Decoupling the climatic and carbon dioxide emission influence to maize crop production in Pakistan



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Abstract

Global warming influencing the agricultural production in several ways due to rainfall, temperature and carbon dioxide emission. The objective of this study is to investigate the climatic and carbon dioxide emission influence to maize crop production in Pakistan for the period of 1988–2017. We used an ARDL approach and Granger causality test to check the dynamic linkage between carbon dioxide emission, maize crop production, area under maize crop, water availability, rainfall and temperature with the evidence of long-run and short-run. Analysis results revealed that maize crop production has positive coefficient that demonstrate the long-term association with carbon dioxide emission with p value 0.0395. Similarly, results also showed a long-run association among water availability, rainfall and temperature with carbon dioxide emission with having positive coefficient and p values 0.0000, 0.0014 and 0.0001. Unfortunately, the coefficient of area under maize crop showed a negative linkage with carbon dioxide emission. Possible conservative policies are needed from the Pakistani government to reduce carbon dioxide emission in order to enhance the agricultural production as well as to boost the economic growth.

Keywords Climate change \cdot Maize crop \cdot CO₂ \cdot Water availability \cdot Temperature

Introduction

A dramatic change in the climate becomes the key challenge for the environment and influencing almost every sector of economy including energy, water, health and biodiversity and also has diverse impact on the agricultural production (GOP 2019). Maize is a key cereal crop after wheat and rice in Pakistan. It accounts about 2.6% contribution to the

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agricultural value added and 0.5% to the gross domestic product (GDP). Its production increased from 5.1% to 6.309 tons with the target of 6 million tons and cultivated in the area of 131,800 ha (GOP 2018). The cropped area for maize has increased to 1334 thousand hectares which shows a substantial improvement of 12.0% over the 1191 thousand hectares planted area (GOP 2017). The agriculture sector has a dynamic role for the sustainable development and also considered the key contributor to boost the economy of Pakistan. Pakistan is located in an arid region and considered with high temperature as well as squat rainfall, and economy is relying on agriculture (Kazmi et al. 2015). The linkage among climate change and agriculture economic outcomes were discussed in many studies to demonstrate the assessment of risk because change in the climate causing the yield of crops around the world (Liang et al. 2017; Di Gregorio et al. 2017).

The association between crops trend and variation in climate provides a favourable chance to determine more accurately recent yields progress and predict climatic influence on sustainable crops production (Ray et al. 2015). Climate change is expected to cause the sustainable agriculture production in different countries, and people who associated with food also affected most susceptible (Asante and Amuakwa-Mensah 2015). The demand of maize crop has increased with the passage of time and considered the key cereal crop in the world. Due to variations in the climate, the crop has been greatly influenced during growing season mainly due to temperature and agronomic management practices. Climate change also impacted the livestock production and cereal crops and necessary to assess and develop the future management strategies (Abbas et al. 2017). Climate change causes the diverse impact on the crop surface science due to upsurge in the temperature, and mitigation changes in the crops management introduces latest varieties with extensive growth that can play significant influence to crops imagery and ultimately intensify the yields under warming tendencies (Lin et al. 2015; Araya et al. 2015; Amin et al. 2015).

Climate change, carbon dioxide emission and agriculture have dynamic linkage, so any adverse effects due to climate will also affect the agricultural productivity. Rainfall, temperature and carbon dioxide emission concentration demonstrate a positive or negative influence to crops production during the time of sowing and illustrate a climatic influence on yields (Cammarano and Tian 2018; Kimball 2010; Cammarano et al. 2016; Allen et al. 2011). Various studies have been conducted to demonstrate the linkage of climate change, carbon dioxide emission, energy usage, energy consumption, fossil fuel energy, ecosystem, crops disease, sustainable food security, fish production, livestock, land restoration, air pollution, cereal yield, global warming and agriculture (Qureshi et al. 2016; Rehman and Deyuan 2018; van Loon et al. 2019; Amjath-Babu et al. 2019; Rehman et al. 2019a, b; Tefera and Ali 2019; Woolf et al. 2018; Chandio et al. 2019; Gebreegziabher et al. 2020; Chandio et al. 2020; Ahsan et al. 2020), but this study seeks to explore the carbon dioxide emission linkage with maize crop production, area under maize crop, water availability, rainfall and temperature by employing the ARDL approach and Granger causality test.

Literature review

Pakistan is the most vulnerable country as compare with others which is serious to the climate change. The country already has been faced the severity of climate change specifically high temperature, crisis of water, drought, increased flooding and disease events in some areas (Smit and Skinner 2002; Abid et al. 2015). Climate change may interrupt the process of hunger in the world, and climatic influence on agriculture production may also cause the supply of food. The impact of climate change on crop productivity may have an impact on food supply, and this global pattern is strong and coherent. Due to short-term changes in supply, the constancy of the entire food system can also threatened by climatic variation. At regional level, however, the potential impacts are less pronounced, but due to climatic change also cause the insecurity of food and hunger in different areas (Wheeler and Von Braun 2013). The multifaceted interface of rainfall,

temperature, solar radiation and other meteorological parameters with plants and soil characteristics makes determining the optimal planting date for the maize production (Erasmi et al. 2014). Several global studies have explored the association between crop yields and indigenous climate such as temperature and rainfall (Lobell et al. 2015).

Maize is key grain crop-wise and has share in the agriculture value added which covering the large area for production (GOP 2015). At regional and global level, climate change was the chief research area in recent decades which have substantial effect on crops production (Lobell et al. 2013; Anjum et al. 2016). Climate has key role in the agricultural productivity, and several organizations have expressed concern about the fundamental role of agricultural vicious benefits, arguing the climatic potential influence on agriculture. Furthermore, it has also effect on livestock production, hydrological balance, input supply and several other agriculture related mechanisms (Aydinalp and Cresser 2008; Grossi et al. 2019).

The world population is growing rapidly, and its forecasted trends related to increasing global food demand have put agriculture in a predicament to gain substantive food in the farmland. If food production does not match the global food demand, it could lead to cause expensive food and also increases hunger and poverty rate (Foley et al. 2011; Ahmad et al. 2016; Godfray et al. 2010; Lashkari et al. 2012). As also mentioned by Ahmed et al. (2019) and Tahir et al. (2015), the high urban population has triggered climate change by increasing pollution, traffic congestion, land use changes and disaster risk.

Due to growing population caused the increased in food consumption in coming decades also amplified the usage of biofuels that greatly increase the pressure on global agriculture, especially in the face of problem of reduced global arable land in the future. Increasing crop productivity on a farmland which is necessary to ensure the sustainable agriculture and food supply (Piao et al. 2010; Lambin and Meyfroidt 2011; Yin et al. 2016). Past obstacles in providing food to the world's growing population have been encountering technological advances, such as the progress seen during the Green Revolution. By developing high yields, global crop yields have been greatly increased, cereal varieties have been modernized, management techniques have been updated and also production and usage of synthetic fertilizers and pesticides has been improved (Zeng et al. 2014; Schauberger et al. 2017; Casadebaig et al. 2016).

In the atmosphere, the increasing concentration of carbon dioxide emission, rainfall, temperature, water supplies and increase of extreme climates all are expected to affect the social, economic and environmental sectors. With regard to crop yields, these variations can lead to a diversity of influences (Trnka et al. 2014; Srivastava et al. 2018). Global climate change has become the most pressing environmental problem due to increasing the greenhouse effect and has a major impact on both human and systems. The recent clear influence is causing the temperature

on global surface due to greenhouse gas emissions on global level (IPCC 2014; Shen et al. 2018; Wang et al. 2016). To reduce the greenhouse gases subsequent from agricultural productivity, all effective efforts have been done regarding systematic adaptation to climate change (FAO 2013).

Methodology

Data sources

This empirical analysis used time series data ranging from 1988 to 2017. The sources of data are World Development Indicators (WDI) and Economy Survey of Pakistan. The variables used are carbon dioxide emission, maize crop production, area under maize crop, water availability, rainfall and temperature. Table 1 illustrates the details of all variables used in this study. The variables trends with logarithmic form are presented in the Fig. 1.

Econometric model specification and unit root tests

The following model was specified to check the variables association as follows:

$$CO_2 e_t = f(MCP_t, AMC_t, WA_t, RF_t, TM_t)$$
(1)

In Eq. (1), CO_2e_t denotes carbon dioxide emission, MCP_t is showing maize crop production, variable AMC_t specifies the area under maize crop, variable WA_t is showing water availability in Pakistan, RF_t denotes rainfall and TM_t denotes temperature in Pakistan. Equation (1) can also be written as follows:

$$CO_2 e_t = \zeta_0 + \zeta_1 MCP_t + \zeta_2 AMC_t + \zeta_3 WA_t + \zeta_4 RF_t + \zeta_5 TM_t + \varepsilon_t$$
(2)

The logarithmic form of all variables in the log-linear model is specified as follows:

$$lnCO_{2}e_{t} = \zeta_{0} + \zeta_{1}lnMCP_{t} + \zeta_{2}lnAMC_{t} + \zeta_{3}lnWA_{t} + \zeta_{4}lnRF_{t} + \zeta_{5}lnTM_{t} + \varepsilon_{t}$$
(3)

Table 1 Variables and their

explanations

Equation (3) is the logarithmic form of carbon dioxide emission, maize crop production, area under maize crop, water availability, rainfall and temperature. Time dimension is denoted by t, ε_t denotes error term, ζ_0 is constant intercept and coefficients of the models ζ_1 to ζ_5 demonstrate the longrun elasticity.

Furthermore for the unit root test, the stationarity of all variables with the involvement of ARDL model has checked via unit root test. The unit root test can be specified as follows:

$$\Delta E_{t} = \gamma_{\circ} + \phi_{\circ} K + \phi_{1} L_{t-1} + \sum_{i=1}^{m} \beta_{1} \Delta L_{t-1} + \varepsilon_{t}$$
(4)

Equation (4) demonstrates the unit root test where Δ illustrate operator of difference.

Specification of ARDL model to cointegration test

In this study, an ARDL approach was employed, and it is developed by Pesaran and Shin (1998). Long-run and shortrun association between variables such as carbon dioxide emission, maize crop production, area under maize crop, water availability, rainfall and temperature were performed by checking the order of integration at I(0) and I(1). The linkage of long-run and short-run between variables examined with Unrestricted Error Correction Model (UECM) and follow as:

$$\Delta LnCO_{2}e_{t} = \lambda_{0} + \sum_{i=1}^{v} \lambda_{1j} \Delta LnCO_{2}e_{t-k}$$

$$+ \sum_{i=1}^{v} \lambda_{2j} \Delta LnMCP_{t-k} + \sum_{i=1}^{v} \lambda_{3j} \Delta LnAMC_{t-k}$$

$$+ \sum_{i=1}^{v} \lambda_{4j} \Delta LnWA_{t-k} + \sum_{i=1}^{v} \lambda_{5j} \Delta LnRF_{t-k}$$

$$+ \sum_{i=1}^{v} \lambda_{6j} \Delta LnTM_{t-k} + \lambda_{7}LnCO_{2}e_{t-1}$$

$$+ \lambda_{8}LnMCP_{t-1} + \lambda_{9}LnAMC_{t-1}$$

$$+ \lambda_{10}LnWA_{t-1} + \lambda_{11}LnRF_{t-1}$$

$$+ \lambda_{12}LnTM_{t-1} + \varepsilon_{1t}$$
(5)

Study variables	Explanations with units	Log-trends of the variables	Sources
CO ₂ e	Carbon dioxide emission (in kt)	LnCO ₂ e	WDI
MCP	Maize Crop Production (000 tons)	LnMCP	GOP
AMC	Area under Maize Crop (000 ha)	LnAMC	GOP
WA	Water Availability (MAF)	LnWA	GOP
RF	Rainfall (Mm)	LnRF	WDI
TEM	Temperature (Celsius)	LnTEM	WDI
	-		

GOP Government of Pakistan, WDI World Development Indicators

Fig. 1 Trends of the variables



LnAMC

1992 1995 1998 2001

2004

2007 2010

2013 2016









$$\Delta Ln MCP_{t} = \xi_{0} + \sum_{i=1}^{\nu} \xi_{1j} \Delta Ln MCP_{t-k}$$

$$+ \sum_{i=1}^{\nu} \xi_{2j} \Delta Ln CO_{2} e_{tt-k} + \sum_{i=1}^{\nu} \xi_{3j} \Delta Ln AMC_{t-k}$$

$$+ \sum_{i=1}^{\nu} \xi_{4j} \Delta Ln WA_{t-k} + \sum_{i=1}^{\nu} \xi_{5j} \Delta Ln RF_{t-k}$$

$$+ \sum_{i=1}^{\nu} \xi_{6j} \Delta Ln TM_{t-k} + \xi_{7} Ln MCP_{t-1}$$

$$+ \xi_{8} Ln CO_{2} e_{t-1} + \xi_{9} Ln AMC_{t-1}$$

$$+ \xi_{10} Ln WA_{t-1} + \xi_{11} Ln RF_{t-1}$$

$$+ \xi_{12} Ln TM_{t-1} + \varepsilon_{2t}$$
(6)

3.15

3.10

3.05

3.00

2.95

2.90

1989

$$\Delta LnAMC_{t} = \varphi_{0} + \sum_{i=1}^{\nu} \varphi_{1j} \Delta LnAMC_{t-k}$$

$$+ \sum_{i=1}^{\nu} \varphi_{2j} \Delta LnMCP_{t-k} + \sum_{i=1}^{\nu} \varphi_{3j} \Delta LnCO_{2}e_{t-k}$$

$$+ \sum_{i=1}^{\nu} \varphi_{4j} \Delta LnWA_{t-k} + \sum_{i=1}^{\nu} \varphi_{5j} \Delta LnRF_{t-k}$$

$$+ \sum_{i=1}^{\nu} \varphi_{6j} \Delta LnTM_{t-k} + \varphi_{7}LnAMC_{t-1}$$

$$+ \varphi_{8}LnMCP_{t-1} + \varphi_{9}LnCO_{2}e_{t-1}$$

$$+ \varphi_{10}LnWA_{t-1} + \varphi_{11}LnRF_{t-1}$$

$$+ \varphi_{12}LnTM_{t-1} + \varepsilon_{3t}$$
(7)

$$\Delta Ln \mathbf{WA}_{t} = \partial_{0} + \sum_{i=1}^{\nu} \partial_{1j} \Delta Ln \mathbf{WA}_{t-k} + \sum_{i=1}^{\nu} \partial_{2j} \Delta Ln \mathbf{AMC}_{t-k}$$

$$+ \sum_{i=1}^{\nu} \partial_{3j} \Delta Ln \mathbf{MCP}_{t-k} + \sum_{i=1}^{\nu} \partial_{4j} \Delta Ln \mathbf{CO}_{2} e_{t-k}$$

$$+ \sum_{i=1}^{\nu} \partial_{5j} \Delta Ln \mathbf{RF}_{t-k} + \sum_{i=1}^{\nu} \partial_{6j} \Delta Ln \mathbf{TM}_{t-k}$$

$$+ \partial_{7} Ln \mathbf{WA}_{t-1} + \partial_{8} Ln \mathbf{AMC}_{t-1}$$

$$+ \partial_{9} Ln \mathbf{MCP}_{t-1} + \partial_{10} Ln \mathbf{CO}_{2} e_{t-1}$$

$$+ \partial_{11} Ln \mathbf{RF}_{t-1} + \partial_{12} Ln \mathbf{TM}_{t-1} + \varepsilon_{4t}$$
(8)

$$\Delta Ln \operatorname{RF}_{t} = \gamma_{0} + \sum_{i=1}^{\nu} \gamma_{1j} \Delta Ln \operatorname{RF}_{t-k} + \sum_{i=1}^{\nu} \gamma_{2j} \Delta Ln \operatorname{WA}_{t-k}$$

$$+ \sum_{i=1}^{\nu} \gamma_{3j} \Delta Ln \operatorname{AMC}_{t-k} + \sum_{i=1}^{\nu} \gamma_{4j} \Delta Ln \operatorname{MCP}_{t-k}$$

$$+ \sum_{i=1}^{\nu} \gamma_{5j} \Delta Ln \operatorname{CO}_{2} e_{t-k} + \sum_{i=1}^{\nu} \gamma_{6j} \Delta Ln \operatorname{TM}_{t-k}$$

$$+ \gamma_{7} Ln \operatorname{RF}_{t-1} + \gamma_{8} Ln \operatorname{WA}_{t-1} + \gamma_{9} Ln \operatorname{AMC}_{t-1}$$

$$+ \gamma_{10} Ln \operatorname{MCP}_{t-1} + \gamma_{11} Ln \operatorname{CO}_{2} e_{t-1}$$

$$+ \gamma_{12} Ln \operatorname{TM}_{t-1} + \varepsilon_{5t} \qquad (9)$$

$$\Delta Ln TM_{t} = \delta_{0} + \sum_{i=1}^{\nu} \delta_{1j} \Delta Ln TM_{t-k} + \sum_{i=1}^{\nu} \delta_{2j} \Delta Ln RF_{t-k}$$

$$+ \sum_{i=1}^{\nu} \delta_{3j} \Delta Ln WA_{t-k} + \sum_{i=1}^{\nu} \delta_{4j} \Delta Ln MCP_{t-k}$$

$$+ \sum_{i=1}^{\nu} \delta_{5j} \Delta Ln AMC_{t-k} + \sum_{i=1}^{\nu} \delta_{6j} \Delta Ln CO_{2} e_{t-k}$$

$$+ \delta_{7} Ln TM_{t-1} + \delta_{8} Ln RF_{t-1} + \delta_{9} Ln WA_{t-1}$$

$$+ \delta_{10} Ln MCP_{t-1} + \delta_{11} Ln AMC_{t-1}$$

$$+ \delta_{12} Ln CO_{2} e_{t-1} + \varepsilon_{6t}$$
(10)

In the above equations, Δ demonstrates the first difference, ε_t is showing the error term and parameters of the equations $\lambda_1, \lambda_2, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \lambda_6; \xi_1, \xi_2, \xi_3, \xi_4, \xi_5, \xi_6; \varphi_1, \varphi_2, \varphi_3, \varphi_4, \varphi_5, \varphi_6; \gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \gamma_6; \gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \gamma_6; \delta_1, \delta_2, \delta_3, \delta_4, \delta_5, \delta_6$ show the coefficient of short-run dynamics. Similarly, λ_7 , $\lambda_8, \lambda_9, \lambda_{10}, \lambda_{11}, \lambda_{12}; \xi_7, \xi_8, \xi_9, \xi_{10}, \xi_{11}, \xi_{12}; \varphi_7, \varphi_8, \varphi_9, \varphi_{10}, \varphi_{11}, \varphi_{12}; \gamma_7, \gamma_8, \gamma_9, \gamma_{10}, \gamma_{11}, \gamma_{12}; \delta_7, \delta_8, \delta_9, \delta_{10}, \delta_{11}, \delta_{12}$ demonstrate the long-run coefficient in the model. Equations (5)–(10) illustrate the no cointegration through null hypothesis between variables are H0: $\lambda_7 = \lambda_8 = \lambda_9 = \lambda_{10} = \lambda_{11} = \lambda_{12} = 0,$ $\xi_7 = \xi_8 = \xi_9 = \xi_{10} = \xi_{11} = \xi_{12} = 0,$ $\gamma_7 = \gamma_8 = \gamma_9 = \gamma_{10} = \gamma_{11} = \gamma_{12} = 0,$ $\gamma_7 = \gamma_8 = \gamma_9 = \gamma_{10} = \gamma_{11} = \gamma_{12} = 0,$ $\delta_{7} = \delta_{8} = \delta_{9} = \delta_{10} = \delta_{11} = \delta_{12} = 0 \text{ against H1:}$ $\lambda_{7} \neq \lambda_{8} \neq \lambda_{9} \neq \lambda_{10} \neq \lambda_{11} \neq \lambda_{12} \neq 0,$ $\xi_{7} \neq \xi_{8} \neq \xi_{9} \neq \xi_{10} \neq \xi_{11} \neq \xi_{12} \neq 0,$ $\varphi_{7} \neq \varphi_{8} \neq \varphi_{9} \neq \varphi_{10} \neq \varphi_{11} \neq \varphi_{12} \neq 0,$ $\gamma_{7} \neq \gamma_{8} \neq \gamma_{9} \neq \gamma_{10} \neq \gamma_{11} \neq \gamma_{12} \neq 0,$ $\gamma_{7} \neq \gamma_{8} \neq \gamma_{9} \neq \gamma_{10} \neq \gamma_{10} \neq \gamma_{11} \neq \gamma_{12} \neq 0,$ $\gamma_{7} \neq \gamma_{8} \neq \gamma_{9} \neq \gamma_{10} \neq \gamma_{11} \neq \gamma_{12} \neq 0,$ $\gamma_{7} \neq \delta_{8} \neq \delta_{9} \neq \delta_{10} \neq \delta_{11} \neq \delta_{12} \neq 0,$ $\gamma_{7} \neq \gamma_{8} \neq \gamma_{9} \neq \gamma_{10} \neq \gamma_{11} \neq \gamma_{12} \neq 0,$ $\delta_{7} \neq \delta_{8} \neq \delta_{9} \neq \delta_{10} \neq \delta_{11} \neq \delta_{12} \neq 0,$ $\gamma_{7} \neq \gamma_{8} \neq \gamma_{9} \neq \gamma_{10} \neq \gamma_{11} \neq \gamma_{12} \neq 0,$ $\gamma_{7} \neq \delta_{8} \neq \delta_{9} \neq \delta_{10} \neq \delta_{11} \neq \delta_{12} \neq 0,$ $\gamma_{7} \neq \delta_{8} \neq \delta_{9} \neq \delta_{10} \neq \delta_{10} \neq \delta_{11} \neq \delta_{12} \neq 0,$

Furthermore, the calculate values of F-statistics are illustrated as in the null hypothesis: F_{lnCO2e} (lnCO₂e/lnMCP, lnAMC, lnWA, lnRF, lnTM), F_{lnMCP} (lnMCP/lnCO₂e, lnAMC, lnWA, lnRF, lnTM), F_{lnAMC} (lnAMC/lnMCP, lnCO₂e, lnWA, lnRF, lnTM), F_{lnWA} (lnWA/lnAMC, lnMCP, lnCO₂e, lnRF, lnTM), F_{lnRF} (lnRF/lnWA, InAMC, InMCP, InCO₂e, InTM) and F_{InTM} (InTM/InRF, lnWA, lnAMC, lnMCP, lnCO₂e), respectively. The dynamic linkage between carbon dioxide emission, maize crop production, area under maize crop, water availability, rainfall and temperature was checked by using ARDL approach. Regarding H0 acceptance and rejection follow that calculated values of F lower the critical boundary values in the upper case. The zero hypotheses without cointegration are rejected, indicating that there is a cointegrated association dependency and invaders between the variables.

Empirical results and discussion

Descriptive analysis and correlation between variables

Descriptive analysis and correlation between variables are displayed in the Tables 2 and 3 and concluded that all variables including carbon dioxide emission, maize crop production, area under maize crop, water availability, rainfall and temperature are correlated each other.

Variables stationarity test results

The variables stationarity was checked by employing two unit roots test including Generalized Dickey-Fuller Least Squares (DF-GLS) (Elliott et al. 1992) and P-P (Phillips and Perron 1988) unit root test. In the order of two, both tests certify that none of the variable gets integration. Table 4 illustrates the results of the unit roots among carbon dioxide emission, maize crop production, area under maize crop, water availability, rainfall and temperature which inveterate that all are integrated at level and at first difference.

ARDL bounds test to cointegration results

The ARDL model was used to check the linkage among variables and explore the long-run equilibrium through bounds

Table 2 Descriptive analysis

	LnCO ₂ e	LnMCP	LnAMC	LnWA	LnRF	LnTM
Mean	11.65402	7.701723	6.882707	4.872463	3.252620	3.020431
Median	11.66534	7.438748	6.851713	4.894025	3.279352	3.022837
Maximum	12.13631	8.720950	7.195937	4.931520	3.572360	3.051166
Minimum	10.97187	7.027315	6.739336	4.720461	2.773720	2.972790
Std. dev.	0.360048	0.556900	0.112072	0.058616	0.197354	0.022352
Skewness	-0.350719	0.346038	0.899076	- 1.239995	-0.661941	-0.657112
Kurtosis	1.832119	1.609386	3.415573	3.429856	2.857600	2.381689
Jarque-Bera	2.319952	3.015969	4.257560	7.918902	2.216177	2.636869
Probability	0.313494	0.221356	0.118982	0.019074	0.330190	0.267554
Sum	349.6205	231.0517	206.4812	146.1739	97.57860	90.61294
Sum sq. dev.	3.759410	8.994003	0.364242	0.099641	1.129505	0.014489
Observations	30	30	30	30	30	30

test to cointegration at 10%, 5%, 2.5% and 1% level of significance. ARDL bounds test to cointegration results are reported in Table 5.

F-statistic value is 4.246437 which shows in the Table 5 and surpassed the higher critical bound. Cointegration test shows the linkage between carbon dioxide emission, maize crop production, area under maize crop, water availability, rainfall and temperature. Furthermore, we also applied the Johansen cointegration test (Johansen and Juselius 1990), and results are presented in Table 6. It confirms the robustness among the variables through long-run connection.

Evidence from long-run and short-run estimation

Table 7 depicts the estimated long-run and short-run analysis results between carbon dioxide emission, maize crop

Correlation t-Statistic Probability	LnCO ₂ e	LnMCP	LnAMC	LnWA	LnRF	LnTM
LnCO ₂ e	1.000000					
	_					
	_					
LnMCP	0.943442	1.000000				
	15.05782	-				
	(0.0000)	-				
LnAMC	0.861764	0.925504	1.000000			
	8.988669	12.93058	-			
	(0.0000)	(0.0000)	-			
LnWA	0.857274	0.692848	0.638420	1.000000		
	8.810684	5.084296	4.389056	-		
	(0.0000)	(0.0000)	(0.0001)	-		
LnRF	-0.010396	0.061959	-0.054448	-0.100667	1.000000	
	-0.055014	0.328488	-0.288537	-0.535401	-	
	(0.9565)	(0.7450)	(0.7751)	(0.5966)	-	
LnTM	0.532927	0.438439	0.404742	0.404733	-0.364593	1.000000
	3.332684	2.581335	2.342103	2.342045	-2.071855	_
	(0.0024)	(0.0154)	(0.0265)	(0.0265)	(0.0476)	_

Table 3	Correlation between
variables	ŝ

Theit we at tasts warmalts

Table 4

Variables	DF-GLS	DF-GLS		
	Level	First difference	Level	First difference
LnCO ₂ e	- 1.381345	- 3.803484***	- 1.318977	-6.717511***
LnMCP	-2.013346	-3.607511**	-2.191672	- 5.072827***
LnAMC	-2.226004	- 5.905495***	-1.831506	- 5.774036***
LnWA	-2.266662	- 8.397525***	-2.178938	-9.52041***
LnRF	-2.766084	-12.01624***	-4.999717***	-12.18112***
LnTM	-4.809257***	-7.705158***	- 5.284226***	- 17.08903***

Double asterisks (**) and triple asterisks (***) denote the significance level at 1% and 5% by rejecting the null hypothesis

production, area under maize crop, water availability, rainfall and temperature. The ARDL approach was used after confirming the cointegration test and explored the dynamic linkage of variables through long-run and short-run estimation.

Table 7 results show that maize crop production has positive linkage with carbon dioxide emission having coefficient 0.162750 with p value 0.0395. Furthermore, results also revealed that water availability, rainfall and temperature in the long-run analysis has positive association with carbon dioxide emission with coefficients 1.978013, 0.289200 and 3.647727 with p values 0.0000, 0.0014 and 0.0001, respectively. Similarly, in the long-run analysis, the coefficient of area under maize crop showed an adverse linkage with carbon dioxide emission.

Climate change has continuing threat to the agricultural production which is impacted through carbon dioxide emission and the global advocacy to respond its adverse influence with utmost determination. The agricultural production and security of food are facing key challenges due to climate change, and sectorial actions are necessary to handle this problem to limit the negative influence which is causing global warming. In addition, the greenhouse gas emissions are increasing from agriculture, and several research studies have been conducted on livestock and agriculture; fisheries

 Table 5
 ARDL bounds test to cointegration results

Test Statistic	Value	K
F-statistic	4.246437	5
Critical value bounds	I(0) bound	I(1) bound
At 10%	2.75	3.79
At 5%	3.12	4.25
At 2.5%	3.49	4.67
At 1%	3.93	5.23

can help economies to identify the major resources to tackle the reduction of carbon dioxide emission simultaneously and discourse the security issues regarding food (Appiah et al. 2018; Surahman et al. 2018; Edoja et al. 2016). Better nutrition, sustainable production, food security and consumption can be achieved through long-term policies which enable to control hunger. However, seeking alternatives to increase the supply of food in order to meet the increasing demand has directed through week practices of agriculture that causes the climatic change (Asumadu-Sarkodie and Owusu 2017; Nath et al. 2018).

The ecosystem has been caused by the climate change affects. It also adversely affected the species and their habitats, water supply, food security and human health. It is considered the supreme hazardous and complicated ecological problems created by human beings. Globally efforts are paying to alleviate the effects of climate change and carbon dioxide emission to limit the global temperature (Waheed et al. 2018; Defleur and Desclaux 2019; Pecl et al. 2017). With the passage of time, the demand of food is increasing with rapid population growth, leading to increased agricultural productivity. The competition between individual farms and local producers has stirred the meditation to increase the agricultural production (Rehman et al. 2019a, b).

The short-run dynamic results also show that all variables have significant linkage with carbon dioxide in spite area under maize crop. Furthermore, diagnostic tests show that normality test, serial correlation, heteroscedasticity and Ramsey RESET p values are 0.3951, 0.3639, 0.4299 and 0.4381, respectively.

Figure 2 depicts the dynamic linkage between study variables. Based on findings, the coefficients of the maize crop production, water availability, rainfall and temperature demonstrate a long-term relationship with carbon dioxide emission, but the coefficient of area under maize crop showed a non-significant linkage with carbon dioxide emission. Additionally, the direction of long-run and short-run among

 Table 6
 Results of the Johansen cointegration tests

Null hypothesis	Trace test statistic	p value	Null hypothesis	Maximum Eigenvalue	p value
$r \leq 0$	203.3826	0.0000	$r \leq 0$	71.55032	0.0000
$r \leq 1$	131.8323	0.0000	$r \leq 1$	53.17542	0.0001
$r \leq 2$	78.65685	0.0000	$r \leq 2$	39.61962	0.0009
$r \leq 3$	39.03723	0.0033	$r \leq 3$	21.45865	0.0450
$r \leq 4$	17.57858	0.0239	$r \leq 4$	16.79189	0.0195
$r \leq 5$	0.786693	0.3751	$r \leq 5$	0.786693	0.3751

r denotes the number of cointegrating equation

Table 7Estimated results oflong-run and short-run

Long-run estimation Long-run estimation LnMCP 0.162750 0.072610 2.241409 0.0395 LnAMC -0.154083 0.144213 -1.068444 0.3012 LnWA 1.978013 0.196726 10.054663 0.0000 LnRF 0.289200 0.075033 3.854328 0.0011 LnTM 3.647727 0.700896 5.204378 0.0001 C -10.436548 2.803263 -3.723000 0.0019 TREND 0.014284 0.004601 3.104428 0.0068 Short-run dynamics DLnCQ-2(-1) 0.016124 0.212480 0.075886 0.9405 DLnMCP 0.160125 0.088111 1.817308 0.0879 DLnMCP 0.16124 0.216712 1.529571 0.1457 DLnWA 0.331476 0.216712 1.529571 0.1457 DLnWA(-1) 1.076187 0.295297 3.644419 0.0022 DLnWA(-2) 0.638124 0.037131 2.792501 0.0130 <td< th=""><th>Variable</th><th>Coefficient</th><th>Std. error</th><th>t-Statistic</th><th>Prob.</th></td<>	Variable	Coefficient	Std. error	t-Statistic	Prob.
LnMCP 0.162750 0.072610 2.241409 0.0395 LnAMC -0.154083 0.144213 -1.068444 0.3012 LnWA 1.978013 0.196726 10.054663 0.0000 LnRF 0.289200 0.075033 3.854328 0.0014 LnTM 3.647727 0.700896 5.204378 0.0019 C -10.436548 2.803263 -3.723000 0.0019 TREND 0.014284 0.004601 3.104428 0.0068 Short-run dynamics 0.151599 0.159507 -0.950423 0.3560 DLnMCP 0.160125 0.088111 1.817308 0.0879 DLnMCC 0.151599 0.159507 -0.950423 0.3560 DLnMC 0.031476 0.216712 1.529571 0.1435 DLnWA(-1) 1.076187 0.295297 3.644419 0.0022 DLnWA(-2) 0.538456 0.313540 1.717340 0.1052 DLnRF 0.081124 0.302355 2.515057	Long-run estimation				
LnAMC -0.154083 0.144213 -1.068444 0.3012 LnWA 1.978013 0.196726 10.054663 0.0000 LnRF 0.289200 0.075033 3.854328 0.0014 LnTM 3.647727 0.700896 5.204378 0.0019 C -10.436548 2.803263 -3.723000 0.0019 TREND 0.014284 0.004601 3.104428 0.0088 Short-run dynamics	LnMCP	0.162750	0.072610	2.241409	0.0395
LnWA 1.978013 0.196726 10.054663 0.0000 LnRF 0.289200 0.075033 3.854328 0.0014 LnTM 3.647727 0.700896 5.204378 0.0010 C -10.436548 2.803263 -3.723000 0.0019 TREND 0.014284 0.004601 3.10428 0.0068 Short-run dynamics DLnCO2e(-1) 0.016124 0.212480 0.075886 0.9405 DLnMCP 0.160125 0.088111 1.817308 0.0879 DLnWA 0.331476 0.216712 1.529571 0.1457 DLnWA(-1) 1.076187 0.23525 2.515057 0.0230 DLnRF 0.081124 0.032255 2.515037 0.00130 DLnRF(-1) 0.103687 0.337617	LnAMC	-0.154083	0.144213	-1.068444	0.3012
LnRF 0.289200 0.075033 3.854328 0.0014 LnTM 3.647727 0.700896 5.204378 0.0001 C -10.436548 2.803263 -3.723000 0.0019 TREND 0.014284 0.004601 3.104428 0.0068 Short-run dynamics DLnCO2e(-1) 0.016124 0.212480 0.075886 0.9405 DLnCO2e(-1) 0.016125 0.088111 1.817308 0.0879 DLnMCP 0.160125 0.088111 1.817308 0.0879 DLnAMC 0.331476 0.216712 1.529571 0.1457 DLnWA(-1) 1.076187 0.23525 2.515057 0.0230 DLnRF 0.081124 0.032255 2.515057 0.0230 DLnRF(-1) 0.103687 0.337617<	LnWA	1.978013	0.196726	10.054663	0.0000
LnTM 3.647727 0.700896 5.204378 0.0001 C -10.436548 2.803263 -3.723000 0.0019 TREND 0.014284 0.004601 3.104428 0.0068 Short-run dynamics 0.075886 0.9405 DLnCQ-gc(-1) 0.016125 0.088111 1.817308 0.0879 DLnAMC -0.151599 0.159507 -0.950423 0.3560 DLnWA 0.331476 0.216712 1.529571 0.1457 DLaWA(-1) 1.076187 0.295297 3.644419 0.0022 DLnWA(-2) 0.538456 0.313540 1.717340 0.1052 DLnRF 0.081124 0.032255 2.515057 0.0230 DLnRF 0.081124 0.032255 2.515057 0.0230 DLnRF(-1) 1.143011 0.412526 2.770760 0.0136 DLnTM(-1) 1.143011 0.412526 2.790726 0.0197 ECT1-1 -0.98376 0.212480 -4.630433 0.0003 <td>LnRF</td> <td>0.289200</td> <td>0.075033</td> <td>3.854328</td> <td>0.0014</td>	LnRF	0.289200	0.075033	3.854328	0.0014
C -10.436548 2.803263 -3.723000 0.0019 TREND 0.014284 0.004601 3.104428 0.0068 Short-run dynamics 0.015866 0.9405 DLnCO.gc(-1) 0.016125 0.088111 1.817308 0.0879 DLnAMC -0.151599 0.159507 -0.950423 0.3560 DLnWA 0.331476 0.225297 3.644419 0.0022 DLnWA(-1) 1.076187 0.295297 3.644419 0.0230 DLnWA(-2) 0.538456 0.313540 1.717340 0.1052 DLnRF 0.081124 0.032255 2.515057 0.0230 DLnRF 0.081124 0.032255 2.515057 0.0230 DLnRF(-1) 0.103687 0.337617 5.215037 0.00130 DLnTM(-1) 1.143011 0.412526 2.70760 0.0136 DLaTM(-2) 0.685213 0.306172 2.237997 0.398 DTrend 0.014053 0.025424 2.590726	LnTM	3.647727	0.700896	5.204378	0.0001
TREND 0.014284 0.004601 3.104428 0.0068 Short-run dynamics DLnCO2ce(-1) 0.016124 0.212480 0.075886 0.9405 DLnMCP 0.160125 0.088111 1.817308 0.0879 DLnAMC -0.151599 0.159507 -0.950423 0.3560 DLnWA 0.331476 0.216712 1.529571 0.1457 DLnWA(-1) 1.076187 0.295297 3.644419 0.0022 DLnWA(-2) 0.538456 0.313540 1.717340 0.1022 DLnRF 0.081124 0.032255 2.515057 0.0230 DLnRF 0.081124 0.032255 2.515057 0.0230 DLnRF(-1) 0.103687 0.337617 5.215037 0.0011 DLnTM(-1) 1.143011 0.412526 2.770760 0.0136 DLnTM(-2) 0.685213 0.306172 2.237997 0.398 DTrend 0.014053 0.005424 2.590726 0.0197 ECTt-1 -0.983876 0.212480 -4.630433 0.0003 Diagnostic tests	С	- 10.436548	2.803263	-3.723000	0.0019
Short-run dynamics DLnCO2ce(-1) 0.016124 0.212480 0.075886 0.9405 DLnMCP 0.160125 0.088111 1.817308 0.0879 DLnAMC -0.151599 0.159507 -0.950423 0.3560 DLnWA 0.331476 0.216712 1.529571 0.1457 DLnWA(-1) 1.076187 0.295297 3.644419 0.0022 DLnWA(-2) 0.538456 0.313540 1.717340 0.1023 DLnRF(-1) 0.010687 0.037131 2.792501 0.0130 DLnRF(-1) 0.103687 0.037131 2.792501 0.0130 DLnRF(-2) 0.099726 0.0337617 5.215037 0.0001 DLnTM(-1) 1.143011 0.412526 2.700760 0.0136 DLnTM(-2) 0.685213 0.306172 2.237997 0.398 DTrend 0.014053 0.005424 2.590726 0.0197 ECTt-1 -0.983876 0.212480 -4.630433 0.0003 Diagnostic tests	TREND	0.014284	0.004601	3.104428	0.0068
DLnCO2e(-1) 0.016124 0.212480 0.075886 0.9405 DLnMCP 0.160125 0.088111 1.817308 0.0879 DLnAMC -0.151599 0.159507 -0.950423 0.3560 DLnWA 0.331476 0.216712 1.529571 0.1457 DLnWA(-1) 1.076187 0.295297 3.644419 0.0022 DLnWA(-2) 0.538456 0.313540 1.717340 0.1052 DLnRF 0.081124 0.032255 2.515057 0.0230 DLnRF(-1) 0.103687 0.037131 2.792501 0.0130 DLnRF(-2) 0.099726 0.035843 2.782346 0.0133 DLnTM(-1) 1.143011 0.412526 2.770760 0.0136 DLnTM(-2) 0.685213 0.306172 2.237997 0.0398 DTrend 0.014053 0.005424 2.590726 0.0197 ECT-1 -0.983876 0.212480 -4.630433 0.0003 Diagnostic tests	Short-run dynamics				
DLnMCP 0.160125 0.088111 1.817308 0.0879 DLnAMC -0.151599 0.159507 -0.950423 0.3560 DLnWA 0.331476 0.216712 1.529571 0.1457 DLnWA(-1) 1.076187 0.295297 3.644419 0.0022 DLnWA(-2) 0.538456 0.313540 1.717340 0.1052 DLnRF 0.081124 0.032255 2.515057 0.0230 DLnRF(-1) 0.103687 0.037131 2.792501 0.0130 DLnRF(-1) 0.103687 0.337617 5.215037 0.0001 DLnTM 1.760687 0.337617 5.215037 0.00130 DLnTM(-1) 1.143011 0.412526 2.770760 0.0136 DLnTM(-2) 0.685213 0.306172 2.237997 0.0398 DTrend 0.014053 0.005424 2.590726 0.0197 ECT-1 -0.983876 0.212480 -4.630433 0.0003 Diagnostic tests	$DLnCO_2e(-1)$	0.016124	0.212480	0.075886	0.9405
DLnAMC -0.151599 0.159507 -0.950423 0.3560 DLnWA 0.331476 0.216712 1.529571 0.1457 DLnWA(-1) 1.076187 0.295297 3.644419 0.0022 DLnWA(-2) 0.538456 0.313540 1.717340 0.1052 DLnRF 0.081124 0.032255 2.515057 0.0230 DLnRF(-1) 0.103687 0.037131 2.792501 0.0130 DLnRF(-2) 0.099726 0.035843 2.782346 0.0133 DLnTM 1.760687 0.337617 5.215037 0.0001 DLnTM(-1) 1.143011 0.412526 2.770760 0.0136 DLnTM(-2) 0.685213 0.306172 2.237997 0.0398 DTrend 0.014053 0.005424 2.590726 0.0197 ECTt-1 -0.983876 0.212480 -4.630433 0.0003 Diagnostic tests R-squared 0.997621 Adjusted <i>R</i> -squared 0.995688 - F-statistic 516.1445 Prob (F-statistic) </td <td>DLnMCP</td> <td>0.160125</td> <td>0.088111</td> <td>1.817308</td> <td>0.0879</td>	DLnMCP	0.160125	0.088111	1.817308	0.0879
DLnWA 0.331476 0.216712 1.529571 0.1457 DLnWA(-1) 1.076187 0.295297 3.644419 0.0022 DLnWA(-2) 0.538456 0.313540 1.717340 0.1052 DLnRF 0.081124 0.032255 2.515057 0.0230 DLnRF(-1) 0.103687 0.037131 2.792501 0.0130 DLnRF(-1) 0.103687 0.337617 5.215037 0.0001 DLnRF(-2) 0.099726 0.035843 2.782346 0.0133 DLnTM 1.760687 0.337617 5.215037 0.0001 DLnTM(-1) 1.143011 0.412526 2.770760 0.0136 DLnTM(-2) 0.685213 0.306172 2.237997 0.0398 DTrend 0.014053 0.005424 2.590726 0.0197 ECTr-1 -0.983876 0.212480 -4.630433 0.0003 Diagnostic tests - - - - - - - - - - - - -	DLnAMC	-0.151599	0.159507	-0.950423	0.3560
DLnWA(-1) 1.076187 0.295297 3.644419 0.0022 DLnWA(-2) 0.538456 0.313540 1.717340 0.1052 DLnRF 0.081124 0.032255 2.515057 0.0230 DLnRF(-1) 0.103687 0.037131 2.792501 0.0130 DLnRF(-2) 0.099726 0.035843 2.782346 0.0133 DLnTM 1.760687 0.337617 5.215037 0.0001 DLnTM(-1) 1.143011 0.412526 2.770760 0.0136 DLnTM(-2) 0.685213 0.306172 2.237997 0.0398 DTrend 0.014053 0.005424 2.590726 0.0197 ECTt-1 -0.983876 0.212480 -4.630433 0.0003 Diagnostic tests - - - - - - - - - - - - - - - - - - - - - - - - - - - -	DLnWA	0.331476	0.216712	1.529571	0.1457
DLnWA(-2) 0.538456 0.313540 1.717340 0.1052 DLnRF 0.081124 0.032255 2.515057 0.0230 DLnRF(-1) 0.103687 0.037131 2.792501 0.0130 DLnRF(-2) 0.099726 0.035843 2.782346 0.0133 DLnTM 1.760687 0.337617 5.215037 0.0001 DLnTM(-1) 1.143011 0.412526 2.770760 0.0136 DLnTM(-2) 0.685213 0.306172 2.237997 0.0398 DTrend 0.014053 0.005424 2.590726 0.0197 ECTt-1 -0.993876 0.212480 -4.630433 0.0003 Diagnostic tests - - -4.630433 0.0003 Prob (F-statistic) 0.997621 - - - - - - - - - - - - - - - - - - - - - - - - - - - <td>DLnWA(-1)</td> <td>1.076187</td> <td>0.295297</td> <td>3.644419</td> <td>0.0022</td>	DLnWA(-1)	1.076187	0.295297	3.644419	0.0022
DLnRF 0.081124 0.032255 2.515057 0.0230 DLnRF(-1) 0.103687 0.037131 2.792501 0.0130 DLnRF(-2) 0.099726 0.035843 2.782346 0.0133 DLnTM 1.760687 0.337617 5.215037 0.0001 DLnTM(-1) 1.143011 0.412526 2.770760 0.0136 DLnTM(-2) 0.685213 0.306172 2.237997 0.0398 DTrend 0.014053 0.005424 2.590726 0.0197 ECTt-1 -0.983876 0.212480 -4.630433 0.0003 Diagnostic tests R-squared 0.997621 Adjusted <i>R</i> -squared 0.995688 F-statistic 516.1445 Yerob (F-statistic) 0.000000 Urbin-Watson stat 2.050256 Normality 1.857058 (0.3951) Serial correlation 1.087565 (0.3639) Heteroskedasticity 0.642244 (0.4299) Ramsey RESET 0.796634 (0.4381) CUSUM Stable USUMSQ Stable	DLnWA(-2)	0.538456	0.313540	1.717340	0.1052
DLnRF(-1) 0.103687 0.037131 2.792501 0.0130 DLnRF(-2) 0.099726 0.035843 2.782346 0.0133 DLnTM 1.760687 0.337617 5.215037 0.0001 DLnTM(-1) 1.143011 0.412526 2.770760 0.0136 DLnTM(-2) 0.685213 0.306172 2.237997 0.0398 DTrend 0.014053 0.005424 2.590726 0.0197 ECTt-1 -0.983876 0.212480 -4.630433 0.0003 Diagnostic tests R-squared 0.997621 Adjusted <i>R</i> -squared 0.995688 - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - -	DLnRF	0.081124	0.032255	2.515057	0.0230
DLnRF(-2) 0.099726 0.035843 2.782346 0.0133 DLnTM 1.760687 0.337617 5.215037 0.0001 DLnTM(-1) 1.143011 0.412526 2.770760 0.0136 DLnTM(-2) 0.685213 0.306172 2.237997 0.398 DTrend 0.014053 0.005424 2.590726 0.0197 ECTt-1 -0.983876 0.212480 -4.630433 0.0003 Diagnostic tests	DLnRF(-1)	0.103687	0.037131	2.792501	0.0130
DLnTM 1.760687 0.337617 5.215037 0.0001 DLnTM(-1) 1.143011 0.412526 2.770760 0.0136 DLnTM(-2) 0.685213 0.306172 2.237997 0.0398 DTrend 0.014053 0.005424 2.590726 0.0197 ECTt-1 -0.983876 0.212480 -4.630433 0.0003 Diagnostic tests R-squared 0.997621 . . . Adjusted R-squared 0.995688 Prob (F-statistic) 0.00000 Durbin-Watson stat 2.050256 Normality 1.857058 (0.3951) Serial correlation 1.087565 (0.3639) Ramsey RESET 0.796634 (0.4381) CUSUMSQ Stable 	DLnRF(-2)	0.099726	0.035843	2.782346	0.0133
DLnTM(-1) 1.143011 0.412526 2.770760 0.0136 DLnTM(-2) 0.685213 0.306172 2.237997 0.0398 DTrend 0.014053 0.005424 2.590726 0.0197 ECTt-1 -0.983876 0.212480 -4.630433 0.0003 Diagnostic tests - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - -	DLnTM	1.760687	0.337617	5.215037	0.0001
DLnTM(-2) 0.685213 0.306172 2.237997 0.0398 DTrend 0.014053 0.005424 2.590726 0.0197 ECTt-1 -0.983876 0.212480 -4.630433 0.0003 Diagnostic tests R-squared 0.997621 0.4030 0.997621 Adjusted R-squared 0.995688 - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - <	DLnTM(-1)	1.143011	0.412526	2.770760	0.0136
DTrend 0.014053 0.005424 2.590726 0.0197 ECTt-1 -0.983876 0.212480 -4.630433 0.0003 Diagnostic tests R-squared 0.997621 - - - - - - - - - - - - - - - - - - - 0.0003 - - - - - 0.0003 0.0003 - - - - - - 0.0003 - - - - - - - - - - 0.0003 - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - <td>DLnTM(-2)</td> <td>0.685213</td> <td>0.306172</td> <td>2.237997</td> <td>0.0398</td>	DLnTM(-2)	0.685213	0.306172	2.237997	0.0398
ECTt-1 -0.983876 0.212480 -4.630433 0.0003 Diagnostic tests R-squared 0.997621 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	DTrend	0.014053	0.005424	2.590726	0.0197
Diagnostic tests 0.997621 Acjusted R-squared 0.995688 F-statistic 516.1445 Prob (F-statistic) 0.00000 Durbin-Watson stat 2.050256 Normality 1.857058 (0.3951) Serial correlation 0.642244 (0.4299) Heteroskedasticity 0.642244 (0.4381) CUSUM Stable	ECTt-1	-0.983876	0.212480	-4.630433	0.0003
R-squared 0.997621 Adjusted R-squared 0.995688 F-statistic 516.1445 Prob (F-statistic) 0.00000 Durbin-Watson stat 2.050256 Normality 1.857058 (0.3951) Serial correlation 1.087565 (0.3639) Heteroskedasticity 0.642244 (0.4299) Ramsey RESET 0.796634 (0.4381) CUSUM Stable	Diagnostic tests				
Adjusted R-squared 0.995688 F-statistic 516.1445 Prob (F-statistic) 0.00000 Durbin-Watson stat 2.050256 Normality 1.857058 (0.3951) Serial correlation 1.087565 (0.3639) Heteroskedasticity 0.642244 (0.4299) Ramsey RESET 0.796634 (0.4381) CUSUM Stable	R-squared	0.997621			
F-statistic 516.1445 Prob (F-statistic) 0.00000 Durbin-Watson stat 2.050256 Normality 1.857058 (0.3951) Serial correlation 1.087565 (0.3639) Heteroskedasticity 0.642244 (0.4299) Ramsey RESET 0.796634 (0.4381) CUSUM Stable CUSUMSQ Stable	Adjusted R-squared	0.995688			
Prob (F-statistic) 0.00000 Durbin-Watson stat 2.050256 Normality 1.857058 (0.3951) Serial correlation 1.087565 (0.3639) Heteroskedasticity 0.642244 (0.4299) Ramsey RESET 0.796634 (0.4381) CUSUM Stable CUSUMSQ Stable	F-statistic	516.1445			
Durbin-Watson stat 2.050256 Normality 1.857058 (0.3951) Serial correlation 1.087565 (0.3639) Heteroskedasticity 0.642244 (0.4299) Ramsey RESET 0.796634 (0.4381) CUSUM Stable CUSUMSQ Stable	Prob (F-statistic)	0.000000			
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CUSUMSQ Stable	CUSUM	Stable			
	CUSUMSQ	Stable			

Fig. 2 Dynamic linkage of variables



variables is reliable, excluding area under maize crop, which revealed negative connection with carbon dioxide emission in both log-term and short-run analysis. Overall findings showed heterogeneity through long-run and short-run which demonstrate a key recommendation for policy.

Granger causality test results

The causality linkage among carbon dioxide emission, maize crop production, area under maize crop, water availability, rainfall and temperature was determined by using Granger causality. Pairwise Granger causality test results are presented in Table 8 and show that unidirectional causality association between carbon dioxide emission and maize crop production. Furthermore, there is also unidirectional association among carbon dioxide emission and temperature.

Figures 3 and 4 illustrate the long- and short-run stability by using CUSUM (cumulative sum) and cumulative sum of square (CUSUMSQ) specifies level of significance at 5%.

Null hypothesis	F-statistic	Prob.
LnMCP do not have Granger causality to LnCO ₂ e	0.05433	0.8175
LnCO2e do not have Granger causality to LnMCP	4.42841**	0.0452
LnAMC do not have Granger causality to LnCO2e	0.38510	0.5403
LnCO2e do not have Granger causality to LnAMC	1.74405	0.1981
LnWA do not have Granger causality to LnCO2e	0.93646	0.3421
LnCO2e do not have Granger causality to LnWA	1.92335	0.1773
LnRF do not have Granger causality to LnCO2e	0.38159	0.5421
LnCO ₂ e do not have Granger causality to LnRF	0.00484	0.9450
LnTM do not have Granger causality to LnCO2e	0.31310	0.5806
LnCO ₂ e do not have Granger causality to LnTM	11.2081***	0.0025

*** and ** show the rejection of null hypothesis at 1% and 5% significance level

Table 8Pairwise Grangercausality Tests



Conclusion and policy recommendations

The major investigation in this study was to check the association between carbon dioxide emission, maize crop production, area under maize crop, water availability, rainfall and temperature in Pakistan for the period of 1988–2017. Data stationarity was checked by employing Generalized Dickey-Fuller Least Squares (DF-GLS) test and Phillips-Perron unit root test. Furthermore, variables dynamic linkage was checked by using autoregressive distributed lag (ARDL) bounds testing approach and Granger causality test. The variables showed a long-term association as carbon dioxide emission has positive influence to maize crop production. Similarly, results also revealed that water availability, rainfall and temperature have positive association with carbon dioxide emission in Pakistan. Unfortunately, the variable area under maize crop demonstrates a non-significant linkage with carbon dioxide emission.



According to the findings of this study, it suggests that possible initiatives are necessary to be taken from the government of Pakistan regarding the reduction of carbon dioxide emission to avoid causing climate change. The global temperature is cumulative due to variations in the climate and carbon dioxide emission that causing the agriculture production. Carbon dioxide emission is now an emerging issue on global level, and possible conservative policies are needed from all countries to pay attention regarding the reduction of carbon dioxide emission to avoid from environmental degradation.

Pakistan has very small contribution to the overall global greenhouse gas emissions; however, nation is committed to combating the climate change by adapting and through reducing the greenhouse gas emissions. Agriculture, livestock, energy, transportation, forestry, urban planning and industrial sectors are main areas where interventions are needed to mitigate the impact of climate change. Due to climate change and global warming, the glaciers are melting in Pakistan which causing the threat of water flow in several rivers of Pakistan. This effect will cause the lives of millions of people in Pakistan. A continued variation in the climate has become increasingly unstable over the past few decades, and this is expected to continue. The detrimental impact of climate change required a core priority in Pakistan on many issues in various sectors including agriculture, ecology, water and forestry. In the emission of greenhouse gasses, Pakistan has less contribution. Pakistan should play his major part in the global community as a responsible member tackling the issue of climate change that has emphasized and gave major attention to all sectors including forestry, livestock, agriculture and energy.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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