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Tracking the carbon footprint of agriculture in Saudi Arabia to promote sustainable food systems

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Growing global population and climate change concerns have caused major challenges for sustainable food production to meet the growing food demand. High mechanization, drought intensity, fertilizer application, energy use, and irregular climate change adaptation are the major challenges faced by agriculture. In the Kingdom of Saudi Arabia, the climate is very harsh, and the country depends highly on agriculture to meet domestic food demands. This generates major challenges for the agricultural system to produce sufficient quantities of food with minimal carbon footprints. Therefore, this study aims to analyze the impact of growing mechanization (Mech), water productivity (WP), climate change technology adaptation (CCA), fertilizer consumption (FC), agriculture growth (AG), and energy consumption in agriculture (ENA) on CO_2 emissions in agriculture in both the short and long run. For this purpose, an autoregressive distributed lag (ARDL) model was applied to the data for 1992–2021. According to the unit root test, all variables were integrated in order I(1), and the ARDL bound test for the cointegration tests ensured the long-run relationships among the variables. Moreover, the ARDL model passed all diagnostic tests, and CUSUM and CUSUMQ confirmed the stability of the model. The findings revealed that Mech has a strong negative impact in the long run while significant positive impact in the short run on CO_2 emission. Both WP and CCA significantly reduced CO_2 emissions in both the short and long run. FC causes an increase in CO_2 emissions in both the short and long run. AG reduces CO_2 emissions, whereas ENA increases CO_2 emissions only in the long run. The findings suggest that the government should focus on efficient and eco-friendly mechanization, energy sources, adoption of efficient irrigation systems, and promote R&D for advanced climate change-oriented technologies to enhance agricultural environmental sustainability by reducing CO_2 emissions in agriculture.

KEYWORDS

carbon footprints, climate change adaptation, resilient food systems, sustainable agriculture, sustainable food systems

Introduction

Global food systems operate under extreme stress caused by population growth and increasing food demand, along with climate change. These factors have stretched the systems to the edge, or beyond, the sustainable consumption of natural resources, causing substantial losses to the natural environment. Global food consumption is projected to increase

temperatures by almost 1 °C by the end of this century, negatively affecting worldwide efforts to sustain a temperature increase below 1.5 °C (Ivanovich et al., 2023). Food systems are the most significant users of global natural resources, with consumption of 70% freshwater resources, occupying half of the land worldwide. This causes water pollution in watersheds and coastal areas (Mekonnen and Hoekstra, 2018). Global food requirements will require a more than 50% increase in agricultural resource usage by 2050 (Springmann et al., 2018). There is an urgent need to change the global food system owing to the expanding dietary needs and requirements for environmental preservation. The issues faced by traditional food systems are diverse and overlapping, and hence demand a transition toward sustainable food systems.

A sustainable food system protects global food security and nutrition while maintaining essential economic and environmental resources for future generations (FAO, 2020). A food system is a complex network of interdependent elements. Sustainable food systems require attention to ensure food security, economic viability, environmental sustainability, and resource conservation (Cui et al., 2023). Growing household income increases the demand for protein-based foods as well as the total caloric consumption. Refined sugar, fats, alcohol, and oils particularly face higher demand due to increased household income (Tilman and Clark, 2014). Without serious efforts to change dietary patterns, blue water use will grow by 34%, agricultural land use will expand by 9%, and greenhouse gas emissions will increase by 44% worldwide, especially in sub-Saharan Africa, by 2050 (Philippidis et al., 2021). Steady changes in eating habits represent a decisive factor in decreasing the carbon footprints of food systems. During sustainability efforts, the three main goals of health, economy, and environment often develop opposing priorities. Protected human health and environmental conservation demand additional resources that create economic instability owing to scarce resource availability. Multiple environmental and social dimensions, together with economic and health aspects, must be evaluated for food system sustainability to fully understand the balancing effects and shared advantages of sustainable food systems (Zhang et al., 2021).

Sustainable food systems minimize environmental consequences and guarantee nutritional security and dietary needs for the coming generations (CFS, 2020; FAO, 2018). The ecological footprint of the sustainable systems should be neutral or positive. The reduction in greenhouse gas emissions will rely on the forest preservation as well as livestock management, sustainable agricultural activities, and carbon sequestration conservation practices (Li et al., 2024; RFF, 2023). The implementation of sustainable land use entails three major strategies, namely, the enhancement of agricultural productivity (MEA, 2005); the integration of trees and shrubs into the farming systems (Altieri et al., 2015); and the encouragement of vertical and urban agriculture to reduce land use (Benke and Tomkins, 2017). Efficient water management consists of effective irrigation methods (Younes et al., 2024) and the growth of plants that require small amounts of water (Jägermeyr et al., 2015). Biodiversity is achieved when farmers combine multiple crops, minimize synthetic chemicals in farming (Altieri et al., 2015), and restore wildlife habitat areas inside agricultural spaces (MEA, 2005).

The carbon footprint of agriculture has reached significant levels due to the massive consumption of global freshwater resources and land occupation (Ritchie et al., 2022; Benton et al., 2021). Multiple forces function as connected elements that lead to biodiversity depletion and climate change (Benton et al., 2021; Hoekstra and Mekonnen, 2012; UNEP, 2021). Food systems released 17 billion tons of carbon dioxide equivalent greenhouse gas emissions in 2019, which corresponded to 31% of the total global emissions (Xu et al., 2021). CO_2 emissions originate from deforestation, while methane from livestock farming and nitrous oxide result from the use of fertilizers (Li et al., 2024; EPA, 2023; RFF, 2023). Habitat loss from expanding agricultural land operations represents the primary cause of extinction threats to 86% of the rare species (UNEP, 2021).

The agricultural sector in Saudi Arabia has made substantial progress by implementing technological developments that strengthen domestic food availability (Elbashir, 2024). The major agricultural products that are produced in Saudi Arabia include dates, along with watermelon and barley, wheat, potatoes, and tomatoes (Abdalla, 2024). The food production has increased dramatically to ensure food security, and this has placed a large burden to the little water available in Saudi Arabia (Climate Transparency, 2020). Such state of affairs requires agricultural policies to ensure the sustainability of the environment and production efficiency. Saudi Arabia carbon footprint analysis shows that the kingdom has a huge negative carbon balance due to the fact that the level of per capita consumption is higher than the national biocapacity levels (Global Footprint Network, 2022; Aldegheishem, 2024). The farming sector bears a collaborative burden to this deficit in carbon since; it absorbs major sector of the carbon footprint in Saudi Arabia. This is a type of unsustainable consumption of the resources, which requires urgent policies in the agricultural sector that will help speed up the process of implementing sustainable food systems in the country. Consequently, the elegant quantitative evaluation of the agricultural carbon footprint of Saudi Arabia is essential in the process of formulating effective food system policies to minimize the environmental effects on the agricultural sector in the country.

This research presents significant contributions to ongoing studies and fills the research gap on carbon footprints and sustainable food systems in agricultural sector. First, this study evaluated the effect of mechanization (Mech), water productivity (WP), climate change technology adaptation (CCA), fertilizer consumption (FC), agriculture growth (AG), and energy consumption in agriculture (ENA) on CO_2 emissions in a single analytical framework, unlike other researchers, who looked at the effect of one factor in a single model. Moreover, the study uses time series data, enabling researchers to study these factor effects across different time periods, diverging from past studies that used cross-sectional data without any causal effects of these variables. Third, this study is one of the pioneering studies that applies adaptation technologies to time series data to analyze their effects on agricultural carbon footprints. The agricultural sector functions both as a player in environmental degradation and as a victim of its destructive impact; therefore, this research holds high value for environmental sustainability and food systems.

Literature review

The use of farm machinery has both negative and positive outcomes. Mech also enhances energy usage and relieves the workers of their labor burden, since it enhances agricultural efficiency. The studies reveal that the impact of Mech on carbon footprints in agriculture varies across different regions worldwide. It is highly

linked to technological development and farming practices. The agricultural activities and the resulting environmental emissions were also raised by 29% due to the fact that farmers started using more diesel-powered machines and equipment powered by fossil fuels (Abbas et al., 2022). Dyer and Desjardins (2003) particularly focused on the farm machinery practices and examined their impact on greenhouse gas emission and fossil fuel consumption. They found that changes in tillage operations and fuel types substantially affected CO_2 emissions. Mech contributes to soil degradation since the soil is greatly compacted thus diminishing the carbon sequestration potential (Zhang et al., 2024). In China, Zhu et al. (2024) found the dual impact of Mech on carbon emissions, as they described that Mech increased the carbon emission intensity by 9.01% and reduced it by 12.18%, indicating the positive outcome of Mech in the form of a net reduction of 3.17%. Conservation tillage and the use of solar-powered equipment have an opportunity to succeed since it will reduce the carbon footprint of the mechanized farms by up to 18% (Sharma et al., 2012). Considering technological improvements, Zhang et al. (2025) found that Mech significantly reduced carbon emissions in Belt and Road economies with advanced technology progress. Guan et al. (2023) used panel data from 30 provinces in China and found an increasing impact of Mech on carbon emissions, while Qinghua and Guangsheng (2023) analyzed 282 cities and found a decreasing impact of agricultural Mech on carbon emission intensity, which implies that Mech reduces carbon footprints significantly.

Over-application of fertilizers in nitrogen and phosphorus continues to be acute carbon threat to natural systems of sustainability. Hu and Liu (2024) confirmed that the use of high amounts of fertilizers does lead to a decline in water quality through the discharge of nitrogen to the environment, which leads to the pollution of water. In developing nations, chemical fertilizer methods result in the release of nitrogen in addition to carbon (Ahmed et al., 2017; Ma et al., 2023). Integrated nutrient management reduces carbon footprint by 27%. This alternative strategy has been more sustainable (Meena and Vishnuvardhan, 2021). Wezel et al. (2009) discovered that production of various crops and organic farming without heavy chemicals reduce carbon footprints.

CCA plays a major role in reducing the carbon footprint and mitigating the vulnerability of climate change in the agricultural sector. Adjustments to climate change like zero tillage, precise irrigation and crop varieties that are resistant to climatic changes have increased agricultural output. CCA technologies and strategies help to decrease water use and GHG emissions, which leads to the reduction of carbon footprint to 20 or 40% (Gakhar et al., 2023). In an attempt to demonstrate this necessary relationship between CCA technologies and the sustainability of the food production process, Nayak et al. (2022) examined the relationship between climate-adaptive rice varieties and a 30% reduction in methane production in Bangladesh.

Agriculture forms a major source of national income especially in the developing countries. The GDP has a high percentage in agricultural activity that poses environmental hazards in cases where sustainability practices are not well applied. The intensive forms of farming that have facilitated the rise in the level of production leave a larger carbon footprint. The techniques may cause damage to the land, water shortage, loss of biodiversity, and greenhouse gas emissions (Kissinger et al., 2012). Sustainable food systems aim at ensuring food security is assured at all times and maintain carbon systems. The environment and productivity must be given equal consideration as regards to agricultural sustainability. According to Springmann et al. (2018), the current food systems cannot be considered sustainable without corrective actions. The destruction of the environment will grow due to the growth of the global food demand (Tilman and Clark, 2014). Sinclair et al. (2019) support agroecology and climate-smart agricultural practices that not only safeguard agricultural GDP but also reduce the harm to the environment. The economic importance of the GDP of agriculture share requires adoption of sustainable methods of practices in order to reduce environmental losses.

The quantity of energy utilized in agriculture is a critical deciding factor. Lal (2020) estimated that agriculture use of energy in the globe contributes 20%–30% of the total greenhouse gas emissions. The carbon footprint of Pakistani major crops was more than 25 times greater than the conventional irrigation system alongside fuel-powered equipment (Ashraf et al., 2021). Panwar et al. (2011) identified that solar-irrigated irrigation systems with use of energy efficient technologies have a potential of reducing carbon intensity by 45% toward sustainable food systems.

WP is an important measure to ensure environmental degradation does not occur. The use of drip and sprinkler irrigation technologies reached efficiency of water conservation by 50%–60%, which led to a reduction of carbon footprints (water-based) by 30% (Yadav et al., 2024). Integration of smart irrigation schemes and rain water harvesting systems minimize the pressure of blue water in dry areas and sustain agricultural production (Grafton et al., 2014). Garnett et al. (2013) endorse transformation of food systems in the world through adopting agroecology since it would reduce GHG emission by half and establish resilient food system.

Empirical studies indicate that optimizing agricultural land use and functional capabilities along with green-powered equipment complements and regulates fertilization requirements and climate-sensitive technologies, and enhances power efficiency and water usage are core methods of minimizing the levels of carbon and creating sustainable agricultural systems. This gained knowledge provides a critical foundation on the future enquiry to integrate sustainable goals with agricultural development, particularly in climate-threatened and low-resource countries.

Materials and methods

Data

The data were obtained from four sources from 1992 to 2021: the World Development Indicators (WDI), the Food and Agriculture Organization (FAO), the Organization for Economic Co-operation and Development (OECD), and our world. Data on CO_2 emission and FC were obtained from the WDI. The patents were used as a proxy for CCA technologies, which were obtained from the OECD. The ENA data were obtained from the FAO. Data regarding Mech, WP, and AG were collected from our world data center. Table 1 presents the sources as well as descriptive statistics of data.

The general functional form shows that CO_2 emission from agriculture is dependent variables and Mech, WP, FC, CCA, AG, and ENA are independent variables.

TABLE 1 Variables source and description.

Variables	Units	Description	Mean	Standard deviation	Sources
CO_2 emission	Mt	Carbon dioxide emissions in agriculture	0.310	0.057	World Development Indicators
FC	Kg	Fertilizer Consumption per hectare of agricultural land	95.915	17.985	
Mech	Nos.	Mechanization, Machinery per unit of agricultural land	0.040	0.004	Our World in Data
WP	US$	Water Productivity, GDP per m^3 of total freshwater withdrawal	23.021	5.277	
AG	% of GDP	Share in GDP	3.798	1.456	
CCA	Patents	Climate change adaptation, patents regarding climate change adaptation technologies	12.964	15.245	Organization for Economic Co-operation and Development
ENA	TJ	Energy consumption in agriculture	12067.680	4800.461	Food and Agriculture Organization

$$CO_{2t} = \beta_0 + \beta_1 \text{Mech}_t + \beta_2 \text{WP}_t + \beta_3 \text{FC}_t + \beta_4 \text{CCA}_t + \beta_5 \text{ASG}_t + \beta_6 \text{ENA}_t + \varepsilon_t$$

where CO_2 indicates carbon dioxide emissions over a period of 30 years, and Mech, WP, FC, CCA, AG, and ENA are mechanization in agriculture, water productivity, fertilizer consumption, climate change adaptation, agricultural growth, and energy consumption in agriculture, respectively. β's are unknown parameters to be estimated and ε is the error term.

Unit root test

None of the variables must be integrated in order I(2), which is the prerequisite condition of the autoregressive distributed lag (ARDL) bound test for cointegration (Pesaran and Shin, 1999; Pesaran et al., 2001). To confirm this, a unit root test for each variable is necessary. Therefore, Augmented Dickey-Fuller (ADF) and Phillips (PP) tests were used to determine the integrated order of variables. The general functional form of ADF and PP test is as follows:

ADF test:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{\rho} \delta_i \Delta y_{t-i} + \varepsilon_t$$

PP test:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \mu_t$$

where y is the time series variable under consideration, t indicates time, α is the intercept, which is optional, βt is the deterministic time trend, which is also optional, γ is the coefficient of the lagged term, ρ shows the number of lagged difference terms, ε is the white-noise error term, and μ is the disturbance term. The null hypothesis of the ADF test considers the existence of a unit root, whereas the alternative hypothesis assumes that the variable is stationary. Therefore, a p-value less than 5% rejects the null hypothesis.

General form of ARDL empirical model

The next step is to determine the existence of long-run relationships between variables. Autoregressive distributed lagged (ARDL) bound test were applied for this purpose. This approach is more flexible than the traditional cointegration approach. Moreover, it provides reliable results, while the variables are integrated in the order of I(0) and I(1). It allows the use of different lag lengths for different variables, and because of the single equation set, its interpretation and application are very simple particularly for small sample sized studies. It effectively tackles the issue of autocorrelation and endogeneity and provides reliable long-run effects (Harris and Sollis, 2003; Jalil and Ma, 2008). To reject null hypothesis, the value of F-statistic must be greater than the upper-bound which implies that there is cointegration among study variables. Moreover, the value of F-statistic lower than the lower bound, then the null hypothesis is accepted, which indicates that there is no cointegration or long-run relationship among the variables. Similarly, if F-statistics falls between the lower and upper bounds, the result is inconclusive (Pesaran et al., 2001). The functional form of cointegration model is given below:

$$\begin{aligned}\Delta CO_{2t} = {} & \partial_0 + \partial_1 \text{Mech}_{t-1} + \partial_2 \text{WP}_{t-1} + \partial_3 \text{FC}_{t-1} + \partial_4 \text{CCA}_{t-1} + \\ & \partial_5 \text{ASG}_{t-1} + \partial_6 \text{ENA}_{t-1} + \sum_{i=0}^{q} \beta_1 \Delta \text{Mech}_{t-i} + \\ & \sum_{i=0}^{q} \beta_2 \Delta \text{WP}_{t-i} + \sum_{i=0}^{q} \beta_3 \Delta \text{FC}_{t-i} + \sum_{i=0}^{q} \beta_4 \Delta \text{CCA}_{t-i} + \\ & \sum_{i=0}^{q} \beta_5 \Delta \text{ASG}_{t-i} + \sum_{i=0}^{q} \beta_6 \Delta \text{ENA}_{t-i} + \varepsilon_t\end{aligned}$$

Where, Δ specifies the change, and based on the sample size and selection criteria, $t-1$ indicates optimal lag length. Where ∂_0 to ∂_7 and β_1 to β_7 are the parameters to be analyzed. Therefore, the following hypothesis was specified based on the above equation.

$$H_0 : \partial_1 = \partial_2 = \partial_3 = \partial_4 = \partial_5 = \partial_6 = \partial_7 = 0$$

$$H_1 : \partial_1 \neq \partial_2 \neq \partial_3 \neq \partial_4 \neq \partial_5 \neq \partial_6 \neq \partial_7 \neq 0$$

If the F-statistic exceeds the upper bound, it confirms the existence of cointegration, implying that there is a long-run relationship among the variables (H_0 rejected). Therefore, both the long-run and short-run effects of the variables were examined using ARDL.

$$\Delta CO_{2t} = \partial_0 + \sum_{i=0}^{q} \beta_1 \Delta Mech_{t-i} + \sum_{i=0}^{q} \beta_2 \Delta WP_{t-i} + \sum_{i=0}^{q} \beta_3 \Delta FC_{t-i} + \sum_{i=0}^{q} \beta_4 \Delta CCA_{t-i} + \sum_{i=0}^{q} \beta_5 \Delta AGS_{t-i} + \sum_{i=0}^{q} \beta_6 \Delta ENA_{t-i} + \partial ECT_{t-1} + \varepsilon_t$$

Where the error correction term (ECT) indicates the speed of adjustment from the short-run shock to long-run equilibrium. The ECT value less than zero and significant is acceptable. The assumption of ARDL bound test is that error term must be normally distributed and serially independent. Autocorrelation, heteroscedasticity, and normality were assessed.

Selection of optimal lags

Before the ARDL estimation, it is important to find out the most desirable lag length of each variable. The selection of the number of lags is an empirical undertaking: the number of lags can be too small to cause model specification error, or it can be too large so as to cause multicollinearity. The selection of optimal lags depends on two main factors, which are the sample size and the selection criteria. As Godil et al. (2022), state that the number of two lags is usually adequate when using annual data, up to eight lags when using quarterly data, and up to 24 lags when using monthly data. A number of statistical selection criteria were applied in determining the best lag structure which included Akaike Information Criterion (AIC), Likelihood Ratio (LR) test, Hannan–Quinn Information Criterion (HQIC), Schwarz Information Criterion (SIC) and Final Prediction Error (FPE).

Model diagnostic tests

In order to confirm their validity, a number of diagnostic tests were conducted. The serial correlation of the residuals was determined by the Breusch Godfrey Lagrange Multiplier (BG-LM) test and the Durbin Watson (DW) d-statistic, whereas the testing of heteroscedasticity, or non-constant residual variance, was done by the White test and Breusch-Pagan-Godfrey (BPG) test. Moreover, Jarque-Braun (JB) test was used to establish whether the residuals were normally distributed, which is a requirement of a sound statistical inference in the model.

Robustness and model stability

The above-mentioned ARDL bound test is especially appropriate based on the short period (of time) and the single country case. It gives a sound estimation of the parameters where there is a small sample of the taken properties of data. Besides these tests, it is important to understand the structural stability of the projected model so as to make sure that the relationship between the variables do not change with time. The cumulative sum of recursive residuals (CUM) and cumulative sum of squares of recursive residuals (CUSUMQ) tests were also used to address the purpose of robustness (Brown et al., 1975). These diagnostics tests analyze the stability of the model coefficients throughout the sample period. The model is considered to be structurally stable when the plotted statistics is within the specified critical limits. The same method of assessing model stability has been suggested by Pesaran et al. (2001) and this indicates the stability and reliability of these diagnostic tests in the analysis of ARDL. Figure 1 shows the methodological flow chart of this study.

Results and discussion

Diagnosing unit root results

Table 2 presents the findings of ADF and PP tests. The stationarity level of each variable with and without including the trend revealed that all the variables were stationary at the 1st difference. This confirms that all variables have an order of integration I(1).

Selection of optimal lag results

All indicators showed one optimal lag for CO_2, two for MECH, one for WP, one for FC, two for CCA, one for AGS, and two for ENA. Based on the sample size, the two optimal lags for small sample sizes were suitable. Therefore, based on the selection criteria for optimal lags, we specified the model as ARDL (1,2,1,1,2,1,2).

Model diagnostic test results

Table 3 provides the diagnostics test which confirm the goodness of fit of model ARDL (1,2,1,1,2,1,2). The *R*-square value indicates that 79% of the variation in the dependent variable is explained by the model. The DW d-statistics is 1.763, which does not provide the strong evidence for no autocorrelation. However, the value of the d-statistics is not far from 2, and based on the BG- LM test, it has been confirmed that there is no issue of serial autocorrelation. The next diagnostic tests for heteroskedasticity, such as the White test and BPG test, fail to reject the null hypothesis of homoscedasticity, which ensures that there is no issue of heteroskedasticity. Moreover, the residuals are normally distributed, as the JB test fails to reject the null hypothesis that the residuals are normally distributed.

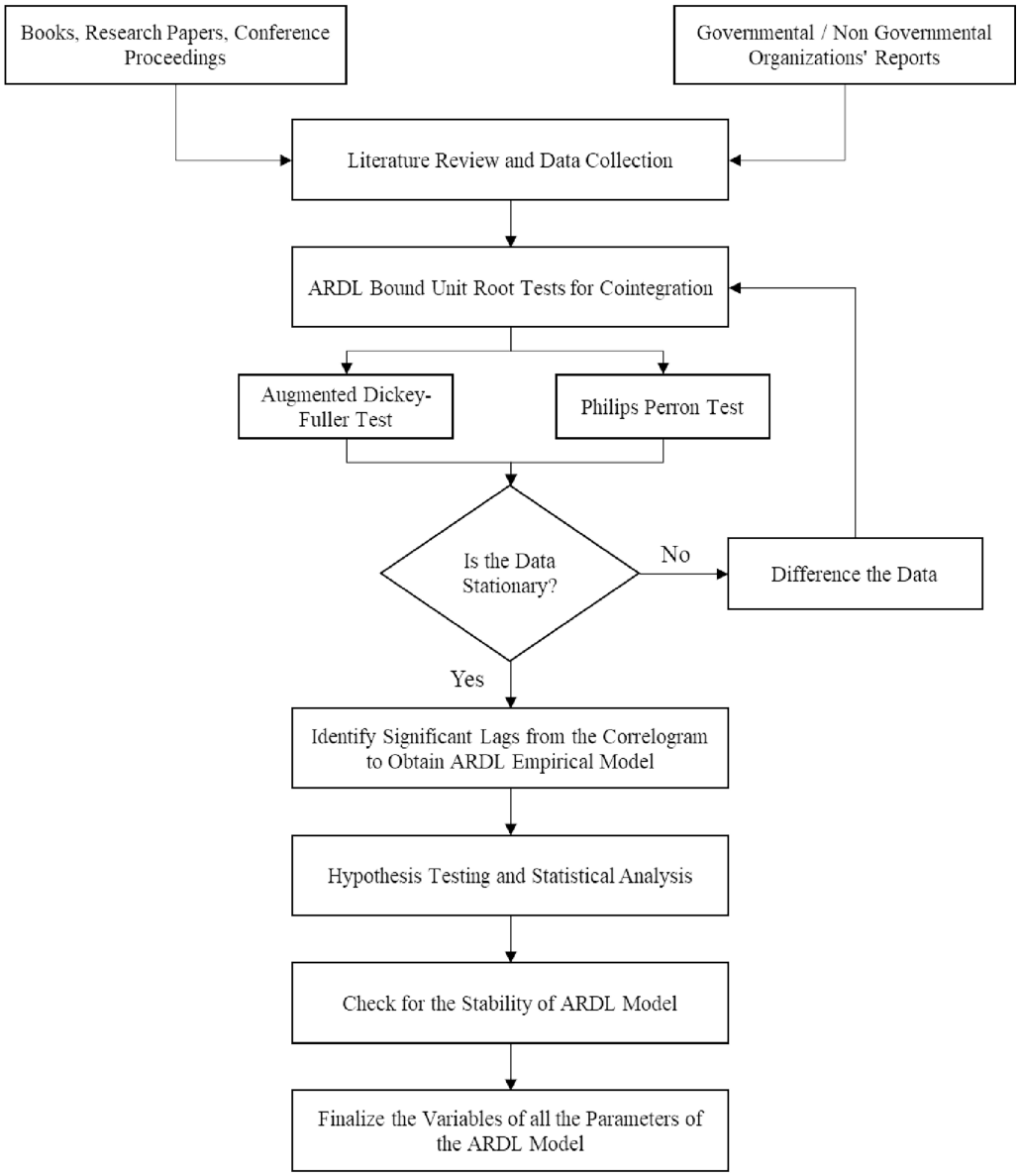

FIGURE 1
Methodology followed for the research.

Cointegration test results

The F-statistics in the results of the ARDL bound test (10.342) in Table 4 confirm that the variables are cointegrated. The findings reveal that the *F*-value is substantially greater than upper bound. Therefore, it is confirmed that the study variables have long run relationship among them.

Long run and short run estimates

Table 5 shows the significant and negative lagged ECT, which shows how speedily the system reaches back to equilibrium after a certain shock in short time period. This confirms that the relationship among the variables is highly stable. Moreover, it indicates that the short run deviation of the equilibrium of the previous period is properly backed by its current period equilibrium.

The findings also present the long- and short-run effects of Mech, WP, FC, CCA, AGS, and ENA on CO_2 emissions from agriculture in Saudi Arabia. The statistical significance of the variables highlights their strong effect on long-term carbon emissions in the agricultural sector in the long run. The signs and significance of Mech, WP, FC, CCA and AGS indicate that these variables strongly contribute to the environmental sustainability of agriculture by reducing CO_2 emissions.

Mech is crucial for the high productivity of farming systems. The findings indicate that a 1% increase in Mech causes a 1.732% reduction in CO_2 emission in agriculture in the long run. Moreover, the positive sign of Mech (first difference = D1) implies that Mech in

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TABLE 2 Diagnosing stationarity of variables.

Variables	At level		At 1st difference	
	With constant and trend	With constant only	With constant and trend	With constant only
ADF				
CO_2	−3.410*	−3.497*	−4.890*	−5.002*
Mech	−1.654	−1.316	−3.371*	−3.460*
WP	−2.279	0.590	−4.267*	−4.117*
FC	−2.988	−3.520*	−4.906*	−4.791*
CCA	−2.350	−0.659	−6.134*	−6.158*
AG	−1.188	−1.016	−4.723*	−4.646*
ENA	−3.620**	−1.277	−7.323*	−7.388
PP				
CO_2	−3.433*	−3.513*	−4.830*	−4.993*
Mech	−2.072	−1.640	−3.239*	−3.363*
WP	−2.276	0.297	−4.312*	−4.156*
FC	−3.057	−3.543*	−4.924*	−4.851*
CCA	−2.185	−0.387	−6.604*	−6.420*
AG	−1.291	−1.003	−4.754*	−4.629*
ENA	−3.603**	−1.156	−8.156*	−8.154*

*, **, and *** shows 1, 5, and 10% levels of significance level, respectively.

TABLE 3 Parameters of assessing goodness of fit of model.

Parameters	χ^2	*p*-value
Normality test		
JB test	4.54	0.103
Heteroskedasticity tests		
White test	28.00	0.411
BPG	16.74	0.403
Autocorrelation tests		
BG-LM	0.003	0.954
DW *d*-statistic	$d = 1.763$	

R-square = 0.79; Adjusted *R*-square = 0.522; *F*-statistics = 2.85; *p*-value = 0.04; χ^2 = Chi Square values.

TABLE 4 Cointegration analysis.

Significance level	F-statistic	
	Lower bound	Upper bound
1%	2.96	4.26
2.5%	2.60	3.84
5%	2.32	3.50
10%	2.03	3.13
F-value	10.342	
K	7	

TABLE 5 Long run and short run estimates.

Study variables	Parameters	Standard error
ECT	−0.722	0.090*
Long-run		
Mech	−1.732	0.606**
WP	−2.023	1.076***
FC	0.808	0.252*
CCA	−0.113	0.022*
AG	−0.398	0.201***
ENA	0.045	0.021**
Short run		
Mech		
D1	2.877	1.208**
LD	1.995	1.412
WP		
D1	−2.042	1.001**
FC		
D1	0.343	0.103*
CCA		
D1	−0.026	0.008*
LD	−0.039	0.005*
AG		
D1	0.257	0.628
ENA		
D1	0.183	0.632
LD	0.061	0.496
Constant	11.711	4.646**

*, **, and *** shows 1, 5, and 10% levels of significance level, respectively.

the short run can enhance carbon emissions with an immediate change in the Mech level in farming in the country. Our findings are in line with those of Guo et al. (2022a, 2022b), who also find a positive short-run impact of Mech on carbon emissions. This implies that immediate changes in Mech can increase energy consumption, leading to high emissions, while in the long run, Mech improves land and resource management and fosters the use of energy-efficient and cleaner technologies over time. The endogenous theory of growth highlights the contribution of technological progress to the efficiency of natural resource consumption and enhances resource recycling while minimizing energy use and environmental pollution (Guan et al., 2023). In the short run, the high level of Mech in agriculture leads to a high consumption of energy to power machinery, which results in high emissions. Moreover, the production and maintenance of machines also add carbon footprints (Guan et al., 2023). In the Long run, Mech in agriculture can reduce agricultural emissions over time by optimizing input use and reducing waste (Castelein et al., 2022). The adoption of Mech in farming leads to the efficient use of farm inputs (Modi et al., 2020) and the sustainable management of soil and land. Over time, advancements in machinery have lowered agricultural emissions by improving farm machinery technologies (Gao et al., 2024). Mech enables the farming community to obtain more output per unit of land (under the constraint of scarce land) and

improves the input application and harvesting of crops (Yan et al., 2024). This implies that high Mech per unit of land can increase productivity and lead to a reduction in deforestation, along with the efficient use of synthetic inputs to lower emissions. Similarly, in the long run, Mech also lowers the risk of soil erosion, as modern machinery leads to minimum soil disturbance with no-till farming (Sharma et al., 2024). This improves soil fertility by increasing the ability of soil to sequester carbon. Similarly, due to water scarcity, the use of modern irrigation techniques, such as drip irrigation and center pivot systems, reduces the energy consumption necessary to pump out and distribute the water, which ultimately reduces emissions in farming systems.

The outcomes of the model indicate that WP has a significantly negative impact on agricultural carbon emissions. This implies that a 1% increase in WP lowers carbon emissions by 2.023% in the long run and by 2.042% in the short run. This implies that, in both the short and long run, improvement in water productivity can improve the environmental sustainability of agriculture. A high WP indicates output per cubic meter of freshwater withdrawals, which is crucial, especially for Saudi Arabia, where water scarcity is a crucial problem. The relationship between WP and carbon emissions is affected by various factors including energy consumption, water resource management, and farming practices. Therefore, improving WP leads to low water pumping for irrigation, which lowers energy consumption and results in low emissions (Chen et al., 2019; Scardigno, 2020). Moreover, a high WP protects the aquifers and stabilizes the level of groundwater, which lowers the deep pumping and energy consumption, leading to low carbon emissions. Similarly, the efficient use of water results in better soil structure by preventing erosion, compaction, and salinization, and promoting the carbon sinking capacity of soil, which ultimately lowers atmospheric carbon (Martin-Gorriz et al., 2021).

The impact of FC on carbon emissions was positive and significant at the 1% level in both the short and the long run. This implies that a 1% increase in FC increases carbon emissions by 0.808% in the long run and 0.343% in the short run. This confirms that FC strongly enhances carbon emissions immediately, and its long-run impact is large over time, as the long-run coefficient is greater than the short-run coefficient. Our findings are in line with those of Guo et al. (2022a, 2022b), who also reported that high fertilizer application in the soil causes high carbon emissions. FC cause carbon emissions in several ways. First, the production of fertilizers causes carbon emissions by consuming high amounts of energy from fossil fuels (Koondhar et al., 2021). Moreover, when fertilizer is applied in the field, it is not absorbed by the crops. Unabsorbed fertilizer is broken down in the soil and causes the emission of gasses (Ashitha and Rakhimol, 2021).

The long-run impact of the CCA indicates a strong negative impact on carbon emissions. This indicates that a 1% increase in adaptation to climate change technologies reduces agricultural carbon emissions by 0.113%. Similarly, the small coefficient of CCA at its 1st difference (=−0.026) than the lagged difference (=−0.039) signifies that CCA also has a favorable impact on improving environmental sustainability through the immediate reduction in carbon emissions, while their full impact is not immediate. Therefore, CCA lowers carbon emissions from agriculture while improving the resilience of farming systems to climate change. Soil management-related technologies, such as conservation agriculture and organic farming, play a crucial role in lowering carbon emissions by improving the carbon sequestration ability of the soil (Chauhan, 2024; Smith and Olesen, 2010). Moreover, the adoption of technologies that improve resource management efficiency lowers waste and carbon emissions in farming systems, particularly in terms of fertilizer application (Santosh et al., 2023). Similarly, the development of drought-resistant and heat-tolerant crop varieties (Jalota et al., 2018; Abhang et al., 2024), efficient irrigation systems (Jalota et al., 2018), and diverse farming activities enhances the capabilities of farming systems to preserve the environment by lowering carbon emissions.

The AG significantly lowered carbon emissions in the long run, as a 1% increase in AG decreases carbon emissions by 0.398%. The increasing share of agriculture in economic growth has prompted governments to focus on sustainable agricultural practices and promote the adoption of environmentally oriented farming practices. For this purpose, the government has promoted efficient water-use technologies, diversification, and mixed farming to reduce dependency on off-farm inputs. Vitunskienė and Lauraitienė (2022) also described the favorable impact of agricultural growth on environmental sustainability of agriculture, while this highly linked with adoption of technologies and innovations in farming system. Our findings are in line with those of Zhang et al. (2019), who also describe the long-run negative impact of agricultural growth on carbon emissions.

ENA also has a strong positive impact on carbon emissions, which implies a 1% increase in energy consumption in agriculture. Agriculture is highly dependent on energy consumption, particularly energy from fossil fuels, which directly increases carbon emissions (Gołasa et al., 2021). Soni et al. (2013) also highlights that the energy consumption in agriculture is gradually increasing which strongly contributes to the carbon emission particularly from the consumption of diesel fuel as energy source in performing farming activities.

Robustness and model stability results

In order to be able to rely on the estimated model and to assume the soundness of its long-run impacts, the structural stability analysis was performed. This test is necessary to ensure that the relationships discovered in the model are the same throughout the sample time and therefore protect the validity of the results. To this end, two complementary tests of diagnostics were used, namely, the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of squares of recursive residuals (CUSUMQ). The two tests are specifically to show if there is structural change or instability of parameters over time and hence a strict check on the stability of the model.

The outcomes of such tests are presented in Figure 2 (CUSUM) and in Figure 3 (CUSUMQ). In both the plotted statistics are all within the critical level of 5% value. The fact that none of the critical threshold lines have been crossed in either of the tests is evidence that the parameters of the model remain stable during the sample period. This result suggests that the structural relationships that the model provides are stable and the estimates are strong which supports the reliability of long-run and short-run inferences. The predictions and estimated effects of the model therefore could be considered credible and this increases the credibility of the outcomes in the development of policies

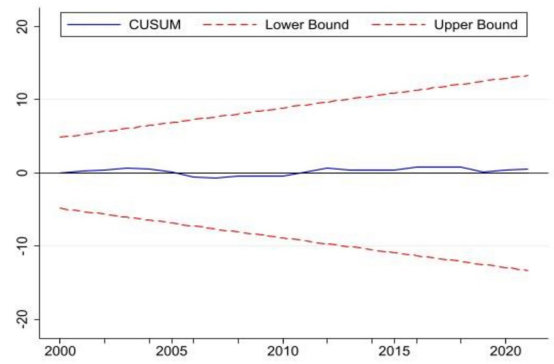

FIGURE 2
CUSUM plot.

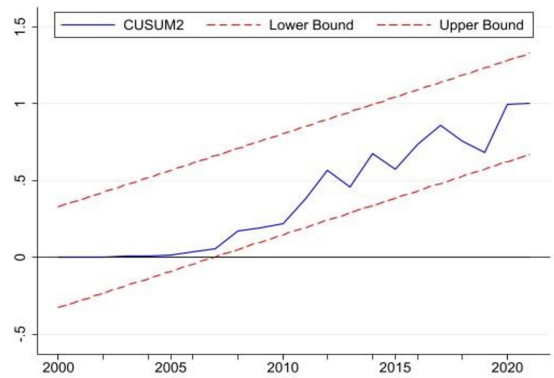

FIGURE 3
CUSUMQ plot.

and applicable decision making in the agricultural and the environmental sectors.

Conclusion

Carbon emissions are responsible for global climate change around the world and have attracted the attention of policymakers and local governments. Moreover, the agricultural sector is a major emitter of CO_2, which has been evaluated to control emissions from this sector. The Kingdom of Saudi Arabia is also facing major challenges in achieving the sustainable development goals, and also facing the issue of climate change. Therefore, this study focuses on CO_2 emissions in the agricultural sector because the Kingdom is highly dependent on agriculture to meet food demands. Growing mechanization, water scarcity, fertilizer consumption, and energy consumption in the agriculture sector are the primary determinants of emissions. However, Saudi Arabia has also focused on climate change adaptation technologies to reduce the impact of climate change by reducing sectoral emissions. The primary objective of this study was to evaluate the impact of Mech, WP, FC, CCA, AG, and ENA on CO_2 emissions from agriculture in a single framework to obtain fruitful insights into lower emissions from the sector. For this purpose, we considered time-series data, including the period 1992–2021.

All variables were integrated in order I(1), and ARDL-bound test-based F-statistics confirmed the existence of co-integration. This preliminary test allowed the use of the ARDL method to obtain the long- and short-run impacts of the variables on CO_2 emissions. The model passed all the diagnostic tests, which ensured no autocorrelation and heteroskedasticity, and confirmed the normality of the residuals. The model was also stable, based on the outcomes of CUSUM and CUSUM2.

The findings revealed that Mech has a favorable impact in the long run by lowering emissions, whereas it increases CO_2 emissions in the short run. WP plays a crucial role in lowering CO_2 emissions in the agriculture sector in both the short and long run. FC strongly contribute to CO_2 emissions in both the short and long run. CCA strongly reduces emissions in both the short and long run, but its impact takes time to materialize. The AG only reduced carbon emissions in the long run, while the ENA increased carbon emissions in the long run. The findings conclude that mechanization has a favorable impact on environmental sustainability over a long period of time, while increasing emissions in the short run. Both water productivity and climate change adaptation technologies have increased environmental sustainability in the short and long run. The application of fertilizers must be considered because they immediately contribute to carbon emissions. Agricultural growth can lower emissions over time, whereas energy consumption can increase.

Policy recommendations, study limitations and future directions

Based on these findings, there are many policy recommendations for increasing agricultural environmental sustainability in the country by reducing carbon emissions from the agricultural sector. As Mech has a strong, long-term, favorable impact, this suggests that policy efforts must focus on the upgradation and quality of farm machinery. In this regard, tax rebates or a targeted subsidy system can be launched to promote the adoption of fuel-efficient machinery. Similarly, water productivity must be increased to reduce the emissions. This necessitates the need for resource-oriented irrigation policies. For this purpose, the government may launch support programs to promote efficient irrigation adoption, particularly in water-stressed regions. Thus, the initial investment threshold in effective irrigation technologies can be reduced by the introduction of low-interest credit schemes. The farmers should be accommodated with the services of soil testing and training programs to reduce the rate of application of fertilizers and timing to achieve lower FC. Besides, awareness campaigns may be initiated to spread the knowledge about the environmental and health consequences of using excessive fertilizer. Additionally, the government needs to contribute to the process of organic farming introduction through supplying equipment, technologies, and information. In a bid to market CCA technologies, the joint venture between the private and public sectors aimed at energy saving and climate-resilient technologies can create more environment-friendly results in the farming business. In addition, CCA can be encouraged by the establishment of effectively functioning technology diffusion

systems, as well as the creation of an effective intellectual property system. There is need to reduce the use of fossil fuels through the implementation of machines that use renewable energy and irrigation systems that use water since the farming activities use much energy in the agricultural sector. Clean energy consumption should also be encouraged to reduce the adverse effect of ENA; this should be achieved through the adoption of solar power irrigation system and the adoption of machinery that is fuel efficient.

Although this research offers valuable information, it is limited in certain ways. To start with, this research employed a one-country model using annual data that was 30 years. Increased time span can also contribute to finding more complicated patterns and relationships between variables. The present research has simply factored in aggregated data on a national level and neglected regional variations in irrigation technologies, mechanization, and agricultural activities. In the future research, regional panel information about various provinces should be considered to derive more precise results which can give a more lifelike picture in order to develop the policies effectively.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

SA: Project administration, Writing – original draft, Methodology, Funding acquisition, Investigation, Formal analysis, Writing – review & editing, Software, Data curation. SH: Writing – review & editing, Software, Investigation, Writing – original draft, Supervision, Conceptualization, Validation. AA: Writing – review & editing, Supervision, Project administration, Validation, Methodology, Writing – original draft. AH: Writing – original draft, Funding acquisition, Writing – review & editing.

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Generative AI statement

The author(s) declared that Generative AI was not used in the creation of this manuscript.

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2026.1741677/full#supplementary-material

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