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An Econometric Analysis of Egypt's Cereal Production and Environmental Emissions for Food Security

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Abstract:
Agricultural production substantially contributes to human-induced greenhouse gas emissions that intensify global climate change. The increasing population, rising food demand, decreasing arable land, and declining soil fertility due to excessive fertilizer use have created a significant challenge to food security, ultimately leading to resource exploitation and environmental degradation. Egypt's economy relies significantly on the agricultural sector, which accounted for roughly 14% of the nation's total GDP in 2023; concurrently, it plays a considerable role in climate change through greenhouse gas emissions that adversely affect the environment. This research aimed to analyze the relationship between GHG emissions and the agricultural sector using the ARDL method of cointegration from 1990 to 2021. The findings revealed that the agricultural sector is the primary source of GHG emissions in Egypt. The expansion of cultivated area will lead to environmental degradation due to increased greenhouse gas emissions in the short term, while cereal production and the enlargement of land for cereals will cause elevated greenhouse gas emissions in the long term due to the utilization of traditional agricultural practices. The study recommended increasing credit to farmers and augmenting agricultural investments to establish modern, environmentally sustainable agricultural systems that enhance production and ensure food security through the application of contemporary agricultural technologies.

Keywords: GHG emissions, Agriculture, Cointegration, Egypt, Cereal, Food Security, ARDL.

1. Introduction

Agriculture provides the global food supply, utilizes 40% of the accessible land, and constitutes the largest sector and significant land use worldwide. Global economic growth is significantly reliant on the agricultural sector, particularly in developing nations, which encounter the most urgent challenges due to population growth and food security (Singh, Singh and Raghubanshi, 2019; Zerssa *et al.*, 2024). Therefore, conventional agriculture is highly productive; however, it concurrently produces significant global environmental and social repercussions. Its environmental impact includes greenhouse gas (GHG) emissions, deterioration of water quality, loss of soil, threats to livelihoods, and challenges to food security (DeLonge, Miles and Carlisle, 2016; Al Dirani *et al.*, 2021).

Food security (FS) has emerged as a formidable challenge due to the burgeoning population, escalating food demand, diminishing arable land, and declining soil fertility resulting from excessive fertilizer application. These factors ultimately led to the exploitation of available resources and environmental degradation (Koondhar *et al.*, 2021). The FAO defines FS as stable when all individuals possess physical and economic access to adequate, safe, and nutritious food that satisfies their dietary requirements and preferences (World Food Summit, 1996). Climate change (CC) extremes are anticipated to negatively impact the four pillars of food security: availability, access, utilization, and stability (Fróna, Szenderák and Harangi-Rákos, 2021). Furthermore, agricultural production significantly contributes to anthropogenic GHG emissions that exacerbate global CC (Duarte *et al.*, 2024; El-khalifa *et al.*, 2024; Raihan and Tuspekova, 2022b; Raihan *et al.*, 2023b; Raihan, Ibrahim and Muhtasim, 2023a). Due to the necessity of producing additional food to satisfy growing and evolving dietary requirements, a further increase in GHG emissions from agriculture is anticipated, where a 70% rise in food output is anticipated from 2005 to 2050 to feed a projected global population of 9.1 billion individuals while maintaining existing dietary patterns (El-khalifa *et al.*, 2024; Raihan *et al.*, 2023b).

Attaining the Sustainable Development Goals (SDGs) has emerged as a universal imperative for all nations, encompassing poverty alleviation, social equity, and the promotion of economic growth alongside environmental sustainability (Ibrahiem, 2020). Goal 2 of the SDGs seeks to eliminate hunger, attain FS, and foster sustainable agriculture by 2030. This entails ensuring sustainable food output systems through agricultural practices that enhance productivity, preserve ecosystems, and bolster resilience to CC, extreme weather, drought, flooding, and other disasters while continuously enhancing land and soil quality (United Nations, 2015). Nonetheless, despite initiatives undertaken in recent decades, food insecurity remains a critical concern in numerous nations, particularly in developing regions. In this context, achieving an appropriate equilibrium among the security of food and nutrition, environmental conservation, and CC reduction continues to pose significant challenges for food system sustainability and the stewardship of land and water resources (Grote *et al.*, 2021; Bouteska *et al.*, 2024).

Africa, while contributing less than 4% to global GHG emissions, remains vulnerable to the detrimental effects of CC variability (Olivier and Peters, 2020; Pickson and Boateng, 2022). Climate change and variability increase food production expenses, resulting in elevated consumer prices (Barrera and Hertel, 2021; Pickson and Boateng, 2022).

Egypt, as an African country, is susceptible to CC impacts. Egypt's economy is heavily dependent on the agricultural sector, which is crucial for the nation's food security, job creation, and economic advancement. Egypt's agricultural sector contributed approximately 17% in 1990 and about 14% in 2023 to the nation's total gross domestic product (GDP), which implies that its role in Egypt is decreasing (MPED, 2023). The agricultural sector employs approximately 55 percent of the labor force, making it a primary or secondary source of income for a substantial segment of the population. The principal agricultural crops include wheat, rice, maize, and sugarcane, along with vegetables, fruits, and dates (El-khalifa *et al.*, 2024). Egypt imports approximately 40 percent of its food needs, resulting in an annual food import expenditure of USD 2.5 billion (https://egyptssp.ifpri.info/).

Egypt's geographical position in a zone characterized by semi-arid to arid conditions, with 94.5% of its total area classified as desert, renders it susceptible to the impacts of CC (Abdelradi, 2020). Nevertheless, the agricultural sector is the primary source of food supply and FS (Javadi *et al.*, 2023); it substantially contributes to CC. GHG emissions from the agricultural sector comprise CO_2, methane, and nitrous oxide generated by crop and livestock output. Agricultural emissions totaled approximately

22.26 Mt CO_2e in 2021, accounting for 7% of the overall emissions for all sectors in 2021. This could adversely impact the productivity of key crops in Egypt (CAIT, 2021). The predominant sources of emissions in agriculture are enteric fermentation (40%), manure left on pasture (16%), chemical fertilizers (13%), rice cultivation (10%), manure management (7%), and the incineration of agricultural waste (5%). Consequently, livestock accounted for nearly two-thirds of total emissions (Meybeck and Gitz, 2010; Abd El Mowla and Abd El Aziz, 2020). However, agricultural emissions significantly harm the environment. The primary reason for this is the widespread use of conventional farming methods and nonrenewable fuels. This exacerbates the degradation of the ecosystem and makes it more difficult for Egyptians to obtain sufficient food and nutrition (Ali, Ullah and Khan, 2021; El-khalifa *et al.*, 2024).

As a result, the analysis of the relationship between GHG emissions and the agricultural sector can aid countries in recognizing opportunities to mitigate emissions and address FS issues, thereby supporting the development of an effective sustainable agriculture policy. In order to do this, the ARDL method of cointegration will be used to look at the long-term effects of Egypt's total cultivated area (TCA), cultivated area under cereal production (CAC), and cereal production (CP). We obtained time series data for Egypt from 1990 to 2021 from the WDI dataset.

2. Literature Review

This research aims to determine how cereal production impacts GHG emissions in Egypt in order to achieve FS. Consequently, we will divide the **literature into two categories:**

Firstly, studies have utilized econometric methodologies to investigate the long-term impacts of agricultural production on emissions:

Numerous studies have identified a link between agricultural production and environmental emissions in numerous nations. Several sources, including (Raihan and Tuspekova, 2022b; Raihan, Ibrahim and Muhtasim, 2023a; Duarte *et al.*, 2024; El-khalifa *et al.*, 2024), have indicated that the use of fossil fuels in agricultural production contributes to CC, which in turn has detrimental effects on the agricultural sector. Therefore, these studies reported an impact of the agricultural sector on the increase in GHG emissions, particularly CO_2.

Several studies, using methodologies such as ARDL, FMOLS, DOLS, and CCR, found a relationship between agricultural production and various agricultural indicators such as agricultural land, CPI, LPI, FP, energy use in agriculture, fertilizer consumption, financial development, agricultural land expansion, deforestation, and economic growth. These studies were conducted in China, Bangladesh, Ghana, Malaysia, and Egypt. Also, Burakov (2019), Naseem, Guang Ji and Kashif (2020), and Gokmenoglu, Taspinar and Kaakeh (2019), using the ARDL and NARDL methods, found that the agricultural sector and agricultural development are statistically significant determinants of carbon emissions in Russia, Pakistan, and China. In addition, Ullah *et al.* (2018) conducted the ARDL, and the Johansen cointegration test, revealing that six diverse types of agricultural activities contribute to increased CO_2E in Pakistan. Studies in Kazakhstan, Bangladesh, Ghana, and Egypt (Ibrahiem, 2020; El-khalifa *et al.*, 2024; Raihan and Tuspekova, 2022b; Raihan *et al.*, 2023b) have discovered that agricultural productivity, green investments, AVA, forest land, technological innovation, and alternative energy resources could potentially reduce CO_2E and enhance environmental quality over time.

However, other studies have confirmed the impact of CC and CO_2E on the production of major agricultural crops, including wheat, maize, sugarcane, and cotton. Rehman *et al.* (2022a), Rehman, Ma and Ozturk (2020), and Chandio *et al.* (2021) found that there was a negative short- and long-run relationship between the CO_2E and the main agricultural crops and land use. This implies that an increase in global CC will lead to a decrease in CP in Pakistan, as measured by the ARDL approach. In addition, the impact of CC on agricultural output, including the emissions of CO_2 and temperature, is positive in the long run in Egypt (Agbo, 2022; El-Khalifa, El-Gamal and Zahran, 2022). Furthermore, Koondhar *et al.* (2021) confirmed, using the ARDL model, that the long-term decrease in cereal food productivity in China will be caused by agricultural carbon emissions from the use of chemical fertilizers. Additionally, they highlighted that farmers can boost farm productivity in a healthy and sustainable setting by transitioning from chemical fertilizers to organic ones.

<u>**Secondly**, the studies that focused on CC, CP, and FS:</u>

Several studies examined the effects of CC on CP and FS in **Africa,** such as (Pickson and Boateng, 2022, Pickson *et al.*, 2023,Bouteska *et al.*, 2024, Mahrous, 2019, Edame *et al.*, 2011, Loum and Fogarassy, 2015, Sassi and Cardaci, 2012, and Yassin, 2016). Researchers discovered that rainfall significantly influences Africa's food security. A study demonstrated a positive correlation between rainfall and the growth of cereal crops. Increased precipitation and expansion of cultivated areas for cereal crops will be advantageous in ensuring global FS. Ethiopia demonstrated that agriculture is susceptible to climate fluctuations and variations in precipitation levels, which pose risks to the FS of rural communities. Furthermore, the cultivation of barley in particular significantly contributes to the exacerbation of food insecurity. Nevertheless, they do not observe a significant and consistent influence of temperature on FS over a prolonged period. However, in the short term, extreme temperatures do hinder food security. The temperature has a negative impact on FS in both the EAC region and SSA. They demonstrated that the economic consequences of CC on FS and agricultural productivity have enduring effects on the sustainability of existing global agroecosystems and the future availability of food. Furthermore, projections indicate that agricultural production will need to increase by at least 70% by 2050 to meet the demands caused by population growth and food consumption patterns. Furthermore, the production of cereals such as millet, maize, and wheat will be impacted by CC in the Gambia and Sudan. Climate variables like temperatures and rainfall influence CP, and these nations are increasingly vulnerable to the effects of CC on food availability and access. Additionally, it was discovered in Egypt that the current policies are ineffective due to the absence of a pertinent legal framework, insufficient collaboration among stakeholders, and limited awareness regarding the impact of CC on FS.

Moreover, some studies indicated that the production and yield of cereals, specifically rice and maize, play a beneficial role in reducing food insecurity, particularly in South Asia (Mughal and Fontan Sers, 2020). However, Javadi *et al.* (2023) have verified that FS will encounter significant obstacles due to anticipated changes in the climate, resulting in a decline in both food supplies and the consumption of goods and services in Iran, particularly under the worst scenarios. Furthermore, the matter of FS is gaining more attention in middle-income countries, such as Tunisia (Jeder, Hattab and Frija, 2020).

This study demonstrates a substantial and enduring relationship between FS and land under cereals, as well as the impact of inflation and food imports. These findings are particularly relevant in the context of potential climate change-related shifts. These results validate that the problem of FS is a matter of peril in both the short and long run. Gbegbelegbe *et al.* (2014), found that extreme weather events in the USA can decrease global maize production, thereby negatively impacting FS in developing countries. If extreme weather conditions affect global FS in 2050 without any worldwide adaptation measures to address CC, the consequences would be more severe.

Furthermore, there is a study that specifically focused on the measurement of risks associated with the cereal supply, particularly in countries that heavily rely on cereal imports (Ali, Manikas and Sundarakani, 2022) discovered that the risk of wheat supply from external sources has risen in the United Arab Emirates (UAE) since 2017. This is due to the heavy reliance on one or two sources that offer competitive prices for cereal imports, which in turn increases the risk of external cereal supply.

Previous research employed diverse methodologies to investigate the correlation between agricultural production and the increase in GHG emissions over both the short and long run. The relationship has had a substantial influence on the food insecurity of cereal crops, particularly in developing nations. These studies suggest that it is crucial to implement various policy measures, such as increasing funding for research and development in CC adaptation and mitigation in agricultural production and FS, as well as enhancing environmental quality. Therefore, this study extends the current literature by providing insights into the correlation between GHG emissions, CP, and their impact on FS in Egypt.

3. Methodology

3.1. Data sources

This research examines the dynamic impacts of TCA, CAC, and CP in Egypt on GHG emissions. We obtained the time series data for Egypt from 1990 to 2021 from the WDI dataset.

We transform the variables into logarithms to confirm the normal distribution of the data. **Table 1** displays the variables, their logarithmic representations, units, and data sources. This study analyzes GHG emissions as the dependent variable, while TCA, CAC, and CP serve as independent variables. We also used EViews software version 12 for data processing and analysis.

Table 1: Variables and data sources

Variables	Definition	Unit	Sources
Ln GHG E	Total greenhouse gas emissions	KT of CO_2 equivalent	World Bank (2021)
Ln TCA	Total cultivated area	Hectares	World Bank (2021)
Ln CAC	Cultivated area under cereal production	Hectares	World Bank (2021)
Ln CP	Cereal production	Tons	World Bank (2021)

3.2. Econometric Model

This study looked at how the relationship between Egypt's TCA, CAC, and CP affects GHG emissions in the long term. The model used GHG emissions as an environmental indicator.

The formula delineates the relationship between variables and GHG E.

$$\mathbf{GHG\ E_t = \mathit{f}\ (TCA_t;\ CAC_t;\ CP_t)} \quad (1)$$

$$\mathbf{Ln\ GHG\ E_t = \beta_0 + \beta_1\ Ln\ TCA_t + \beta_2\ Ln\ CAC_t + \beta_3\ Ln\ CP_t + \varepsilon_t} \quad (2)$$

where β_0 and ε_t represent the intercept and error term, respectively. Furthermore, β_1, β_2, and β_3 represent the coefficients.

3.3. Testing for data stationarity

In order to confirm that the variables used in the regression are stationary and to reduce spurious regression, the unit root test must be performed. To achieve this, we use stationary processes to estimate the relevant equation and to differentiate the variables (Robinson and Mahadeva, 2004). Establishing the order of integration is essential prior to assessing cointegration among the variables. Furthermore, to precisely ascertain the integration order of a series, it is imperative to utilize multiple unit root tests. The efficacy of unit root tests varies based on sample size. Numerous of research, including those by Saboori, Rasoulinezhad and Sung (2017), Adebayo *et al.* (2021), and Raihan *et al.* (2022a), have underscored the necessity of employing multiple unit root tests. This study utilized the ADF and PP tests (Dickey and Fuller, 1979; Perron, 1988) to detect the existence of an autoregressive unit root.

The following assumptions underpin the ADF and PP tests:

The investigational series is non-stationary, suggesting the existence of a unit root, according to the null hypothesis (H_0). The alternative hypothesis (H_1) states that there is no unit root in the studied series since it is stationary.

3.4. ARDL bounds testing

The Autoregressive Distributed Lag (ARDL) bounds test, formulated by Pesaran and Shin (1999) and Pesaran, Shin and Smith (2001), serves as a technique to assess the existence of cointegration among the series. This test for cointegration is better in many ways than other tests, such as Engle and Granger cointegration (Engle and Granger, 1987) and Johansen and Juselius cointegration (Johansen and Juselius, 1990), which find the same level of integration. **Firstly,** time series data exhibiting a combination of integrated orders at I(0), I(1), or both can employ the ARDL bounds test, as it does not require any specific assumptions. **Secondly**, it demonstrates a significantly greater degree of reliability, especially when handling small samples. **Finally**, it offers an accurate evaluation of both short-term and long-term projections.

Formula (3) represents the ARDL bounds test:

$$\mathbf{\Delta Ln\ GHG\ E_t = \alpha_0 + \sum_{k=1}^{\rho} \alpha_{1k}\, \Delta Ln\ GHG\ E_{t-k} + \sum_{k=0}^{\rho} \alpha_{2k}\, \Delta Ln\ TCA_{t-k} + \sum_{k=0}^{\rho} \alpha_{3k}\, \Delta Ln\ CAC_{t-k} + \sum_{k=0}^{\rho} \alpha_{4k}\, \Delta Ln\ CP_{t-k} + \beta_1 Ln\ GHGE_{t-1} + \beta_2\, LnTCA_{t-1} + \beta_3\, LnCAC_{t-1} + \beta_4 LnCP_{t-1} + \varepsilon_t} \quad (3)$$

where $\triangle$ denotes the first difference operator, t-1 signifies time lag, and εt indicates the error term. α and β are the coefficients to be estimated.

The ARDL bounds test utilizes the F-statistic, with critical values proposed by Pesaran and Timmermann (2005). The Bound F test is utilized to evaluate the presence of a long-term relationship among the variables. The H_1 indicates cointegration between Ln GHG E and the variables in the long term, while the H_0 asserts the absence of such a relationship. The computed F-statistic is being contrasted with critical values at the upper bound I(1) and lower bound I(0), as referenced in Narayan (2005) and Pesaran, Shin and Smith (2001). If the estimated F-statistic exceeds the critical values, the H_0 is rejected, signifying the existence of a long-term cointegration relationship among the variables. If the computed F-statistic falls short of the critical values, we reject H_1, suggesting a lack of cointegration. If the calculated F-statistic resides within the limits set by the lower and upper boundaries, the existence of cointegration among the variables remains indeterminate.

The following phase of the ARDL model is to estimate the error correction model (ECM) and short-run coefficients, following the bound test's confirmation of a long-run relationship.

$$\Delta \mathbf{Ln\ GHG\ E_t} = \boldsymbol{\alpha_0} + \sum_{k=1}^{\rho} \boldsymbol{\alpha_{1k}}\, \Delta \mathbf{LnGHG\ E_{t-k}} + \sum_{k=0}^{\rho} \boldsymbol{\alpha_{2k}}\, \Delta \mathbf{LnTCA_{t-k}} + \sum_{k=0}^{\rho} \boldsymbol{\alpha_{3k}}\, \Delta \mathbf{LnCAC_{t-k}} + \sum_{k=0}^{\rho} \boldsymbol{\alpha_{4k}}\, \Delta \mathbf{LnCP_{t-k}} + \boldsymbol{\lambda} \mathbf{ECM_{t-1}} + \boldsymbol{\varepsilon_t} \quad \mathbf{(4)}$$

where λ represents the speed of adjustment (ECM), it should be negative and statistically significant (Granger, 1988; Khan, Abdullah and Samsudin, 2016). It measures the speed with which the dependent variable and independent variables balance from short-run to long-run.

After estimating the ARDL model, we conducted several diagnostic tests to confirm the accuracy of the coefficient estimates. We employed the Breusch-Godfrey serial correlation (LM Test) (Godfrey, 1978), the Jarque-Bera normality test (Jarque and Bera, 1980), and the Breusch-Pagan-Godfrey test (Engle, 1982) to detect autocorrelation, normality distribution, and heteroscedasticity, respectively. We assessed the stability of the ARDL model using the cumulative sum and cumulative sum of squares of residuals. Both CUSUM and CUSUMSQ must remain within the critical thresholds to achieve stability at the 5% level of significance (Granger, 1988; Borensztein, Gregorio and Lee, 1998).

3.5. Granger causality test

This research employed the paired linear Granger-causality test, introduced by Granger (Granger, 1969), to investigate the causal relationships among the variables. The aim was to find out if a causal relationship exists among the variables. Predictive analysis underpins the statistical concept of Granger causality. It presents numerous advantages relative to alternative methodologies of time-series analysis (Winterhalder *et al.*, 2005). If time series Y can predict the future of time series X, then Y is said to "Granger-cause" X. Let the time series of these two variables have a data length T, with their values at time t represented by Xt and Yt (t=1,2,…,T). We can model them using a bivariate autoregressive (AR) model:

$$\mathbf{X_t} = \sum_{\square=\square}^{\square} (\mathbf{a_{11,l}\, X_{t-l}} + \mathbf{a_{12,l} Y_{t-l}}) + \boldsymbol{\varepsilon_t}$$

$$\mathbf{Y_t} = \sum_{\square=\square}^{\square} (\mathbf{a_{21,l}\, X_{t-l}} + \mathbf{a_{22,l} Y_{t-l}}) + \boldsymbol{\xi_t} \quad \mathbf{(5)}$$

where ρ is the model order, aij,l (i,j=1,2) are coefficients of the model, and ε_t and ξ_t denote residuals. Ordinary least squares can estimate the coefficients, and the F-statistic can establish the Granger causality between X and Y (Tam, Chang and Hung, 2013). The Granger causality test rejects the H_0 if the F-statistic value is less than the 5% significance level. This signifies the presence of a causal relationship among the examined variables.

4. Results

4.1. Descriptive and correlations analysis

The findings of the descriptive analysis for the variables are shown in **Table 2**. It includes the estimated values of skewness, probability, kurtosis, and Jarque-Bera normality tests. Each variable comprises 32 observations of time series data covering the period from 1990 to 2021 for Egypt. The negative skewness of the variables suggests that they all exhibit a normal distribution. The kurtosis analysis showed that TCA has a leptokurtic distribution, while the other variables have platykurtic distributions, which means they are not normal, since their values are less than 3 (Westfall, 2014). Moreover, the findings of the Jarque-Bera test suggest that all variables demonstrated a normal distribution.

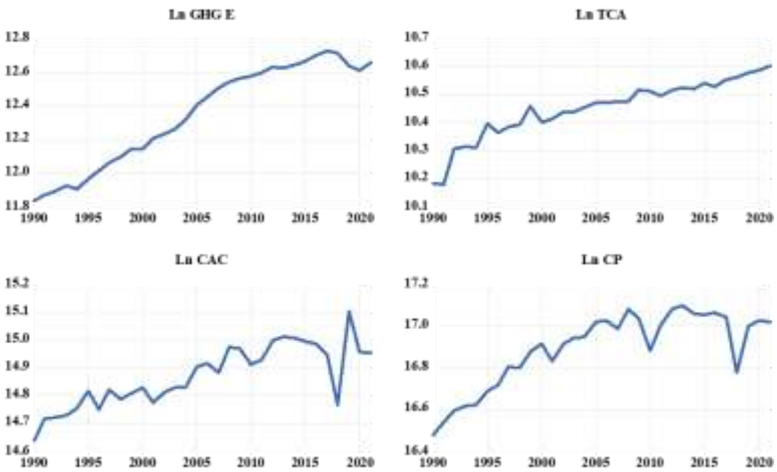
Furthermore, **Table 2** displays the correlation analysis conducted to ascertain the relationships among variables. The results demonstrate a correlation among all variables. This points to a highly positive correlation among the variables, suggesting that raising the value of one causes the other to rise as well and vice versa.

Furthermore, the study variables' annual trends are shown in **Figure 1.** The data indicates a rising trend in GHG emissions and TCA, while the CAC and CP in Egypt exhibit fluctuations over the years. Moreover, the time series of the TCA indicates an expansion of agricultural land in recent years, driven by the increasing demand for food production resulting from rapid population growth. Agricultural land expanded from 26.5 thousand square kilometers in 1990 to 40.3 thousand square kilometers in 2021, signifying an escalating emission intensity from Egypt's agricultural sector.

Table 2: Descriptive analysis and the matrix of correlations

Variables	Mean	Median	Std. D	Skewness	Kurtosis	Jarque-Bera
Ln GHG E	12.349	12.429	0.302	-0.336	1.590	3.255 (0.196)
Ln TCA	10.445	10.471	0.106	-0.920	3.478	4.823 (0.089)
Ln CAC	14.871	14.857	0.110	-0.006	2.167	0.926 (0.629)
Ln CP	16.893	16.945	0.178	-0.829	2.495	4.01 (0.135)
The matrix of correlations						
	Ln GHG E	**Ln TCA**	**Ln CAC**	**Ln CP**		
Ln GHG E	1					
Ln TCA	0.923	1				
Ln CAC	0.858	0.834	1			
Ln CP	0.872	0.869	0.892	1		

Figure 1: The study variables exhibit temporal trends over time



Source: World Bank

4.2. Outcomes of unit root tests

To find out how well the variables fit together, this study used the ADF and PP as unit root tests. **Table 3** displays the results of the ADF and PP tests, taking into account trends and constants. Both tests demonstrate that Ln GHG E and Ln CP were non-stationary at the level but achieved stationarity at the first difference. Conversely, Ln TCA and Ln CAC were stationary at the level and continued to be stationary at the first difference. This signifies that the variables exhibit a combination of integrated orders I(0) and I(1) with significance levels of 1% and 5%. This offers a legitimate justification for employing the ARDL cointegration test.

Table 3: The outcomes of unit root tests

Variables	At level		At 1st difference	
	ADF	PP	ADF	PP
Ln GHG E	0.255	0.137	-4.221**	-4.087**
Ln TCA	-5.275***	-4.285**	-6.746***	-8.768***
Ln CAC	-5.353***	-5.378***	-6.901***	-19.35***
Ln CP	-2.612	-2.409	-6.268***	-18.32***

Notes: The lag order selection according to the (SIC) Schwarz information criterion. ADF refers to Augmented Dickey-Fuller and PP refers to Phillips-Perron. ** and *** indicate the 5% and 1% statistical significance levels, respectively.

4.3. The outcomes of ARDL bounds testing

The research uses the ARDL bounds test to determine if cointegration is present after confirming the series' stationarity properties. To find out if there is a significant long-run relationship among parameters, we do the bound F test. If the computed F-test statistic exceeds both the lower and upper bounds, it confirms the relationship. The numbers in **Table 4** show that the estimated F-statistic value of 15.56 is higher than the upper bound's critical values. This indicates a long-term link among the variables Ln GHG E, Ln TCA, Ln CAC, and Ln CP. The ARDL bounds test predicts an increase in GHG emissions in the future.

Table 4. The outcomes of ARDL bounds test

F-Statistic	Significance levels	I(0) Bound	I(1) Bound
	10%	2.37	3.2
15.561* **	5%	2.79	3.67
	2.5%	3.15	4.08
K 3	1%	3.65	4.66

Notes: *** indicates significance at the 1% level.

Furthermore, **Table 5** demonstrates that the selected ARDL (1,1,2,0) yielded the model's long-term and short-term results, particularly those related to statistically significant variables. **Table 5** illustrates a significant and positive long-run elasticity between CP and GHG emissions. A 1% increase in CP leads to a 1.63% rise in GHG emissions. The 1% increase in cereal cultivation areas in Egypt is not statistically significant, yet it would lead to a 0.63% rise in GHG emissions. A 1% increase in the TCA in Egypt will result in a 0.39% reduction in GHG emissions.

CP is the principal factor influencing GHG emissions, resulting in an approximate increase of 1.63%. Thus, an increase in CP in Egypt will lead to heightened GHG emissions and ensuing environmental degradation. The agricultural output volume of cereal crops could potentially lead to increased GHG emissions, heightened use of mineral fertilizers, and increased pesticide application, among other factors. Therefore, we ought to examine these reasons and their implications in subsequent research.

Table 5. The findings of ARDL model in the long and short run

Dependent variable: Ln GHG E; selected model: ARDL (1,1,2,0)			
Long-run			
	Coefficients	**Std. Error**	**t-statistic**
Ln TCA	-0.391	0.961	-0.407
Ln CAC	0.625	0.767	0.814
Ln CP	1.627	0.613	2.654**
Short-run			
△ Ln TCA	0.255	0.105	2.437***
△ Ln CAC	-0.261	0.054	-4.816***
ECM(-1)		**-0.178*** **	

Notes: ** and *** indicate the 5% and 1% statistical significance levels, respectively.

Moreover, **Table 5** indicates that the coefficient of the ECM signifies the presence of a short-run equilibrium relationship. We employ this model to analyze the cointegrating relationships among the variables (Jalil, Mahmood and Idrees, 2013; Kılıçarslan and Dumrul, 2017; El-Khalifa, Zahran and Ayoub, 2022). The ECM coefficient exhibited a negative value and attained statistical significance at the 1% level. We adjusted the model from a short-term to a long-term equilibrium by 18% and confirmed the cointegration of the variables. The short-run elasticity indicates a significant and positive relationship between the TCA in Egypt and GHG emissions. A 1% raise in TCA leads to a 0.26% increase in released GHG E. The expansion of cultivated land for cereal production significantly exacerbates GHG emissions. A 1% raise in the CAC leads to an approximate 0.26% reduction in GHG emissions in the short term.

4.4. Diagnostic & stability tests

Various tests evaluated the robustness and precision of the ARDL model. **Table 6** presents the test results, including the Jarque-Bera test, which indicates a normal distribution. The LM Test also showed that there were no serial correlations between the residuals and that the model did not have any conditional heteroscedasticity. For accurate statistical inferences and unbiased estimate-gathering, the ARDL model proved to be robust and fulfilled all diagnostic requirements.

Several authors who employed the same diagnostic tests in previous studies also validated the model's goodness and suitability (Ibrahiem, 2020; Rehman, Ma and Ozturk, 2020; Chandio *et al.*, 2021; Koondhar *et al.*, 2021; Agbo, 2022; El-Khalifa, Zahran and Ayoub, 2022; El-khalifa *et al.*, 2024; Raihan and Tuspekova, 2022b; Raihan, Ibrahim and Muhtasim, 2023a).

This research used the CUSUM and CUSUMSQ tests to check how stable the parameters were in the ARDL (1,1,2,0) model. This confirmed that the variables' parameters would stay stable over the long term (Pesaran and Pesaran, 1997). Both the CUSUM and CUSUMSQ exhibit statistical significance at the 5% significance level, as illustrated in **Figures 2 and 3**. By maintaining constant estimated coefficients for all variables over the course of the study, we have demonstrated that the chosen ARDL model is stable.

These results indicate that the ARDL model confirms the long-term relationship among the variables and GHG emissions. A lot of research studies have used the CUSUM and CUSUMSQ tests to check the model's stability, goodness, and fitness (Ibrahiem, 2020; Rehman, Ma and Ozturk, 2020; Chandio *et al.*, 2021; Koondhar *et al.*, 2021; Agbo, 2022; El-Khalifa, Zahran and Ayoub, 2022; Raihan and Tuspekova, 2022b; Raihan, Ibrahim and Muhtasim, 2023a).

Table 6. The results of diagnostic tests

Tests	Coefficient	*p*-value	Results
Jarque-Bera	0.099	0.952	Residuals are normally distributed
Breusch-Godfrey LM test	0.239	0.789	No serial correlation
Breusch-Pagan-Godfrey test	0.881	0.537	No heteroscedasticity

Notes: the *p*-value is the probability value**.**

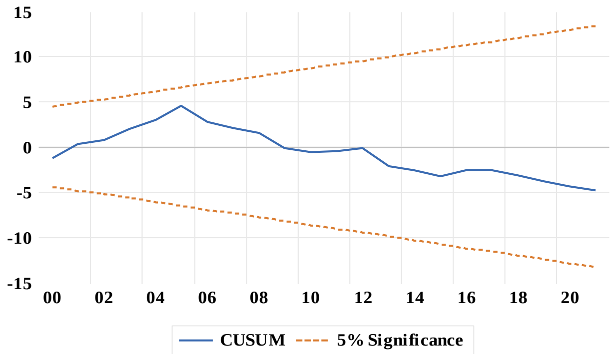


Figure 2. Plot of CUSUM test

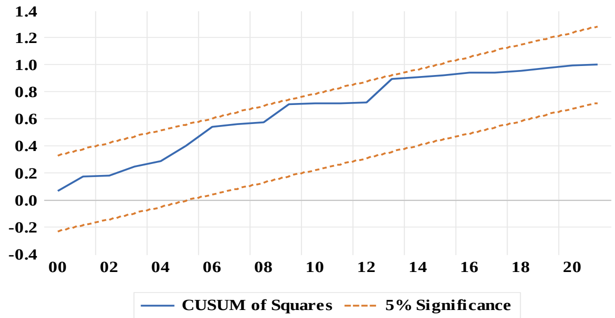


Figure 3. Plot of CUSUMSQ test

4.5. The Granger test for causality

The F-statistic indicates the existence of causality based on the correlation among the variables. **Table 7** presents the description of pairwise Granger causality, detailing the directional causality between the variables, indicated as left to right (→) and right to left (←). The results of the pairwise Granger causality test indicate unidirectional causality between Ln GHG E and Ln TCA, Ln GHG E and Ln CAC, Ln CP and Ln GHG E, and Ln TCA and Ln CAC. The statistically significant F-statistic corroborates this.

Both the overall cultivated area and the specific cultivated area for cereal production in Egypt significantly contribute to GHG emissions. Moreover, cereal cultivation contributes to the emission of GHGs. The cultivation of cereal crops contributes to the expansion of the overall cultivated area in Egypt.

Table 7: The outcomes of Pairwise Granger Causality tests

Null hypothesis	F-statistic	Prob.	Direction
Ln TCA does not Granger Cause Ln GHGE	0.191	0.666	-
Ln GHGE does not Granger Cause Ln TCA	5.087	0.032**	GHGE←TCA
Ln CAC does not Granger Cause Ln GHGE	2.287	0.142	-
Ln GHGE does not Granger Cause Ln CAC	24.81	0.000***	GHGE← CAC
Ln CP does not Granger Cause Ln GHGE	14.33	0.000***	CP→ GHGE
Ln GHGE does not Granger Cause Ln CP	2.817	0.104	-
Ln CAC does not Granger Cause Ln TCA	1.657	0.208	-
Ln TCA does not Granger Cause Ln CAC	10.42	0.003***	TCA← CAC
Ln CP does not Granger Cause Ln TCA	0.614	0.439	-
Ln TCA does not Granger Cause Ln CP	3.659	0.066	
Ln CP does not Granger Cause Ln CAC	2.043	0.164	-
Ln CAC does not Granger Cause Ln CP	0.304	0.585	

***rejection of the null hypothesis at 1%; **Rejection of the null hypothesis at 5% level.

5. Discussion

The research's results reveal that the agricultural sector is a significant source of GHG emissions in Egypt. The results indicated a positive correlation between total cultivated area and GHG emissions in the short term, suggesting that an expansion of cultivated land will result in environmental degradation through heightened GHG emissions attributed to traditional agricultural practices. Raihan *et al.* (2023b), Asumadu-Sarkodie and Owusu (2016c), Raihan *et al.* (2022a), and El-khalifa *et al.* (2024) all reported a positive correlation between the expansion of agricultural land and CO_2 emissions. Egypt may require additional arable land in the future to guarantee FS for its growing population. It is essential to implement policies, strategies, and action plans for land management to enhance agricultural production and ensure FS through the utilization of modern agricultural technologies.

Furthermore, this study found a positive correlation between CP, the CAC, and GHG emissions. The results indicate that heightened CP and expanded cultivated land for cereals will result in elevated GHG emissions in the long run. Raihan *et al.* (2023b) and Asumadu-Sarkodie and Owusu (2016c) corroborate our findings. On the other hand, Koondhar *et al.* (2021) indicated that agricultural GHGs contribute to CC, which directly diminishes crop production, as agriculture is a sensitive industry; fluctuations in temperature and precipitation consequently impact crop yield. Bouteska *et al.* (2024) confirmed the need to utilize advanced agricultural techniques to mitigate the impacts of climate shocks. Ethiopia must implement enhanced irrigation systems to facilitate the cultivation of diverse crops that are resilient to climatic variations. Furthermore, the agricultural sector significantly contributes to CO_2 emissions in Pakistan (Hussain *et al.*, 2018).

This outcome suggests that innovative technologies should replace traditional agricultural methods to enhance agricultural output, reduce emissions, and safeguard food security. We need to encourage farmers to use more modern farming methods and utilize modern agro-technologies like high-yield and disease-resistant crop varieties to increase cereal agricultural output.

The adoption of advanced technology by smallholder farmers can improve their income and livelihoods (Adenle, Wedig and Azadi, 2019). Consequently, it necessitates various strategies to train farmers in implementing sustainable agriculture, utilizing their traditional knowledge to enhance grain production with reduced external inputs.

In this context, credit to the agricultural sector serves as a catalyst for enhancing farmers' engagement in agricultural finance and agricultural transformation, facilitating the adoption of modern technologies and the efficient utilization of resources. Chandio *et al.* (2021) discovered that financial development had a positive influence on CP in the long term in Pakistan, facilitating sustainable growth, technology adoption, and poverty alleviation (Das and Hossain, 2019). Bouteska *et al.* (2024) emphasized the necessity of facilitating access to finance and coordinating the integration of smallholder farmers into larger cooperatives and groups with government support in Ethiopia.

Egyptian agriculture is characterized by small farms and conventional practices, which only need minor adjustments to meet international standards (Abdelgawwad and Kamal, 2023). Al Dirani *et al.* (2021) reported that small family farms possess significant knowledge regarding the causes of CC and susceptibility to food insecurity, prompting them to implement various adaptation and mitigation strategies. Farmers frequently employ crop-based adaptation strategies, such as mixed cropping, crop rotation, and intercropping, as risk mitigation measures. Moreover, they indicated that nations in semi-arid and arid regions experience significant water scarcity, rendering sustainable agricultural practices essential for adapting to the detrimental impacts of CC on agriculture. Egypt is situated in an arid to semi-arid zone, where climate variability significantly affects the productivity of these lands (El-khalifa and Zahran, 2022). The World Bank indicates a decreasing contribution of Egypt's agriculture sector to its GDP over time (https://databank.worldbank.org/). The decline is attributable to decreasing agricultural productivity, low labor productivity, reliance on traditional agricultural methods, and the effects of CC (El-khalifa *et al.*, 2024).

Nassr *et al.* (2021) indicated that CC will result in a reduction in aggregate food production by 3% in 2030 and 3.8% in 2050, attributable to diminished productivity per unit area of key cereal crops (wheat, maize, and rice) due to climatic alterations. A decline in aggregate food production will result in an increase in the overall price level, causing a reduction in per capita food consumption by approximately 1.7% in 2030 and 3.8% in 2050. Rising temperatures pose a significant challenge to the production of strategic crops, such as cereals, which the IPCC indicated will experience a decline in yield; additionally, CC will increase the risk of hunger and malnutrition by 20% by 2050 (IPCC, 2017).

Egypt confronts numerous challenges regarding food and nutrition security due to inefficient agricultural resource utilization, ineffective policies, subpar labor skills, deficient market information systems, escalating CC impacts, poverty, reliance on rainfall for irrigation, and lack of infrastructure. Thus, these factors contribute to diminished agricultural output and escalating environmental degradation, which adversely affects agrarian livelihoods (Abdelradi, 2020).

In this context, achieving an appropriate equilibrium between food and nutritional security, environmental protection, and CC mitigation continues to pose significant challenges for sustainable food systems and the management of land and water resources (Grote *et al.*, 2021; Bouteska *et al.*, 2024).

Therefore, Javadi *et al.* (2023) emphasized the necessity of sustaining and augmenting the production of strategic crops, such as wheat and rice, to attain FS. Additionally, implement drought- and heat-resistant cultivars, alter the planting dates of these crops to mitigate adaptation to moisture stress, utilize modern irrigation systems, and enhance farmers' incomes.

To attain sustainable global food and nutritional security, it is imperative to implement sustainable agricultural practices that enable increased production while minimizing the consumption of natural resources. A variety of approaches, including water-saving agronomic techniques, integrated nutrient management, biofertilizers, precision agriculture, organic farming, conservation agriculture for soil management, and integrated nutrient management systems, can achieve the core goals of sustainable agriculture (Mutyasira, Hoag and Pendell, 2018; Zerssa *et al.*, 2024).

6. Conclusion

This study indicated that increased cereal production will lead to environmental degradation due to elevated greenhouse gas emissions over time, stemming from conventional agricultural practices. Egypt can swiftly address food security challenges by implementing sustainable production practices, including the reduction of fertilizer usage and ensuring the availability of high-quality seeds that comply with international standards.

Consequently, innovative technologies ought to supplant conventional agricultural practices to improve agricultural productivity, diminish emissions, and ensure food security. This may occur by providing additional credit to farmers, enabling them to swiftly adapt to climate change, acquire enhanced inputs, and implement cleaner technologies to sustainably increase cereal production.

Therefore, this study suggests that financial institutions provide increased credit to farmers for sustainable agricultural production. Furthermore, augmenting agricultural investments, whether public or private, in research and development is essential to establish modern, environmentally sustainable agricultural systems that enhance production and ensure food security through the application of contemporary agricultural technologies.

Moreover, Egyptian policymakers must formulate new investment strategies to implement climate-smart technologies and adopt innovative production practices that could enhance agricultural yield and mitigate environmental degradation. This includes supplying farmers with crop varieties resistant to heat and drought, refining agricultural practices, and educating farmers. This can also benefit family farming, which constitutes the majority of farms in Egypt, by reducing production costs and enhancing competitiveness, thereby enabling them to withstand fluctuating market conditions and economic hardships.

As a result, smart agriculture reduces GHG emissions, increases agricultural income and productivity, and adapts to CC, thus achieving the economic, social, and environmental goals of sustainable agricultural development.

Abbreviations

GHGs: Greenhouse gases; CC: Climate Change; FS: Food security; SDGs: Sustainable Development Goals; CO_2: Carbon dioxide; CP: Cereal production; EAC: East African Community; SSA: Sub-Saharan Africa; WDI: World Development Indicators; FAO: Food and Agricultural Organization of the United Nations; CO_2E: Carbon dioxide emissions; AVA: Agriculture value added; CPI: Crop production index; FP: Fisheries production; GDP: Gross domestic product; LPI: Livestock production index; ADF: Augmented Dickey-Fuller; PP: Phillips-Perron; IPCC: Intergovernmental Panel on Climate Change.

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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