate summary statistics of the variables are reported in Table 2. Cereal production has a higher mean value of 36,454,962 metric tonnes, followed by the land under cereal production, rainfall, CO_2, rural population, and temperature. In terms of variance, highest variance is for cereal production, followed by land under cereal production, CO_2, rainfall, rural population and temperature.

Before doing regression analysis, it is mandatory to check whether the 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. For this purpose, we have used second-generation unit root tests, i.e. CADF, and CIPS. The results of these tests are reported in Table 3. 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 since all the variables are found to be stationary at level.

Next, we analyze the long-run relationship between cereal production, temperature, rainfall, CO_2 emissions, cultivated land, and rural population by employing the Pedroni cointegration test. The result of the test reported in Table 4 reveals that out of seven statistics, five statistics reject the null hypothesis of absence of cointegration at 1% level of significance. So, it is concluded that cereal production, temperature, rainfall, CO_2 emissions, cultivated land, and rural population are cointegrated.

After performing the Pedroni cointegration test, 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 the 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. The result of the 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, 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 between the FE and RE models. In the Hausman test, the null hypothesis states that the RE model is appropriate against the alternative hypothesis. The null hypothesis is rejected at 1% 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 groupwise 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

Table 2 Descriptive statistics

Variables	Observations	Mean	Std. Dev.	Maximum	Minimum
CP	506	36,454,962	57,891,297	3.00E+08	432,000
AAT	506	25.059	2.024	28.2362	19.346
AAR	506	132.188	65.856	298.39	15.983
CO_2	506	132.604	317.076	2371.75	2.292
LCP	506	15,961,662	27,119,838	1.10E+08	645,000
RPOP	506	71.373	10.139	92.099	45.251

Table 3 Unit root test results

Variables	CADF			CIPS		
	Intercept	Intercept and trend	Order of integration	Intercept	Intercept and trend	Order of integration
lnCP	−3.238***	−3.300***	I(0)	−3.238***	−3.300***	I(0)
lnAAT	−4.655***	4.874***	I(0)	−4.655***	−4.874***	I(0)
lnAAR	−6.047***	−6.203***	I(0)	−6.047***	6.203***	I(0)
lnCO_2	−2.054	−3.038***	I(0)	−1.942	−3.038***	I(0)
lnLCP	−3.370***	−3.352***	I(0)	−3.370***	−3.352***	I(0)
lnRPOP	−3.535***	−3.108***	I(0)	−3.237***	−2.930***	I(0)

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

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 groupwise heteroskedasticity, a modified Wald test by Baum (2000) is applied. The null hypothesis of panel groupwise homoscedasticity is rejected at 1% level of significance. The result of the Wald test indicates the presence of groupwise heteroscedasticity in the model. Thus, the diagnostic tests conclude that the FE model has serial correlation, CSD and groupwise heteroscedasticity problems. In order to resolve these problems, the FGLS and FMOLS techniques are used, and for robustness purpose, the study further employs, DOLS and Driscoll-Kraay standard model.

The FGLS and FMOLS results are presented in Table 8, and the summary of the long-run estimates between the considered variables are reported in Fig. 5. According to the findings of FGLS, the coefficient of average temperature is statistically significant and negative, with 1% level of significance. In terms of magnitude, the value of the coefficient of average temperature reveals that a 1% increase in AAT leads to a fall in total cereal production by 0.70% 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, a rise in global average temperature by 0.5°C 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%, leading to a rise in market price (Nelson et al. 2009). Moreover, the increased average temperature has adversely impacted 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% (Matthews 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. This finding is similar to those of Brown et al. (2010), Akram (2012), Dasgupta (2013), Mishra and Sahu (2014), Loum and Fogarassy (2015), Praveen and Sharma (2019b), and Attiaoui and Boufateh 2019).

The coefficient of rainfall is found to be positive, with 1% 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 0.18%, with a 1%

Table 4 Pedroni cointegration test

	Statistics	p-value	Weighted statistics	p-value
Alternative hypothesis: common AR coefficients (within-dimension)				
Panel v-statistic	−1.115	0.867	−3.138	0.999
Panel rho-statistic	0.126	0.550	−2.454***	0.007
Panel PP-statistic	−3.182***	0.000	−7.100***	0.000
Panel ADF-statistic	−3.487***	0.000	−7.463***	0.000
Alternative hypothesis: individual AR coefficients (between-dimension)				
Group rho-statistic	0.727	0.766		
Group PP-statistic	−4.054***	0.000		
Group ADF-statistic	−2.975***	0.001		

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* (0.518)	0.070	−0.829** (0.359)	0.021
lnAAR	0.084* (0.050)	0.090	0.271*** (0.042)	0.000
lnCO2	0.312*** (0.016)	0.000	0.306*** (0.017)	0.000
lnLCP	0.998*** (0.045)	0.000	0.766*** (0.029)	0.000
lnRPOP	−0.422*** (0.112)	0.000	−0.671*** (0.109)	0.000
Constant	−1.897 (1.856)	0.307	7.631*** (1.473)	0.000
Observations	506		506	
Number of groups	11		11	
R^2	0.806		0.768	
Hausman test		Statistics	*p*-value	
		−1699.4***	0.005	

Note: Standard errors in parentheses

***p<0.01, **p<0.05, *p<0.1

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 would impact cereal yields. This empirical result is in line with those of Brown et al. (2010), Dumrul and Kilicarslan (2017), Attiaoui and Boufateh (2019), and Guntukula (2020).

The coefficient of CO_2 is positive, with 1% level of significance. It implies that CO_2 emission has a positive effect on cereal production. The coefficient of CO_2 reveals that a 1% 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 cereal 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. 2020; Demirhan 2020; Baig et al. 2020)

Similarly, the coefficient of the land under cereal production is found as positive, with 1% 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 0.78% with every 1% rise in LCP. Land under cereal production refers to the harvested area; this reflects that harvested area increases cereal crop production in these 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 land cereal production in LMI countries was 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. 2020). However, the estimated long-run coefficient of the rural population is −0.18, and the *p*-value is 0.22, which shows that the association between the rural population and cereal production is negative and insignificant.

Additionally, the findings of FMOLS estimation suggested that a 1% increase in AAT results in a decrease of 1.18% in cereal production for LMI countries. The impact of AAR on

Table 7 Diagnostic tests

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

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

Table 8 Long-run regression results (dependent variable is cereal production)

	FGLS		FMOLS	
Variable	Coefficient	Standard error	Coefficients	Standard error
lnAAT	−0.702***	0.223	−1.185***	0.273
lnAAR	0.184***	0.022	0.501***	0.061
lnCO2	0.204***	0.023	0.267***	0.045
lnLCP	0.785***	0.028	0.780***	0.051
lnRPOP	−0.184	0.150	−1.110***	0.232
Observations	506		506	
Number of groups	11		11	
The Wald chi^2	1841.48***			
R^2			0.988	

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

CP is found statistically significant and positive, resulting 0.50% increase in cereal production. Similarly, the effects of CO_2 emissions is positive and having a value of 0.26%. Moreover, 1% increase in LCP increases cereal production by the magnitude of about 0.78% in lower-middle-income countries. However, the rural population's coefficient is negative and significant at a 5% level of significance. This finding is unexpected and suggests that the rural population have an adverse effect on cereal production. But this finding is consistent with that of Warsame et al. (2021), who estimated the

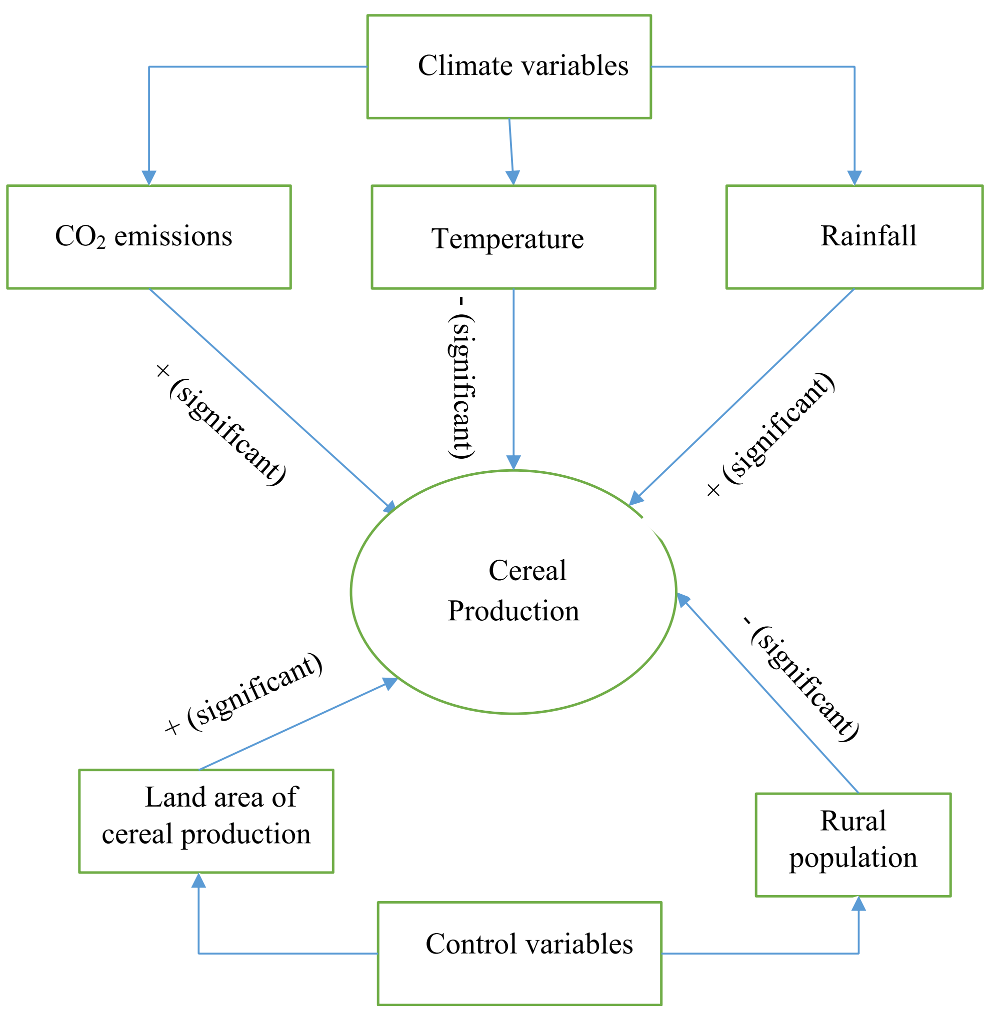

Fig. 5 Summary of findings

impact of climate change on cereal production in Somalia. One possible explanation for the negative effects might be that when more labor force works on the same land, agricultural productivity decreases because land cannot produce more than its capacity (Zakaria et al. 2019).

Robustness analysis

Considering the issues of heterogeneity and the cross-sectional dependence, we have further included Driscoll and Kraay (1998) and the DOLS panel regression model. This technique is robust in the case of endogeneity panel heterogeneity and cross-sectional dependence and has been used substantially 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 and DOLS 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 among all variables. This implies that the outcome documented in Table 9 highlights that the FGLS approach is consistent with the regression results of the Driscoll-Kraay standard error estimator and DOLS model. Though in terms of magnitude, the coefficients seem to be different among the variables.

Pairwise Granger causality results

Dumitrescu-Hurlin (2012) test is used for pairwise granger causality. The results presented in Table 10 show the bidirectional causal relationship between temperature and cereal production; CO_2 emissions and cereal production; cultivated land and cereal production; and cultivated land and CO_2 emissions. Likewise, this work also found unidirectional causality running from rainfall to cereal production; rural population to cereal production; temperature to rainfall; CO_2 emissions to temperature; cultivated land to temperature; rainfall to cultivated land; and the rural population to cultivated land. On the contrary, no causal relationships have been found between rural population and temperature, CO_2 emissions and rainfall, rural population and rainfall, and rural population and CO_2 emissions.

Conclusion and policy implication

This paper sets out to explore the effects of climate change on cereal production in 11 lower-middle-income countries during 1971–2016. The study has resolved the issues of serial correlation, panel groupwise heteroscedasticity, cross-sectional dependence and heterogeneity by adopting the FGLS and FMOLS model. The average annual temperature and rainfall have been used to measure climate change. The findings of the study reveal that climate change significantly affects 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 raises the production of cereal crops. Similar results have been found using Driscoll-Kraay standard error and DOLS techniques which ensure the robustness of the estimated models. Further, using Dumitrescu-Hurlin pairwise causality test, bidirectional causality of cereal production is found with temperature and CO_2 emissions. A unidirectional effect of rainfall on cereal production, temperature on rainfall, and CO_2 emissions on temperature is detected.

The study results would help the policymakers focus on mitigating the ill effects of temperature and chalk out the future strategies to enhance the farmers' adaptive capacity to increase cereal production in the lower-middle-income countries. It is a staple food for millions of the household in these countries. Since temperature negatively affects cereal

Table 9 Robustness testing

Variable	Driscoll-Kraay		DOLS	
	Coefficient	Driscoll-Kraay standard error	Coefficient	Standard error
lnAAT	−0.938	0.65	−0.599	0.752
lnAAR	0.084*	0.043	0.041	0.128
lnCO2	0.312***	0.018	0.145***	0.045
lnLCP	0.998***	0.09	1.561***	0.14
lnRPOP	−0.422***	0.106	−1.554***	0.351
Observations	506		506	
Number of ID	11		11	
R^2	0.929		0.985	

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

Table 10 Pairwise Dumitrescu-Hurlin Granger causality test

Null hypothesis:	W-Stat.	Zbar-Stat.	Prob.
lnAAT ↛ lnCP	6.772**	2.520	0.011
lnCP ↛ lnAAT	7.360***	3.111	0.001
lnAAR ↛ lnCP	7.335***	3.086	0.002
lnCP ↛ lnAAR	5.545	1.291	0.196
lnCO_2 ↛ lnCP	7.302***	3.052	0.002
lnCP ↛ lnCO_2	7.201***	2.951	0.003
lnLCP ↛ lnCP	6.452**	2.199	0.027
lnCP ↛ lnLCP	7.266*	1.658	0.097
lnRPOP ↛ lnCP	8.092***	3.844	0.000
lnCP ↛ lnRPOP	5.903*	1.650	0.098
lnAAR ↛ lnAAT	4.860	0.604	0.545
lnAAT ↛ lnAAR	7.694**	2.031	0.042
lnCO_2 ↛ lnAAT	9.579***	3.668	0.000
lnAAT ↛ lnCO_2	4.764	0.507	0.611
lnLCP ↛ lnAAT	6.350**	2.097	0.035
lnAAT ↛ lnLCP	5.699	1.445	0.148
lnRPOP ↛ lnAAT	9.503	5.259	1.000
lnAAT ↛ lnRPOP	4.497	0.240	0.810
lnCO2 ↛ lnAAR	3.781	−0.477	0.632
lnAAR ↛ lnCO_2	4.360	0.102	0.918
lnLCP ↛ lnAAR	4.799	0.542	0.587
lnAAR ↛ lnLCP	7.038***	2.787	0.005
lnRPOP ↛ lnAAR	4.500	0.242	0.808
lnAAR ↛ lnRPOP	5.021	0.765	0.444
lnLCP ↛ lnCO_2	6.510**	2.258	0.023
lnCO_2 ↛ lnLCP	6.368**	2.116	0.034
lnRPOP ↛ lnCO_2	9.545	5.301	1.000
lnCO_2 ↛ lnRPOP	9.171	4.926	8.000
lnRPOP ↛ lnLCP	7.726***	3.477	0.000
lnLCP ↛ lnRPOP	3.912	−0.346	0.729

Note: ***p<0.01, **p<0.05, *p<0.1, ↛ indicates "does not granger cause"

production, heat-resistant varieties of cereal crops should be researched and developed to ensure food security. The results of the study suggest that CO_2 is increasing the cereal production. However, carbon-rich food can pose severe health challenges. Therefore, the research must also focus on carbon-free cereal production. Further, an increase in temperature affects cereal production by increasing heat stress on cereal crops, a rise in evapotranspiration, an increase in irrigation, and a change in cropping seasons. In this direction, the negative effect of the temperature can be lowered by modifying crop sowing and cultivation and exploring short duration crop varieties (Ali and Erenstein 2017).

Moreover, climate policies should be appropriately designed and implemented in response to specific climate change problems. For example, when there was a change in precipitation in 11 African countries, they changed the planting period. When there was a temperature change, the farmers switched to non-farm activities, increased water conservation, and changed crop varieties (Maddison 2007). Similarly, in the study of Bryan et al. (2009), the climate change strategies adopted by farmers consisted of changing dates of irrigation and planting, practicing soil conservation, cultivating trees, planting various crops and varieties which led to a rise in the production of cereal yield in Ethiopia and South Africa. Therefore, in this regard, lower-middle-income countries should also take lessons from these countries to adopt suitable climate policy to cope with the negative consequences of temperature on cereal production.

Nevertheless, it is also evident that the rural population harms cereal production in the sample countries. This relationship clearly shows that the rural population has lower productivity in the agricultural sector. Hence, efforts are needed for policymakers of these countries to increase the farm labor productivity by improving farming techniques and technology. The improvement in agricultural productivity could be achieved by introducing mechanization and enhancing the skills of the rural population in entrepreneurial and management strategies to optimize human resources in farming. All these combined efforts could lead to higher production of cereal yields and reduce the food security problem in these economies.

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