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Do agricultural input resources contribute to economic growth in China? A dynamic ARDL simulation approach

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Sustainable agricultural inputs are essential for enhancing food security, promoting development, and ensuring resilience in rapidly emerging economies; however, studies utilizing the advanced autoregressive distributed lag (ARDL) approach to investigate their impact on agriculture-driven economic growth remain limited. This research aims to fill this gap by employing a dynamic ARDL simulation model to analyze the relationship between sustainable agricultural inputs and economic growth in the agricultural sector, utilizing annual time series data spanning from 1983 to 2023. The analysis includes unit root tests, which affirm the stationarity of all variables, and the ARDL bounds test, which reveals a significant long-run cointegrating relationship among them. Our findings indicate that the expansion of irrigated areas and increased usage of chemical fertilizers contribute significantly to agricultural economic growth in both the short and long run, while agricultural mechanization only positively affects growth in the short run. Notably, the variable representing crop-sown land does not exhibit a statistically significant impact on agricultural economic growth across both time frames. Furthermore, the results from novel DYARDL simulations, which assess the implications of 10% positive and negative shocks, further substantiate both short-run and long-run analysis outcomes. The insights generated from this study highlight the critical role that sustainable agricultural inputs play in agricultural economic dynamics and provide evidence-based recommendations for fostering resilient, low-input systems that support global food security and agro-environmental sustainability.

KEYWORDS

agricultural mechanization, irrigated area, chemical fertilizer consumption, crop sown land, agricultural economic growth, DYARDL model, cointegration analysis

1 Introduction

Modern high-yield agriculture relies on inputs such as synthetic fertilizers, pesticides, machinery, and hybrid seeds to meet global food demand (Ahvo et al., 2023). Their unaffordability due to supply chain disruptions and climate shocks hinders productivity, inflates costs, and destabilizes food security, particularly in import-dependent regions (Khan et al., 2024). Overreliance also risks environmental degradation, such as soil

depletion and water pollution, undermining long-term sustainability (Liu et al., 2021). This in turn affects the huge efforts to transition to resilient, input-efficient systems that balance productivity with ecological and economic stability in a climate-uncertain future (Brunelle et al., 2024; Hou et al., 2023; Shen et al., 2013).

The associations of different shocks, natural (climate extremes and soil degradation, natural disasters and so on) and anthropogenic disasters (trade constraints and unsustainable practices), on agricultural economy are increasingly well-understood (Holst et al., 2013; Lin and Wang, 2024; Rezaei et al., 2023). Very little is known, however, about how positive and negative shocks from agricultural inputs affect the agricultural economy as a whole, whether at large scale-national or regional scale. Few studies, for instance, Ahvo et al. (2023), use the random forest machine learning algorithm to study the combined impact of agricultural input shocks in high-yielding areas of the world. Based on this study, response from a 50% reduction in key agricultural inputs could slash global maize yields by up to 26% and wheat by 21%, exposing critical vulnerabilities in food systems. McArthur and McCord (2017) developed an input-yield-economy nexus framework using a combination of fixed effect and instrumental variable specifications. In their estimate, a total positive shock from fertilizer, water, and modern seeds could increase yields and the economy, resulting in a structural shift in the economy.

There is a growing body of literature that estimates the impact of policy-driven shocks on China's agricultural input resources and agricultural economic growth temporal associations. The positive shocks that drive the agricultural economic growth is mainly from ongoing land reforms, subsidy policies, technological advancements, research and development investments, and institutional restructuring (Fan et al., 2023; Gong, 2018; Huang et al., 2020; Ullah et al., 2024; Zhang et al., 2011). Studies in the field of agricultural input shocks have only focused on single input shocks (excessive chemical fertilizer, and so on) on specific outcomes (for example, grain production; Xu et al., 2023). The increase in electricity consumption, mechanization, and crop land area has also been positively associated with agricultural-driven economic growth (Zeng et al., 2022). Liu and Wang (2005) revealed that the practice of mechanized farming, plastic film inputs, and education contributes to agricultural economic growth. Similarly, research conducted in Pakistan by Chandio et al. (2019a,b) demonstrated a long-term positive correlation between fertilizer use, water availability, and crop area with growth in agricultural production.

In an investigation into the recent decline of China's agricultural economy, Zhao and Tang (2018) identified a decrease in the growth rate linked to negative shock arising from factors such as land, water, technology, and energy. Their study underscores the importance of investing in technological progress that optimizes the use of energy, water, and land to promote agricultural growth in China. Similarly, a study conducted in Pakistan demonstrated a long-term positive correlation between fertilizer use, water availability, and crop area with growth in agricultural production (Chandio et al., 2019a,b).

Despite the existing body of literature, significant research gaps persist regarding the comprehensive impact of agricultural

input shocks on the national agricultural economy. Specifically, it remains unclear how these input shocks exert both positive and negative effects at the macroeconomic level. Furthermore, prior studies have largely overlooked the application of advanced time-series analysis, which is essential for accurately assessing how distinct agricultural inputs influence China's economic growth over both short- and long-time horizons. This gap in understanding hinders effective policy formulation and highlights the need for a robust analytical framework to elucidate these complex dynamics. Addressing these deficiencies is crucial for developing targeted strategies to optimize agricultural productivity and economic resilience. We selected China as the focus of our study due to its immense agricultural sector, which features a wide range of climates, terrains, and farming practices, from smallholder farms to large-scale mechanized operations. This rich diversity provides a unique opportunity to analyze the effects of various agricultural inputs on economic growth in distinct contexts. Furthermore, China's significant role in global food production and its ongoing transformation toward sustainable agricultural practices make it a critical case for understanding the interplay between agriculture and economic development. By examining China, we aim to derive insights that can inform policies and strategies applicable both domestically and globally.

Consequently, the questions come into play: (1) In what ways do the combined temporal effects of both positive and negative shocks to agricultural machinery, land, fertilizer, and irrigation interact to affect agricultural economic growth? (2) Do positive and negative shocks from various critical agricultural inputs have reinforcing effects on agricultural economic growth? (3) What is the relative significance of positive and negative shocks from each critical agricultural input in influencing the overall effect on agricultural economic growth? (4) What policy measures can be proposed to improve agricultural resilience and promote sustainable growth while addressing the potential trade-offs between positive and negative shocks to various critical agricultural inputs regarding resource allocation and policy implementation for agricultural economic growth? The resolution of an issue should be achieved through investigations employing advanced models, specifically ARDL. Therefore, this investigation aims to examine the combined impacts of the positive and negative shocks from critical agricultural inputs (machine, land, fertilizer, and irrigation) on agricultural economic growth. We also estimate the short- and long-run effect of the change/shocks in individual inputs from the combined effect to identify the inputs that would most affect the economy. We used a novel dynamic autoregressive distributive lag model (ARDL) simulation to conduct the assessment using China's 41 years of data spanning 1983–2023. The model enabled us to estimate the input shocks at different levels (used $\pm 10\%$ for this study). The simulation approach allowed for capturing key inputs shock and time-sensitive growth impacts.

This study offers important theoretical and practical contributions to agricultural economics. (1) Theoretical contribution: By using advanced dynamic Autoregressive Distributed Lag (DYARDL) methods, it enhances our understanding of how different inputs affect growth in the short and long run. This challenges traditional views and enriches theoretical frameworks in agricultural production. (2) Practical

contribution: The research aids policymakers in China by highlighting the need for sustainable input efficiency to ensure food security and resilience in low-input farming. By promoting strategies that balance synergies, address diminishing returns, and support sustainability, this study provides valuable insights for creating effective, environmentally friendly agricultural policies. This study informs policies that balance synergies, diminishing returns, and sustainability through spatiotemporal optimization to mitigate input-driven risks. Furthermore, we contribute to adjustments to align China's rural revitalization with the sustainable development goals (SDGs) (No. 8: decent work and economic growth, particularly related to 8.4: efficiency in consumption and production toward economic growth) through balanced input-growth-sustainability pathways.

The study is organized to facilitate a clear and logical progression of ideas, ensuring that readers can easily follow the research narrative. Section 2 provides a comprehensive review of the existing literature on agricultural inputs and economic growth, effectively establishing the research context and highlighting the critical gaps in current knowledge. Section 3 outlines the methodology in detail, including a rigorous explanation of the advanced ARDL bounds testing, the dynamic ARDL simulation approach, and the specific data sources and variables utilized in the analysis. Section 4 presents and analyzes the empirical findings, encompassing necessary unit root tests, cointegration results, short-run and long-run effects of inputs, and DYARDL shock simulations, thereby providing a thorough examination of the data. Finally, Section 5 synthesizes the key conclusions and articulates actionable policy implications based on the findings, ensuring that the research is relevant and applicable for policymakers. This structured approach not only enhances clarity but also strengthens the manuscript's contribution to the field.

2 Literature review

The topic of agricultural economic growth (AEG) has drawn extensive attention from scholars worldwide. Thus, this study emphasizes three issues. The first issue is the quantification and calculation method of AEG (Lin et al., 2021; Bi et al., 2022; Mei et al., 2022; Wang, 2022). The second issue focuses on the factors either driving or influencing AEG. Studies in this issue can be dissected into four perspectives.

First, only few studies examined the association of land tenure and AEG (Kuang et al., 2022; Liu and Wang, 2005; Sun and Chen, 2020). Second, there are several studies focusing on the association between farmers' agricultural practices and their effect on AEG (Abdul-Rahim et al., 2018; Gupta and Kannan, 2024). These studies argued that soil and water conservation practices, crop diversification, cropping intensity, and proper fertilizer use, enhance productivity and thereby improve AEG. Third, the effect of energy consumption and CO₂ emission on AEG is the foremost important area of studies in many countries, such as China, Pakistan, Iran, Ghana, and Europe (Ali et al., 2019; Chandio et al., 2019a,b; Najafi Alamdarlo, 2016; Zafeiriou and Azam, 2017). Fourth, how natural disaster influence AEG is also an important area of prior research (Lin and Wang, 2024; Yuan et al., 2022).

Recent studies identify the association between agricultural input factors and AEG to examine how this association promotes sustainable agricultural development. For instance, agricultural input factors, including the increase in rural electricity consumption, total power of agricultural machinery, and crop-sown area, also increased AEG (Zeng et al., 2022). A study by Liu and Wang (2005) found that the practice of mechanized farming, plastic film inputs, and education contribute to AEG. Seeking to understand why AEG in China is declining recently, Zhao et al. (2018) found the decline in AEG associated with a scarcity of land, water, technology, and energy, and argued that investment to enhance technology progress that save energy, water, and land enables the sustainable development of agriculture in China. A study in Pakistan explored that fertilizer use, water availability, and cropped area have long-term positive relationship with agricultural production growth (Rehman et al., 2019). A study by Khan et al. (2022) used dynamic ARDL model to investigate the long- and short-run nexus between chemical fertilizers, area under greenhouses, and renewable energies and AEG, finding that increasing the use of renewable energy and the expansion of greenhouse areas contribute to the growth of AEG.

The third issue is the application of the ARDL model to AEG, which is the focus of several studies. While ARDL applications across diverse contexts (Asumadu-Sarkodie and Owusu, 2016; Najafi Alamdarlo, 2016; Warsame et al., 2023; Zafeiriou and Azam, 2017) consistently model AEG-environment linkages, they suffer from two critical limitations: (1) an over-reliance on aggregate variables (e.g., total CO₂ emissions and undifferentiated resource use) that masks how specific inputs (fertilizer and mechanization) differentially drive growth and degradation, and (2) an inability to translate broad correlations (long-run equilibria) into actionable insights for input-level management within distinct agricultural systems, despite contextual nuances (e.g., wheat's mitigation role in Somalia).

Considering the existing body of evidence, understanding the factors influencing agricultural economic growth has garnered significant attention from researchers. While existing literature extensively employs the ARDL approach to model agricultural dynamics, critical gaps persist. Studies by Bambi and Pea-Assounga (2024, 2025), Derouez and Alqattan (2025), Hasan et al. (2023), Karasoy (2024), and Zhang et al. (2024) predominantly focus on ARDL's capacity to analyze environmental impacts, multifactor interactions, or aggregate production outcomes. However, these applications often treat agricultural inputs implicitly within broader models or prioritize environmental consequences over direct, disaggregated economic growth linkages. Crucially, they lack investigation into how specific, discrete inputs (irrigation, fertilizer, machinery, and land) distinctly drive agricultural economic growth in both the short and long run, particularly within rapidly emerging economies such as China. Furthermore, the study seldom utilizes advanced simulations, such as dynamic ARDL, to forecast input-specific shocks. This study directly addresses this gap by applying dynamic ARDL to isolate and quantify the differential growth contributions of individual inputs.

This study distinguishes itself by offering new insights into the relationship between agricultural input resources, specifically agricultural mechanization, irrigated area, chemical fertilizer use, crop sown land, and agricultural economic growth. It employs a

novel dynamic ARDL model, which has not been applied in prior studies on this topic. This allows for a deep understanding of the long- and short-term dynamics of agricultural input resources and their impact on agricultural economic growth. The findings of this study will contribute critical evidence for shaping input resource strategies aimed at advancing agricultural development. This is particularly relevant for China's 2035 plan to create modern agriculture and revitalize rural areas. By examining both positive and negative shocks of input resources, this study provides valuable knowledge that can guide future research into the environmental aspects of agricultural development and help bridge existing gaps in the literature (Table 1).

3 Methodology and data source

3.1 Data sources and processing

The main goal of this study is to examine the impact of agricultural mechanization (AM), irrigation area (IA), chemical fertilizer consumption (CF), and crop sown land (CL) on agricultural economic growth (AEG) in China. To this end, the data used in this study come from the China Agricultural Statistical Yearbook (<https://data.stats.gov.cn>). This study used secondary annual time series data for China covering a period of 41 years, from 1983 to 2023. The dependent variable in this study is AEG. It is represented by the value-added of the agriculture, forestry, animal husbandry, and fishery industries (originally it was in Chinese yuan and converted into the current USD value). Existing research uses various indicators as a measure of AEG, such as agricultural total factor productivity (Kuang et al., 2022), gross output value of agriculture, forestry, animal husbandry, and fishery (Guo et al., 2021; Yuan et al., 2022; Zeng et al., 2022).

In this study, the logarithm of the value-added of the agriculture, forestry, animal husbandry, and fishery industries serve as a comprehensive measure of AEG, which reflect the value realized by the whole industrial chain of agricultural production, processing, logistics, marketing, and services (Lin et al., 2021; Bi et al., 2022; Mei et al., 2022; Wang, 2022). It represents the development level of the agricultural economy. Including AEG as a dependent variable is motivated by the increasing recognition of the agriculture sector's critical role in achieving food security, enhancing farmers' livelihoods, promoting rural development, and stabilizing the national economy in the face of global challenges.

Additionally, the total power of agricultural mechanization (AM; 10,000 kW) is used as a measure of agricultural mechanization level (Zou et al., 2024). It is a useful available variable that can be used to assess the level of mechanization. Theoretically, AM accelerates AEG by increasing productivity and efficiency, allowing farmers to achieve higher yields with less labor and time (Lu and Huan, 2022; Lu et al., 2024; Meng et al., 2024). Moreover, it reduces production costs and encourages investment and frees farmers to look for off-farm employment which further enhances the competitiveness and sustainability of the agricultural sector (Ma et al., 2023).

The other independent variable in this study is irrigation area (IA), hectares of cultivated land. It serves as a crucial indicator of water conservation efforts in farmland throughout

China. It refers to the total extent of fields that are watered and those equipped with irrigation systems or equipment for regular irrigation purposes. Theoretically, IA of cultivated land directly influences crop yields and resource efficiency, thereby enhancing agricultural productivity (Liu et al., 2024). Existing studies support that expanding IA supports food security and rural development, making it a vital factor for sustainable economic growth (Li et al., 2024). Furthermore, consumption of chemical fertilizers (CFs; 10,000 tons), an independent variable, refers to the amount of chemical fertilizer used in farming during a given year. While a study by Khan et al. (2022) highlighted that chemical fertilizer consumption does not show direct long-term or short-term effects on AEG, Yousaf et al. (2017) reported that chemical fertilizer improves crop production, thereby contributing to AEG.

Another important independent variable in this study is crop sown land (CL; 1,000 hectares). It refers to the total land area, whether cultivated or uncultivated, that is planted or transplanted with crops intended for harvest within a given calendar year by agricultural producers. Existing studies revealed the association between CL and AEG. The amount of cultivated crop land in China declined due to land use change driven by urbanization, which imposes a reduction in agricultural production, thereby affecting the overall agricultural growth (Lu et al., 2024; Xiao et al., 2018). A study by Doll (2021) highlighted that the decline of arable land caused by land waste imposes huge pressure on agricultural development. Establishing a foundation on existing studies, this study evaluates the association of these input resources with AEG for building illustrations for the realization of the agricultural modernization goal of the Chinese government as early as the 2050s.

3.2 Model estimation

This study employed Autoregressive Distributed Lag (ARDL) modeling and a novel Dynamic Autoregressive Distributed Lag (DYARDL) simulation forecast to explore both long- and short-term relationships between agricultural economic growth (AEG) and four independent variables: agricultural mechanization (AM), irrigation area (IA), chemical fertilizer consumption (CF), and crop sown land (CL). To address potential heteroskedasticity and mitigate the impact of extreme values or outliers, all variables were transformed into their natural logarithmic forms. The research utilized a log-linear regression model to analyze how AM, IA, CF, and CL influence AEG in China, highlighting the intricate interdependencies among these factors. Figure 1 shows the analytical frameworks of this study. This comprehensive approach not only clarifies the individual contributions of each variable to agricultural economic growth but also provides insights into their collective impact, thereby enhancing the understanding of agricultural development dynamics in the region. The log-linear regression model in Equation 1 is as follows:

$$\ln AEG = \beta_0 + \beta_1 \ln AM + \beta_2 \ln IA + \beta_3 \ln CF + \beta_4 \ln CL + \varepsilon_t \quad (1)$$

Where t stands for time period, $\ln$ denotes natural log, β_1 , β_2 , β_3 , and β_4 represent coefficients, and ε is an error term.

TABLE 1 Summary of existing studies on factors affecting agricultural economic growth.

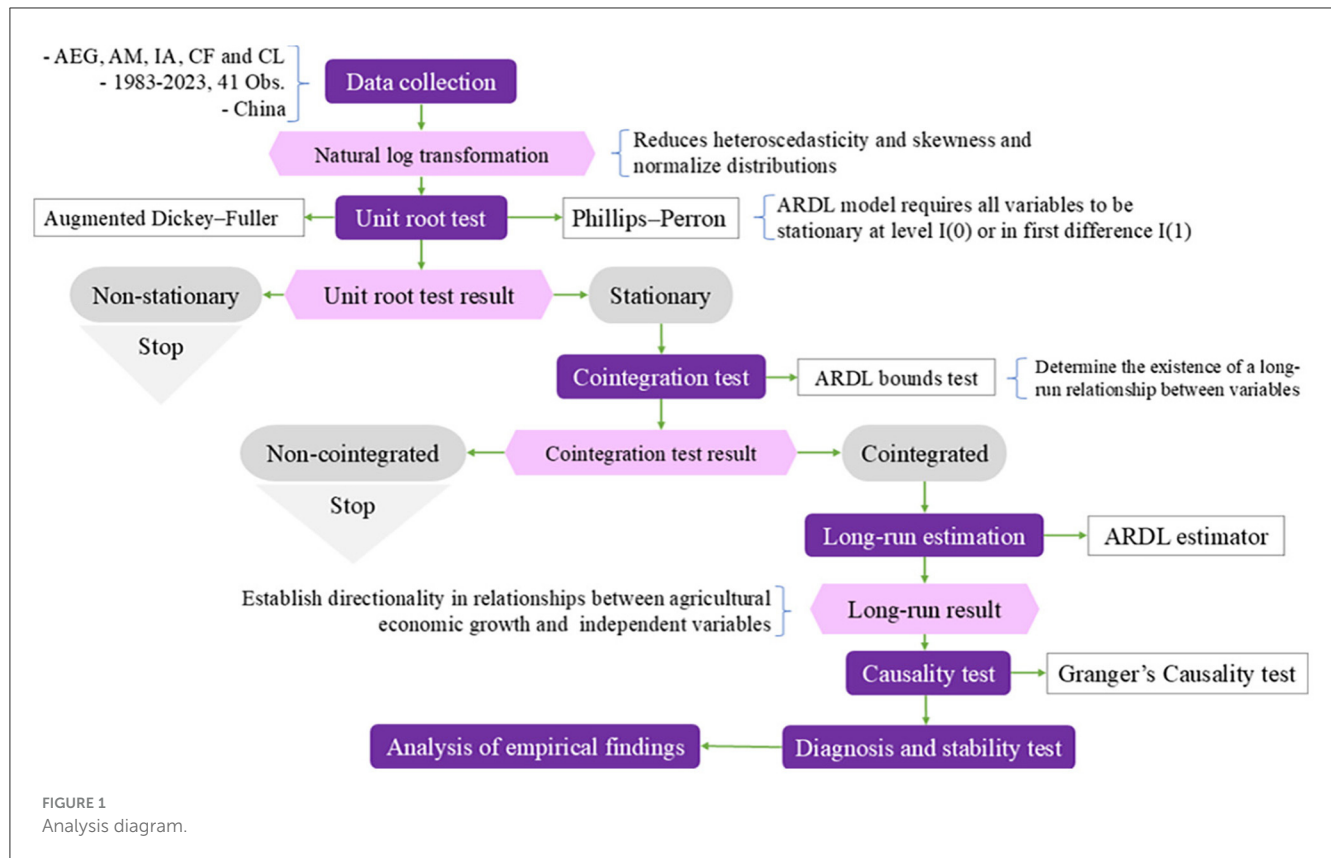
References	Sample	Period	Methodology	Main findings
Mei et al. (2022)	China	2014–2018	FGLS	↑Internet finance and rural finance-↑AEG
Guo et al. (2021)	China	2001–2018	MS(M)-AR(p) model	↑Agricultural Support Policies-↑AEG
Kuang et al. (2022)	China	2005–2018	Intermediary effect test model	↑Farmland transfer-↑AEG
Lin and Wang (2024)	China	2004–2020	Fixed-effect model	↑Natural disasters-↓AEG
Liu and Wang (2005)	China	1991–1999	Extended production model	↑Technological progress-↑AEG
Nan et al. (2019)	China	1997–2014	Two-step generalized method	↑Rural credit cooperatives'-↑AEG
Zeng et al. (2022)	China	2007–2019	Random effects model	↑Agricultural insurance-↑AEG
Wang (2022)	China	1985–2019	ARDL	↑CO ₂ emissions, ↑AGExp, ↑OILC, and ↑GASC-↑↓AEG
Sun and Chen (2020)	China	1970–1987	OLS method	↑Household responsibility system-↑AEG
Hu et al. (2023)	China	2000–2019	Logarithmic Mean Divisia index method	↑Agricultural energy consumption-↓AEG
Zhao et al. (2018)	China	1978–2015	Modified production function model	↑Capital-↑AEG
Abdul-Rahim et al. (2018)	China	2003–2012	Cobb–Douglas production function	↑Soil and water conservation-↑AEG
Gao et al. (2014)	China	1978–2010	Provincial index approach	↑Rural-urban income gaps-↓AEG
Yin et al. (2024)	China	2000–2019	Panel-fixed-effects models	↑Geographical indications-↑AEG
Li and Li (2021)	China	2007–2017	Dynamic spatial panel lag model	↑Water pollution-↓AEG
Deng et al. (2024)	China	2011–2020	The synthetic control method	↑Farmland use right mortgage loan-↓AEG
Yuan et al. (2022)	China	1991–2018	Benchmark panel regressions	↑Temperature fluctuation-↓AEG
Warsame and Daror (2024)	Somalia	1985–2017	ARDL and VECM	↑Environmental degradation-↓AEG
Adedoyin et al. (2020)	Sub-Saharan Africa	1980–2014	PMG-ARDL	↑CO ₂ emissions-↓AEG
Aydogan and Vardar (2020)	E7 countries	1990–2014	EKC and Granger causality	↑CO ₂ emissions, real GDP, non-renewable energy use-↑↓AEG
Najafi Alamdarlo (2016)	Iran	2001–2013	EKC	↑Water consumption and CO ₂ emissions-↑↓AEG
Zafeiriou and Azam (2017)	Europe	1992–2014	ARDL and EKC	↑Environmental degradation-↓AEG
Asumadu-Sarkodie and Owusu (2016)	Ghana	1961–2012	ARDL and VECM	↑CO ₂ emissions and agriculture, land use ↑↓AEG
Ali et al. (2019)	Pakistan	1961–2014	ARDL	↑CO ₂ emissions, land under cereal crops↑ ↑↓AEG
Chandio et al. (2021)	Pakistan	1984–2016	ARDL	↑Energy consumption ↑↓AEG
Chandio et al. (2019a,b)	Pakistan	1980–2016	ARDL	↑Environmental degradation-↓AEG
Rehman et al. (2019)	Pakistan	1987–2017	ARDL	↑Cropped area, ↑energy consumption, ↑fertilizer use, ↑GDP per capita, and ↑water availability and ↑CO ₂ emissions-↑↓AEG
Chandio et al. (2019a,b)	Pakistan	1977–2014	ARDL	↑CO ₂ emissions, ↑financial development and ↑fertilizer use-↑↓AEG
Ali et al. (2019)	Pakistan	1960–2014	ARDL	↑CO ₂ emissions-↓AEG
Gupta and Kannan (2024)	India	1981/2– 2019/20	Bai–Perron multiple breakpoint method	↑Trade terms, ↑irrigation, ↑cropping intensity, ↑public investment, ↑fertilizer use, and ↑labor, ↑crop diversification-↑↓AEG

↑↓ denote increase and decrease, respectively.

3.2.1 ARDL model

The ARDL model was developed by Pesaran et al. (2001) to estimate the long- and short-run relationships among variables. Unlike conventional cointegration tests,

which require all time series data to be non-stationary and integrated of the same order [typically I(1)], the ARDL model can be estimated using time series data with mixed orders of integration [I(0) and I(1)], but not I(2), and it



allows for different lag lengths for both regressors and the dependent variable.

Applying the ARDL technique, unbiased long-run estimates can be obtained. The ARDL model is also a useful approach for small and finite sample sizes and uses a combination of endogenous and exogenous variables, unlike a VAR model, which is strictly for endogenous variables. However, if any variable in the data is stationary at the second difference, $I(2)$, the ARDL approach cannot be applied. In the ARDL model, there must be no autocorrelation among the error terms. Additionally, the data should exhibit no heteroscedasticity, meaning that the variance and mean must remain constant throughout the model. The data should also follow a normal distribution. In the ARDL model, if the variables are not cointegrated, only the short-run ARDL model can be specified. The generalized ARDL (p, q) model is specified in Equation 2:

$$Y_t = \gamma_{0i} + \sum_{i=1}^p \delta_i Y_{t-i} + \sum_{i=0}^q \beta'_i X_{t-i} + \varepsilon_{it} \quad (2)$$

Where Y_t : The dependent variable at time t .

γ_{0i} : The constant or intercept term.

$\sum_{i=1}^p \delta_i Y_{t-i}$: The autoregressive (AR) part of the model, where Y_{t-i} are lagged values of the dependent variable and δ_i are the coefficients associated with these lags. $\sum_{j=0}^q \beta'_j X_{t-j}$: The distributed lag (DL) part of the model, where X_{t-j} are the lagged values of the independent variable(s) and β'_j are the coefficients associated with these lags. ε_t : The error term at time t , capturing all other influences on Y_t not included in the model.

Equation 3 shows the ARDL model of this study for long-run and short-run estimations.

$$\begin{aligned} LnAEG_t = & \vartheta_0 + \sum_{t-1}^p \vartheta_1 LnAM_{t-1} + \sum_{t-1}^p \vartheta_2 LnIA_{t-1} \\ & + \sum_{t-1}^p \vartheta_3 LnCF_{t-1} + \sum_{t-1}^p \vartheta_4 LnCL_{t-1} + \sum_{t-1}^q \Delta LnAM_{t-1} \\ & + \sum_{t-1}^q \Delta LnIA_{t-1} + \sum_{t-1}^q \Delta LnCF_{t-1} + \sum_{t-1}^q \Delta LnCL_{t-1} \\ & + ECT_{t-1} \end{aligned} \quad (3)$$

The signs $\vartheta_1, \vartheta_2, \vartheta_3, \vartheta_4$ represent long-run estimates; Δ denotes the short-run regressors; the error correction term is ECT_{t-1} , which indicates adjustment speed toward the long-run in a short time period. The p and q symbolize lag lengths; while t stands for time. The optimal lag length is selected based on the AIC. Although the inclusion of additional lags improves the regression fit, it comes at the cost of higher variance in the coefficient estimates. To balance this trade-off, we employed a data-driven approach for optimal lag selection using the automatic Akaike Information Criterion (AIC) method, which is a popular technique for determining the best lag length in time series analysis (Kripfganz and Schneider, 2023). Recently, several researchers have also utilized automatic selection of the optimal lag order with the AIC in their studies to determine the best lag length for fitting the ARDL model (Wang, 2022).

3.2.2 The novel dynamic ARDL simulations

This study uses the novel DYARDL developed by [Jordan and Phillips \(2018\)](#) to investigate the effect of the main agricultural input resources on AEG. Unlike the ARDL model, the DYARDL can better capture the dynamics of data with feedback effects, making it more flexible in handling complex time series relationships ([Abdullahi et al., 2024](#)). The variables should be stationary at $I(1)$ and $I(0)$, and they must be cointegrated. In the DYARDL model, the other variables in the equation remain unchanged. [Equation 4](#) presents the error correction form of the novel DYARDL model used in the current study:

$$(\Delta \text{LnAEG})_t = \alpha_0 + \theta_0 \text{LnAEG}_{t-1} + \beta_1 \Delta \text{LnAM}_t + \theta_1 \text{LnAM}_{t-1} + \beta_2 \Delta \text{LnIA}_t + \theta_2 \text{LnIA}_{t-1} + \beta_3 \Delta \text{LnCF}_t + \theta_3 \text{LnCF}_{t-1} + \beta_4 \Delta \text{LnCL}_t + \theta_4 \text{LnCL}_{t-1} + \varepsilon_t \quad (4)$$

3.2.3 Stationarity test

This study used the Augmented Dickey-Fuller (ADF), the Phillip-Perron (PP), the Kwiatkowski-Phillips-Schmidt-Shin (KPSS), and the Zivot-Andrew's test to check the stationarity of the variables. In the unit root test, the null hypothesis posits that the data are non-stationary, while the alternative hypothesis asserts that the data are stationary. [Equation 5](#) illustrates the unit root test applied to the current dataset.

$$\Delta Y_t = \alpha_0 + \beta_0 T + \beta_1 Y_{t-1} + \sum_{i=1}^m \alpha_i \Delta Y_{t-i} + \varepsilon_t \quad (5)$$

In [Equation 5](#), Y is the variable being examined for unit root; T represents the linear trend; ΔY_{t-1} indicates the lag difference; α_0 is the constant term; and t indicates the time trend. The null and alternative hypotheses of “unit root test” can be represented as $\beta_1 = 0$ OR $H_1: \beta_1$.

3.2.4 Cointegration testing

This study followed the ARDL bound test introduced by [Pesaran et al. \(2001\)](#) for examining the existence of long-run cointegration between variables. When conducting a cointegration test, if the F -statistic and t -test values exceed the upper bound critical value by $<5\%$, this suggests a long-run cointegration relationship between the dependent variable and the regressors; otherwise, no cointegration exists. However, if the computed F -statistic and t -test fall between the lower and upper bound critical values, the results are inconclusive ([Asumadu-Sarkodie and Owusu, 2016](#)). To test the long-run cointegration, two hypotheses are formulated.

$$H_0: b_{11} = b_{21} = b_{31} = b_{41} = b_{51} = 0$$

$$H_1: \text{At least one } b_{i1} \neq 0, (\text{where } i = 1, 2, 3, 4, 5)$$

To perform the bounds test for long-run cointegration, the conditional ARDL (P, q_1, q_2, q_3, q_4) model with four variables is

specified in [Equations 6–11](#):

$$\begin{aligned} \Delta \text{LnAEG}_t = & a_{01} + b_{11} \text{LnAEG}_{t-1} + b_{21} \text{LnAM}_{t-1} + b_{31} \text{LnIA}_{t-1} \\ & + b_{41} \text{LnCF}_{t-1} + b_{51} \text{LnCL}_{t-1} + \sum_{i=1}^p a_{1i} \Delta \text{LnAEG}_{t-i} \\ & + \sum_{i=1}^{q_1} a_{2i} \Delta \text{LnAM}_{t-i} + \sum_{i=1}^{q_2} a_{3i} \Delta \text{LnIA}_{t-i} \\ & + \sum_{i=1}^{q_3} a_{4i} \Delta \text{LnCF}_{t-i} + \sum_{i=1}^{q_4} a_{5i} \Delta \text{LnCL}_{t-i} + e_{1t} \end{aligned} \quad (6)$$

$$\begin{aligned} \Delta \text{LnAM}_t = & a_{01} + b_{11} \text{LnAM}_{t-1} + b_{21} \text{LnAEG}_{t-1} + b_{31} \text{LnIA}_{t-1} \\ & + b_{41} \text{LnCF}_{t-1} + b_{51} \text{LnCL}_{t-1} + \sum_{i=1}^p a_{1i} \Delta \text{LnAM}_{t-i} \\ & + \sum_{i=1}^{q_1} a_{2i} \Delta \text{LnAM}_{t-i} + \sum_{i=1}^{q_2} a_{3i} \Delta \text{LnIA}_{t-i} \\ & + \sum_{i=1}^{q_3} a_{4i} \Delta \text{LnCF}_{t-i} + \sum_{i=1}^{q_4} a_{5i} \Delta \text{LnCL}_{t-i} + e_{1t} \end{aligned} \quad (7)$$

$$\begin{aligned} \Delta \text{LnIA}_t = & a_{01} + b_{11} \text{LnIA}_{t-1} + b_{21} \text{LnAM}_{t-1} + b_{31} \text{LnAEG}_{t-1} \\ & + b_{41} \text{LnCF}_{t-1} + b_{51} \text{LnCL}_{t-1} + \sum_{i=1}^p a_{1i} \Delta \text{LnIA}_{t-i} \\ & + \sum_{i=1}^{q_1} a_{2i} \Delta \text{LnAM}_{t-i} + \sum_{i=1}^{q_2} a_{3i} \Delta \text{LnIA}_{t-i} \\ & + \sum_{i=1}^{q_3} a_{4i} \Delta \text{LnCF}_{t-i} + \sum_{i=1}^{q_4} a_{5i} \Delta \text{LnCL}_{t-i} + e_{1t} \end{aligned} \quad (8)$$

$$\begin{aligned} \Delta \text{LnCF}_t = & a_{01} + b_{11} \text{LnCF}_{t-1} + b_{21} \text{LnAM}_{t-1} + b_{31} \text{LnIA}_{t-1} \\ & + b_{41} \text{LnAEG}_{t-1} + b_{51} \text{LnCL}_{t-1} + \sum_{i=1}^p a_{1i} \Delta \text{LnCF}_{t-i} \\ & + \sum_{i=1}^{q_1} a_{2i} \Delta \text{LnAM}_{t-i} + \sum_{i=1}^{q_2} a_{3i} \Delta \text{LnIA}_{t-i} \\ & + \sum_{i=1}^{q_3} a_{4i} \Delta \text{LnCF}_{t-i} + \sum_{i=1}^{q_4} a_{5i} \Delta \text{LnCL}_{t-i} + e_{1t} \end{aligned} \quad (9)$$

$$\begin{aligned} \Delta \text{LnCL}_t = & a_{01} + b_{11} \Delta \text{LnCL}_{t-1} + b_{21} \Delta \text{LnAM}_{t-1} + b_{31} \text{LnIA}_{t-1} \\ & + b_{41} \text{LnCF}_{t-1} + b_{51} \text{LnAEG}_{t-1} + \sum_{i=1}^p a_{1i} \Delta \text{LnCL}_{t-i} \\ & + \sum_{i=1}^{q_1} a_{2i} \Delta \text{LnAM}_{t-i} + \sum_{i=1}^{q_2} a_{3i} \Delta \text{LnIA}_{t-i} \\ & + \sum_{i=1}^{q_3} a_{4i} \Delta \text{LnCF}_{t-i} + \sum_{i=1}^{q_4} a_{5i} \Delta \text{LnCL}_{t-i} + e_{1t} \end{aligned} \quad (10)$$

Then, if there is no cointegration, the ARDL (P, q_1, q_2, q_3, q_4) model is specified in [Equation 12](#).

$$\begin{aligned} \Delta \text{LnAEG}_t = & a_{01} + \sum_{i=1}^p a_{1i} \Delta \text{LnAEG}_{t-i} + \sum_{i=1}^{q_1} a_{2i} \Delta \text{LnAM}_{t-i} \\ & + \sum_{i=1}^{q_2} a_{3i} \Delta \text{LnIA}_{t-i} + \sum_{i=1}^{q_3} a_{4i} \Delta \text{LnCF}_{t-i} \\ & + \sum_{i=1}^{q_4} a_{5i} \Delta \text{LnCL}_{t-i} + e_t \end{aligned} \quad (11)$$

If there is cointegration, the error correction model (ECM) representation is specified in [Equation 13](#).

$$\begin{aligned} \Delta \text{LnAEG}_t = & a_{01} + \sum_{i=1}^p a_{1i} \Delta \text{LnAEG}_{t-i} + \sum_{i=1}^{q_1} a_{2i} \Delta \text{LnAM}_{t-i} \\ & + \sum_{i=1}^{q_2} a_{3i} \Delta \text{LnIA}_{t-i} + \sum_{i=1}^{q_3} a_{4i} \Delta \text{LnCF}_{t-i} \\ & + \sum_{i=1}^{q_4} a_{5i} \Delta \text{LnCL}_{t-i} + \lambda \text{ECT}_{t-1} + e_t \end{aligned} \quad (12)$$

Where, $\lambda = \left(1 - \sum_{i=1}^p \delta_i\right)$, speed of adjustment parameter with a negative sign; $\text{ECT} = (\text{LnAEG}_{t-1} - \theta X_t)$; the error correction term; $\theta = \frac{\sum_{i=0}^q \beta_i}{\alpha}$, is the long-run parameter; $a_{1i} a_{2i} a_{3i} a_{4i} a_{5i}$ are the short-run dynamic coefficients of the model's adjustment to the long-run equilibrium. Obtain the short-run dynamic parameter by estimating the ECM associated with the long-run estimates. The short-run causal effect is represented by the

t -statistic on the explanatory variables (short-run coefficients). The long-run relationship between the variables indicates that there is Granger causality in at least one direction, which is determined by the t -statistic on the coefficient of the lagged error correction term.

3.2.5 Granger causality test

We further apply Granger causality analysis to evaluate the causal effect between the variables (Granger, 1969). Similarly, before conducting the Granger causality test, it is necessary for the variables to be stationary. Additionally, after estimating the model, diagnostic checks were performed to ensure that residuals do not exhibit serial correlation, which could otherwise affect the validity of the test results (Figure 1). While testing the Granger causality, the null hypothesis (H_0) is that $Y(t)$ does not Granger-cause $X(t)$, meaning that all coefficients associated with lagged values of $Y(t)$, when included in a regression model predicting $X(t)$, are equal to zero. The alternative hypothesis (H_1) is that $Y(t)$ does Granger-cause $X(t)$, meaning at least one coefficient associated with lagged values of $Y(t)$, when included in such a regression model, is non-zero (Granger, 1969). The f -value was estimated to reject the null hypothesis if the F -statistic is greater than the f -value. The following two equations were used to find $\beta_j = 0$ for all lags j .

$$X(t) = \sum_{i=1}^p \alpha_i X(t-i) + c_1 + u_1(t) \quad (13)$$

$$X(t) = \sum_{i=1}^p \alpha_i X(t-i) + \sum_{j=1}^q \beta_j Y(t-j) + c_2 + u_2(t) \quad (14)$$

The f -statistics was calculated using the following equation:

$$F = \frac{ESS_R - ESS_{UR}/q}{ESS_{UR}/(n-k)} \quad (15)$$

Where ESS_R : Error sum of squares for the restricted model (Equation 13); ESS_{UR} : Error sum of squares for the unrestricted model (Equation 14); q : Number of restrictions [equal to the number of lagged terms of $Y(t)$]; n : Number of observations; k : Total number of parameters in the unrestricted model.

The null hypothesis was rejected if the F -statistic exceeded the critical value from the F -distribution table or if the p -value was less than the significance level (e.g., 0.05). This indicates that $Y(t)$ Granger-causes $X(t)$. Otherwise, the null hypothesis failed to be rejected, implying no evidence that $Y(t)$ Granger-causes $X(t)$.

4 Empirical results and discussion

4.1 Descriptive statistics

The descriptive statistics in Table 2 show that these series are obviously heterogeneous. The average AM is larger than that of the other independent variables. The standard deviation clearly shows that AEG value is the highest, followed by the AM, suggesting that there have been more changes in agricultural development during the study period, and show great fluctuation. As we see in Table 2, the skewness values for all variables were between -1 and 1 , which

TABLE 2 Descriptive statistics.

Statistic	LnAEG	LnAM	LnIA	LnCF	LnCL
Mean	26.288	20.1344	10.921	17.494	18.532
Median	26.238	20.2189	10.903	17.602	18.537
Std.	1.169	0.5934	0.156	0.397	0.044
Skewness	−0.329	−0.3536	0.099	−0.905	−0.604
Kurtosis	1.939	1.7095	1.754	2.550	2.936
Min	24.065	19.0097	10.692	16.624	18.414
Max	27.931	20.8531	11.179	17.913	18.596
Jarque-Bera	5.664	10.8616	8.858	5.694	3.241
Probability	0.058	0.0044	0.012	0.058	0.199
Observation	41	41	41	41	41

TABLE 3 Correlation matrix.

Variables	LnAEG	LnAM	LnIA	LnCF	LnCL
LnAEG	1.000				
LnAM	0.9851	1.000			
LnIA	0.979	0.9647	1.000		
LnCF	0.951	0.9577	0.891	1.000	
LnCL	0.366	0.2906	0.464	0.177	1.000

generally shows approximately symmetric distributions, which is an indicator of normality of all variables.

The correlation matrix analysis in Table 3 demonstrates the strength and direction of relationships between variables.

Except for CL in Figure 2, the plots of the other variables during the study period show an increasing trend, highlighting the presence of relationships among the study variables.

4.2 Unit root tests

The analysis in this study begins with checking whether the variables are stationary at level $I(0)$ or first difference $I(1)$, followed by the establishment of the system's optimal lag length, k , as it is the essential requirement for further investigation. This study applied the augmented Dickey and Fuller (ADF), Phillips and Perron (PP), Kwiatkowski-Phillips-Schmidt-Shin (KPSS), and Zivot-Andrews unit root tests are four widely used methods for time series analysis (Dickey and Fuller, 1979; Phillips and Perron, 1986). Conducting both the ADF and PP tests provides a more comprehensive analysis of the stationarity of a time series, helping to validate findings and better understand the underlying data characteristics. They have different methodologies and underlying assumptions, which can yield complementary insights.

Table 4 shows the results of ADF, PP, and KPSS stationarity tests at $I(0)$ and $I(1)$. The unit root test results reveal important insights into the stationarity characteristics of various agricultural variables. AEG is found to be stationary at the level according to the ADF

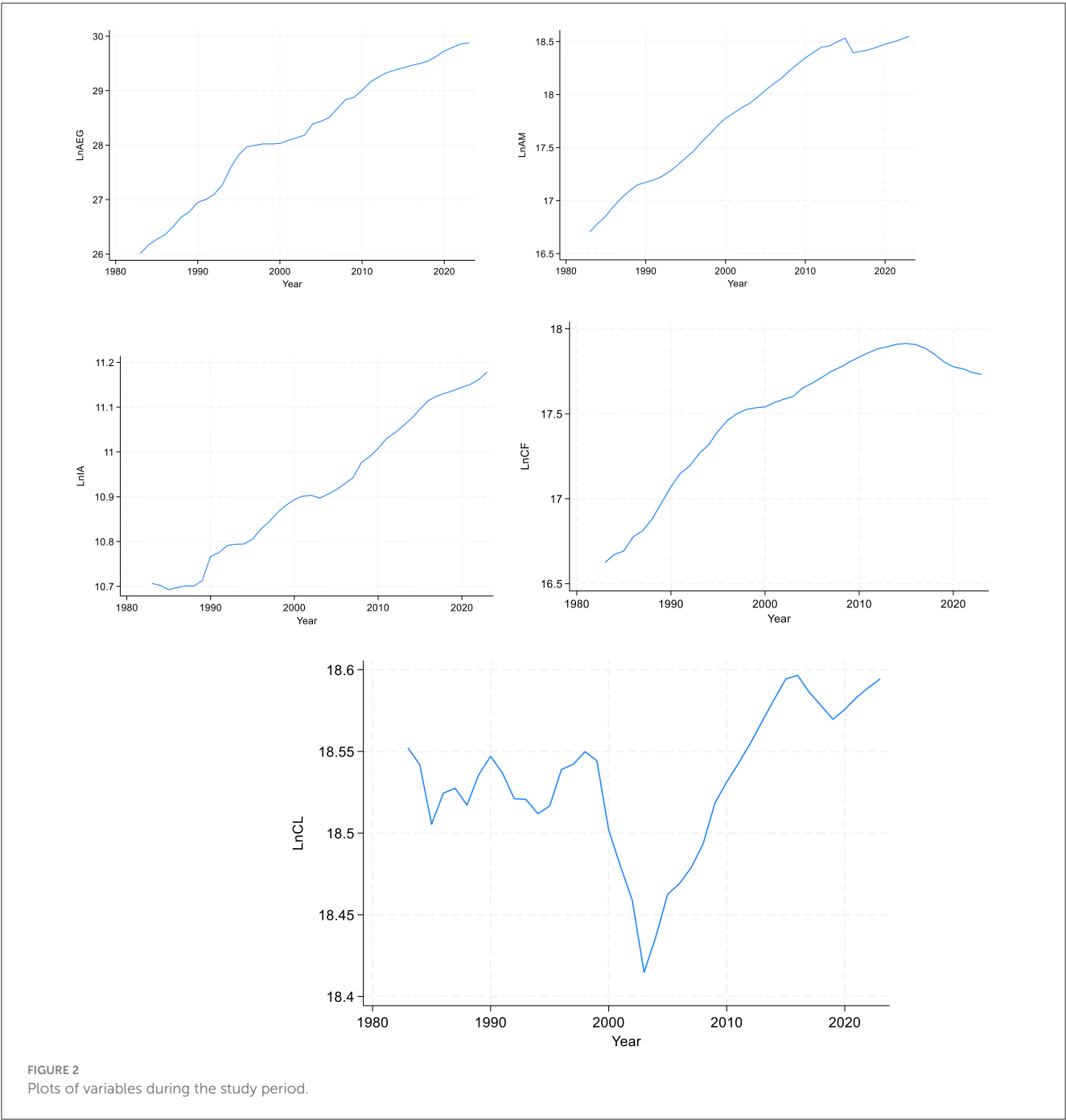


TABLE 4 Unit root test analysis.

Variable	Level ADF	Δ ADF	Level PP	Δ PP	Level KPSS	Δ KPSS
LnAEG	-2.688*	-3.584***	-2.215	-3.584***	0.637	0.074***
LnAM	-3.398**	-3.910***	-2.692*	-3.948***	0.780	0.145***
LnIA	0.774	-4.589***	0.544	-4.527***	0.273	0.105***
LnCF	-6.009***	-1.862	-3.932***	-1.645	0.899	0.15***
LnCL	-0.840	-4.220***	-1.348	-4.246***	0.650	0.094***

Δ : first difference. ***, **, * Illustrates null hypothesis 1%, 5%, and 10% significance level, respectively.

TABLE 5 Zivot-Andrews unit root test with structural breaks.

Variable	Level Z Andrew	Breaking year	Δ Z Andrews	Breaking year
LnAEG	−4.059	1994	−4.980*	1996
LnAM	−3.594	2010	−7.285***	2016
LnIA	−4.095	2002	−5.336**	1991
LnCF	−3.281	2011	−4.463	1991
LnCL	−4.525	2000	−5.834***	2004

Δ : first difference, *represents 10% significance level, **shows 5% significance level, and ***indicates 1% significance level.

tests, but it exhibits stationarity at first difference across the PP and KPSS tests.

In the case of AM, the ADF and PP tests identify it as stationary at level, while the KPSS test suggests that it is stationary at first difference. IA is consistently non-stationary at the level in all tests, but it becomes stationary upon taking the first difference. CF presents a mixed picture, being stationary at the level according to the ADF and PP tests, yet it is stationary at the first difference in the KPSS test. Finally, CL remains non-stationary at the level in all tests, transitioning to stationarity at first difference across the board (Table 4). These findings underscore the necessity of differencing for ensuring stationarity in time series analyses involving these agricultural indicators.

The ADF and PP unit-root tests are the most commonly used in previous research. However, they may create a bias toward non-rejection of the unit root for small sample sizes. Thus, this study further implemented the structural break unit root test developed by Zivot and Andrews (1992). This unit root test offers the variables with a breaking stationary series, assisting in exploring the factors that affect the agricultural input resource in the time series. Table 5 shows the results of the structural break unit root test. The structural break unit root test shows that the t -statistic for agricultural economic growth exceeded the critical value at a significance level below 10%, with a break occurring in 1996. The mid-1990s was a period in which economic reforms and urbanization spurred off-farm work, increasing wage labor and self-employment opportunities, which significantly boosted farmers' incomes (Wang et al., 2011). Moreover, since the mid-1990s, China's agricultural productivity has benefited from plant biotechnology innovations such as Bt cotton, enhancing agricultural outcomes (Huang et al., 2002). The 15-year contract of the Household Responsibility System (HRS), a system that decentralized land control to individual households, was extended from 15 to 30 years, creating stability in land contract system and resulting in boosting agricultural productivity (Huang et al., 2020; Huang and Rozelle, 2017).

Agricultural mechanization rejects the null hypothesis at a significance level below 1%, with a structural break in 2016. The unexpected rise in agricultural mechanization in China around 2016 may have been driven by the 2014 land transfer policy, which promoted the separation of the "three rights" (land ownership, contract, and management). This policy facilitated the consolidation of large-scale farms and the uptake of agricultural machinery, boosting agricultural productivity and

incomes (Duan et al., 2021; Gong et al., 2022). In the case of the irrigated area, the null hypothesis was rejected at a significant level below 5% with a structural break in 1991. The expansion of irrigated area in China at the beginning of the 1990s can be associated with the first China's water law, which was enacted in 1988, largely in response to the decline in irrigated land (Lohmar et al., 2003). Following this, government investment in water infrastructure grew to 2.9% of total investments, driven by both the need to repair and maintain infrastructure and a broader national focus on infrastructure development. By 1990, the area of irrigated land increased to 48.39 million hectares, slightly surpassing the 1978 level (Wang et al., 2020).

The results of chemical fertilizer showed no significant difference at both levels and first difference in the years 2011 and 1991, respectively. Because, in 1991, the use of chemical fertilizer is just at the start of its rising stage, as the period was the initial stage of a dual system of central planning and market adjustment, and the surge of chemical fertilizer was inconsiderable (Li et al., 2013). The structural break unit root test shows that the t -statistic for crop sown land surpassed the critical value at a significance level below 1%, with a break occurring in 2004. The sharp increase in the agricultural sown area in 2004 was largely due to the introduction of China's new agricultural subsidy system, which protected farmers' rights, and the 2002 Rural Land Contract Law, which legally defined collective land ownership, fostering the development of large-scale agriculture (Du et al., 2011; Zhou et al., 2020). Currently, policies are in action to protect the existing crop land and reclaim the degraded and abandoned land (Table 5).

4.3 ARDL bound cointegration tests

The stationarity of the included variables enables us to continue to the cointegration test. This study probed the cointegration between agricultural mechanization level, irrigated area, chemical fertilizer consumption, crop land, and agricultural economic growth using the ARDL bound cointegration testing approach based on Kripfganz and Schneider (2023). The results of the cointegration test in Table 6 show that the values of F -state and t -test are 9.225 and −6.370, respectively. These values exceed the upper and lower bound critical values at 1% significance level, supported by the P -value. Thus, we reject the null hypothesis (H_0) of no-cointegration and confirm the existence of cointegration among the study variables. This indicates the presence of a long-run equilibrium relationship between agricultural mechanization level, irrigated area, chemical fertilizer consumption, crop land, and agricultural economic growth. In this context, the cointegration indicates that while this variable may exhibit short-term fluctuations, it converges to a stable equilibrium over time. Moreover, the cointegration among these variables implies that a change in one of the independent variables will likely result in corresponding adjustments in agricultural economic growth. Using the ARDL bound test approach, existing studies also proved the presence of cointegration among variables, such as chemical fertilizer consumption and agricultural economic growth in China and Pakistan (Rehman et al., 2019; Chandio et al., 2019a,b; Khan et al., 2022).

TABLE 6 ARDL bounds testing with Kripfganz's novel *p*-values.

$K = 4$		10%		5%		1%		<i>P</i> -value	
		I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
<i>F</i> -stat	9.225	2.45	3.52	2.86	4.01	3.74	5.06	0.000***	0.000***
<i>t</i> -test	−6.370	−2.57	−3.66	−2.86	−3.99	−3.43	−4.60	0.000***	0.000***

*** Denotes the symbol for 1% significance level, I(0) specifies the critical value of the lower bound, I(1) represents the critical value of the upper bound.

TABLE 7 The results of DYARDL short-run and long-run estimations.

Variable	Coefficient	Std. error	<i>t</i> -test	<i>P</i> -value
Long-run associations				
ECT_1 (LnAEG)	−1.001922	0.1572952	−6.37	0.000***
LnAM	−0.5418306	0.1551827	−3.49	0.004***
LnIA	7.018342	0.5788395	12.12	0.000***
LnCF	1.216259	0.1320637	9.21	0.000***
LnCL	−0.4695141	0.3921578	−1.20	0.251
Short-run associations				
Δ LnAM	0.4372458	0.2450047	1.78	0.096*
Δ LnIA	3.704872	1.162639	3.19	0.007***
Δ LnCF	1.665627	0.7618401	2.19	0.046**
Δ LnCL	0.3342545	0.9569157	0.35	0.732
Constant	−52.189	11.20783	−4.66	0.000***
R^2 : 0.9109	Adj R^2 : 0.7710	RootMSE: 0.0341		
Number of Observations: 37		Log Likelihood: 90.449		

***, **, * Illustrates null hypothesis 1%, 5%, and 10% significance level, respectively.

H₀: No long-run and short-run relationship. H₁: There exists a long-run and short-run relationship.

4.4 Dynamic ARDL short-run and long-run estimation

The results of the DYARDL model estimation are detailed in Table 7, covering both short- and long-run analysis. In the long run, the agricultural mechanization level is shown to be highly significant with a negative coefficient of −0.541. This finding leads to the rejection of the null hypothesis at the 1% significance level, supporting the alternative hypothesis. It indicates that a 1% increase in agricultural mechanization level will decrease agricultural economic growth by 0.541% in the long run. In the short run, however, a 1% increase in agricultural mechanization level will increase agricultural economic growth by 0.437%, which is significant at the 10% significance level. Signs of coefficients differ between short- and long-term. This is because short-run gains likely arise from immediate efficiency improvements, such as faster reducing labor bottlenecks, boosting output with existing resources. Long-run negatives emerge as mechanization reduces labor demand faster than alternative employment emerges, while potentially creating overcapacity or diverting capital from more productive investments such as R&D or irrigation.

The significant negative long-run effect likely reflects labor displacement, where mechanization reduces overall agricultural employment faster than new opportunities emerge. It may also indicate structural inefficiencies, such as misallocated capital investment or reduced productivity in contexts with abundant, underutilized labor. The results are supported by previous researchers, such as Zou et al. (2024), highlight that agricultural mechanization in China has reduced the need for labor, leading to a shift of young people away from farming toward non-agricultural employment. This migration diminishes the local labor force available for agriculture and lowers household consumption, which ultimately impedes the growth of the agricultural economy. However, these results differ from those of Lu et al. (2024), which revealed that agricultural mechanization boosts green productivity via enhanced management, factor efficiency, and industrial diversification.

In the case of the irrigation area, the coefficient is positive, higher, and significant at the 1% level in the long run. The result suggests that a 1% increase in irrigation area will increase agricultural economic growth by 7.018% in the long run. In the short run, the irrigation area with a positive coefficient is also significant. A 1% increase in irrigation area will increase agricultural economic growth by 3.704% in the short run. This substantial long-run and short-run multiplier likely reflects irrigation enabling intensified production (multi-cropping, higher-value/higher-yield crops) and reduced yield volatility, significantly boosting output. It also suggests that irrigation acts as catalytic infrastructure, triggering wider investments in complementary inputs and facilitating a structural shift toward more productive farming systems. The results are in line with Li et al. (2024), who found that the expansion of irrigated land is a key driver of increased water use for irrigation, which directly boosts agricultural productivity. Furthermore, irrigation can be used for maize cultivation to increase crop yield, thereby improving the agricultural economy (Liu et al., 2023). As more land is irrigated, crop yields rise, supporting greater food production and economic growth in the agricultural sector. This growth enhances food security, raises farmer incomes, and stimulates rural economies.

Considering chemical fertilizer consumption, the long-run relationship is highly significant with a positive coefficient. The results show that a 1% increase in the chemical fertilizer consumption will increase agricultural economic growth by 1.216% in the long run. In the short run, it can also be seen that chemical fertilizer has a positive effect on agricultural economic growth with a 1% significance level, leading to the rejection of the null hypothesis. A 1% increase in chemical fertilizer consumption resulted in a 1.665% increase in agricultural economic growth in the short run. The results show that the reduction in chemical fertilizer hinders the growth of agricultural output. Simply reducing fertilizer

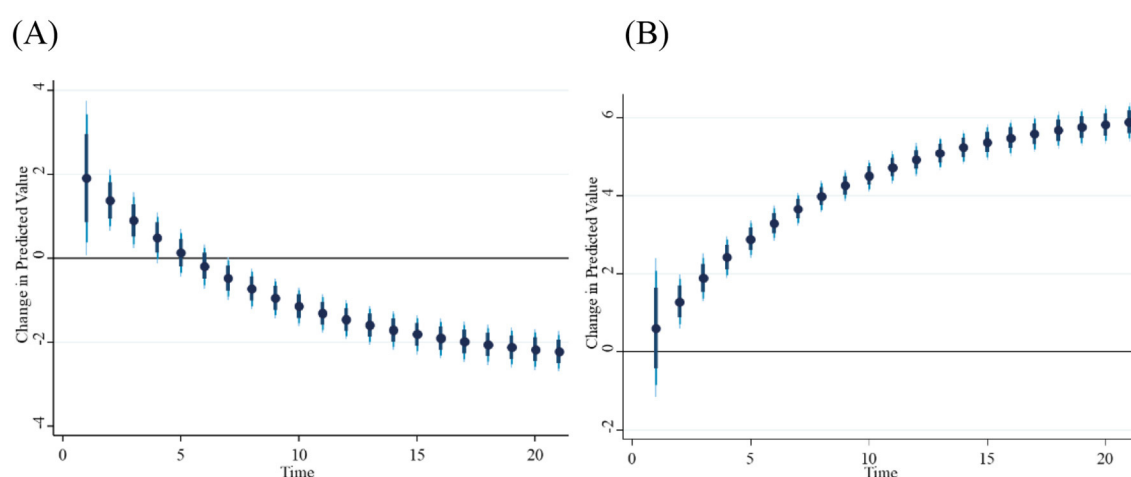


FIGURE 3
Counterfactual 10%, positive (A) and negative (B) shocks from LnAM to LnAEG.

use in crop cultivation could intensify the tension between boosting crop yields and conserving land resources in China, potentially leading to a decline in agricultural economic growth (Hu and Liu, 2024). However, this result is inconsistent with a study by Khan et al. (2022), which concludes that the short- and long-run association between chemical fertilizer use and agricultural economic growth is non-significant. This implies the need for further investigation.

In terms of crop sown land, it is noticeable that the coefficient of crop land toward agricultural economic growth has a positive effect with a negative coefficient in the long run, while a positive coefficient in the short-run and non-significant both in the long- and short-run. It suggests that we cannot reject the null hypothesis with regard to agricultural economic growth. In economically advanced and major grain-producing areas, the pressure on cultivated land does not correspond directly to economic growth, as the expansion of agricultural productivity often outpaces land constraints. This disconnect suggests that agricultural economic growth can be driven more by technological advancements and efficiency gains rather than by the mere increase in cultivated land (Wu et al., 2022). Moreover, the error correction term (ECT_{t-1}) exhibits a negative coefficient with a P -value significant at the 1% level, indicating a rapid adjustment toward long-run equilibrium within a short timeframe and suggesting resistance to shocks. The model's outcomes show both R-square and adjusted R-square values that are notably strong.

4.5 Novel dynamic ARDL simulations forecast

This study further estimated a dynamic ARDL simulation forecast model to visualize the possible effect of a counterfactual change in one regressor at a single point in time and its impact on the dependent variable, holding the other independent variables constant, using stochastic simulation techniques. In particular, we predicted a 10% positive or negative shock in the main independent

variables, which could be used to measure its impact on AEG in China. The dark blue lines indicate predicted mean values, and the light blue area to dark blue area represents 70%, 90%, and 95% confidence intervals. The impulse response results are shown in Figures 3–6. An impulse response plot is a graphical representation used in time series analysis and econometrics to show the reaction of a variable in a dynamic system to a shock or impulse over time. It illustrates how a one-time change in an input (in our case, an agricultural input resource) affects the output variable (such as AEG) at various time intervals. The importance of impulse response plots lies in their ability to capture the short-term and long-term effects of shocks in a system. The points in each graph (Figures 3–6) represent the average predicted values and impact pathways of agricultural economic growth, derived from the shocks introduced by each regressor (explanatory variables).

Figure 3A represents the influence of a 10% positive shock in the LnAM on AEG in China. The impulse response graph reveals that a 10% increase in LnAM reduces AEG while a 10% decrease in LnAM increases LnAEG (Figure 3B), both in the long- and short-run. In consistent with these findings, a study by Zou et al. (2024) found that the agricultural mechanization in China has diminished labor demand, prompting young people to pursue non-farming jobs, which in turn lowers local agricultural labor supply and household consumption, hindering the growth of the agricultural economy. Additionally, mechanization has shifted production from cash crops to grain crops, resulting in a decline in AEG. The results are also consistent with the result in Table 7.

Figures 4A, B depicts the impulse response plot of irrigated area, which shows that a 10% positive shock from LnIA to LnAEG in Figure 4A induces a slight decrease in AEG both in the long and short run. This finding aligned with a study by Li et al. (2024), which revealed that an increase in the irrigated area led to a national increase in water productivity and AEG over the period between 1982 and 2017 in China. A 10% negative shock in Figure 4B also represents a small increase in AEG in both the long and short term. This might be due to the fact that the majority of grain production comes from irrigated areas that are affected by water

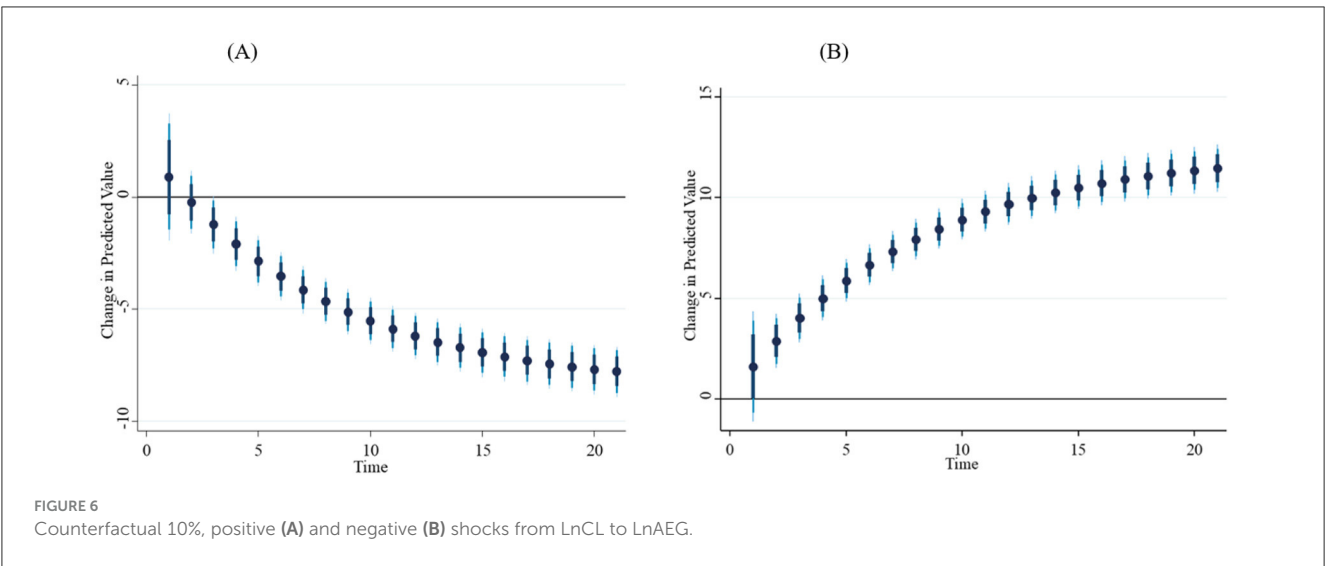
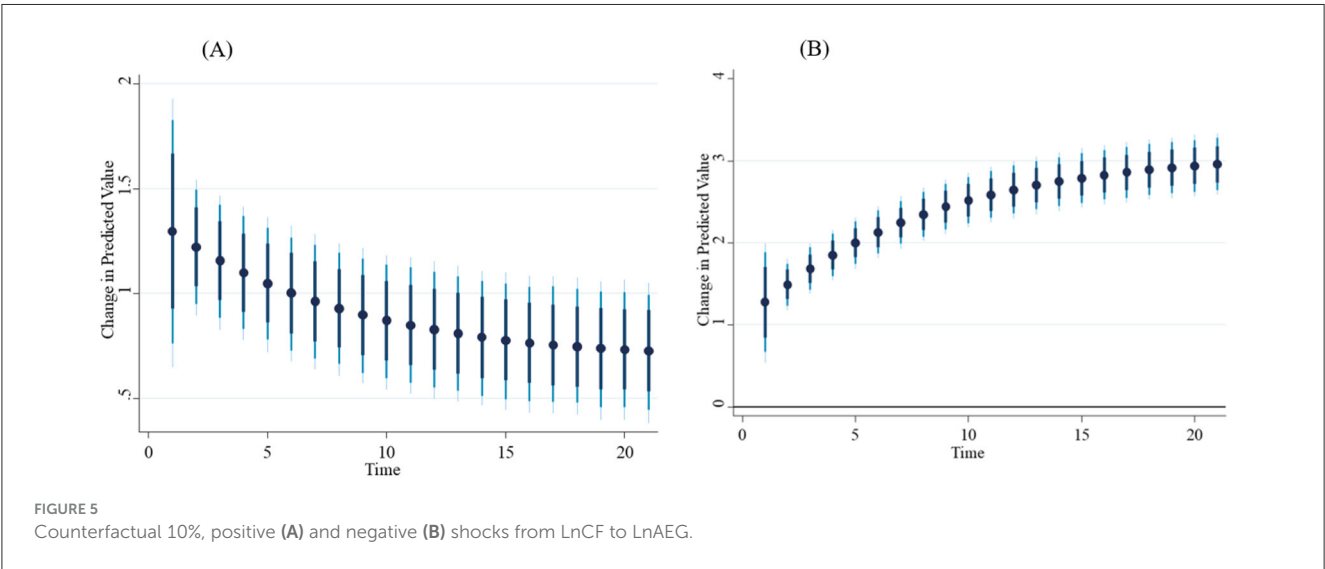
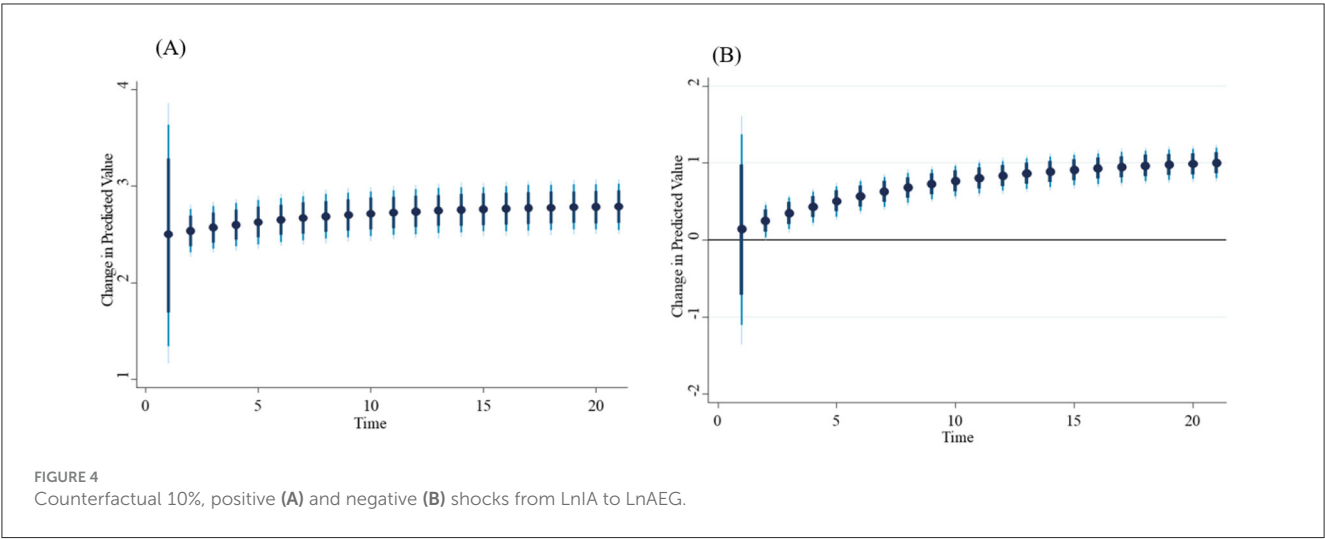


TABLE 8 Outcome of Granger causality Wald tests result.

→AEG		→AM		→IA		→CF		→CL	
AM→AEG	0.019**	AEG→AM	0.513	AEG→IA	0.000***	AEG→CF	0.000***	AEG→CL	0.001***
IA→AEG	0.000***	IA→AM	0.795	AM→IA	0.075*	AM→CF	0.002***	AM→CL	0.034**
CF→AEG	0.000***	CF→AM	0.271	CF→IA	0.000***	AI→CF	0.001***	AI→CL	0.030**
CL→AEG	0.000***	CL→AM	0.033**	CL→IA	0.000***	CL→CF	0.000***	CF→CL	0.006***
ALL→AEG	0.000***	ALL→AM	0.031**	ALL→IA	0.000***	ALL→CF	0.000***	ALL→CL	0.000***

***, **, * illustrates null hypothesis 1%, 5%, and 10% significance level, respectively. H₀: No Granger causality. H₁: There exists Granger causality.

scarcity, and the decoupling of irrigation area expansion from grain production through agricultural water productivity growth may result in an increase in AEG (Ju et al., 2023; Qi et al., 2022). These conflicting results need further investigation as the association between irrigation area expansion, water scarcity, and agricultural production is exacerbated by climate change and industrial water consumption (Liu et al., 2024).

Figure 5A shows the impulse response plot, which indicates the impact of LnCF on AEG. A 10% positive shock in LnCF declines AEG, which prevents fertilizer-caused environmental pollution. Figure 5B also shows that a 10% negative shock in LnCF results in an increase in LnAEG in the long and short run. This finding is supported by Khan et al. (2022), who found that the reduction of chemical fertilizer in China induces a significant increase in AEG. Several studies also argued that the reduction in chemical fertilizer through replacing it with organic fertilizer increases agricultural production without affecting the environment (Duan et al., 2021). Preventing excessive application of chemical fertilizer and pesticide promotes environmental sustainability without affecting agricultural production (Liu et al., 2021), and this can be achieved through a system change, particularly the agri-food system (Brunelle et al., 2024) and by providing agricultural subsidy on fertilizer use (Fan et al., 2023).

Figures 6A, B demonstrates the impulse response plot, which illustrates that a 10% positive shock in crop sown land leads to a decrease in AEG (Figure 5A) both in the short and long term, while a 10% negative shock results in an increase in AEG (Figure 6B). Crop land expansion induces huge environmental destruction, such as biodiversity loss, forest loss, carbon emission, loss of ecosystems' functions, and land degradation (Ceddia, 2020; Zeng et al., 2018). This might provide a short-term promise to increase agricultural production but at the expense of the environment, which in turn affects agricultural production, leading to a decline in overall food production. A study in the United States found that the newly converted crop land was unsuitable for crop production, producing much lower crop yields than the national average (Lark et al., 2020). To compensate for the need for additional crop land for securing agricultural production, studies in China suggest the role of reclamation of degraded land and abandoned land (Guo et al., 2023). Moreover, Schneider et al. (2022) explored that instead of new crop land expansion at the expense of the environment, it is crucial to identify suitable, cultivable, and available land for crop production. Multiple cropping is also an important mechanism to promote land-use intensification and prevent crop-land expansion, which resulted in a long-term decline in AEG (Xiang et al., 2022).

TABLE 9 Normality test results.

Source test	Chi ²	df	p-value
Cameron & Trivedi's decomposition of IM-test			
Heteroskedasticity	37.00	36	0.4226
Skewness	21.26	22	0.5049
Kurtosis	0.09	1	0.7676
Total	58.34	59	0.4996

4.6 Granger causality test

The Granger causality test in Table 8 reveals a highly interconnected agricultural system. AEG is primarily driven by increases in IA, CF, and CL, with significant causality ($p \leq 0.001$). Although AM has a weaker effect on AEG (p -value = 0.019), it significantly influences both CF and CL with p -values of 0.002 and 0.034, respectively, indicating that technological advancements in farming play a key role in input adoption and land utilization. IA shows strong causality with AEG ($p = 0.000$) and moderates strong relationships with AM, CF, and CL, underscoring its central role in the agricultural system. CF not only significantly drives agricultural growth ($p = 0.000$) but also influences AM, IA, and CL ($p \leq 0.006$). Similarly, CL exhibits strong causality with AEG, IA, and CF, and a moderate effect on IA ($p = 0.033$; Table 8). Overall, the results suggest that agricultural development is shaped by a dynamic, interdependent network of factors, where changes in one input resource, such as irrigation or fertilizer use, can trigger widespread shifts in others, ultimately driving economic growth in the sector.

4.7 Diagnostic tests

In addition, the diagnostics tests have been performed to identify any heteroscedasticity issues, abnormality issues, and serial correlation problems, as presented in Tables 9, 10. A normality test presented in Table 9 was conducted, revealing no evidence of heteroskedasticity based on Cameron and Trivedi's decomposition of the IM-test. Additionally, both skewness and kurtosis were found to be statistically insignificant, indicating that the residuals conform to the assumption of normality. This supports the conclusion that the regression model satisfies key assumptions for valid inference. The Breusch-Godfrey LM test

results in Table 9 support the null hypothesis of no autocorrelation, indicating that the selected variables are not autocorrelated. Furthermore, to detect serial correlation, in addition to analyzing residuals against their lags, the Durbin–Watson test is employed. The result shows a value of 2.11, which falls within the range of 1.5–2.5, indicating that there is no significant autocorrelation present in the data.

4.8 Stability test

The study also conducted stability tests using the cumulative sum (CUSUM) and CUSUM squared methods to verify the stability of both long-run and short-run parameters. The CUSUM results, illustrated in Figures 7, 8, indicate that the statistical values fall within acceptable limits. To address minor inconsistencies identified in earlier goodness-of-fit assessments, we applied the CUSUM test with ordinary least squares (OLS), as introduced by Ploberger and Krämer (1996). The findings presented in Figure 8 indicate that the CUSUM trend remains well within the 95% confidence interval, confirming the stability of both long- and short-run coefficients. These results strongly suggest that the model is stable and provides an excellent fit. Furthermore, this stability testing approach has been utilized in numerous studies, such as Khan et al. (2021), reinforcing its validity.

TABLE 10 Outcome of diagnostic test.

Lags (p)	Chi ²	df	Prob > F
Breusch–Godfrey LM test for autocorrelation			
1	0.259	1	0.6105
Durbin–Watson d-statistic (19, 37) = 2.119649			

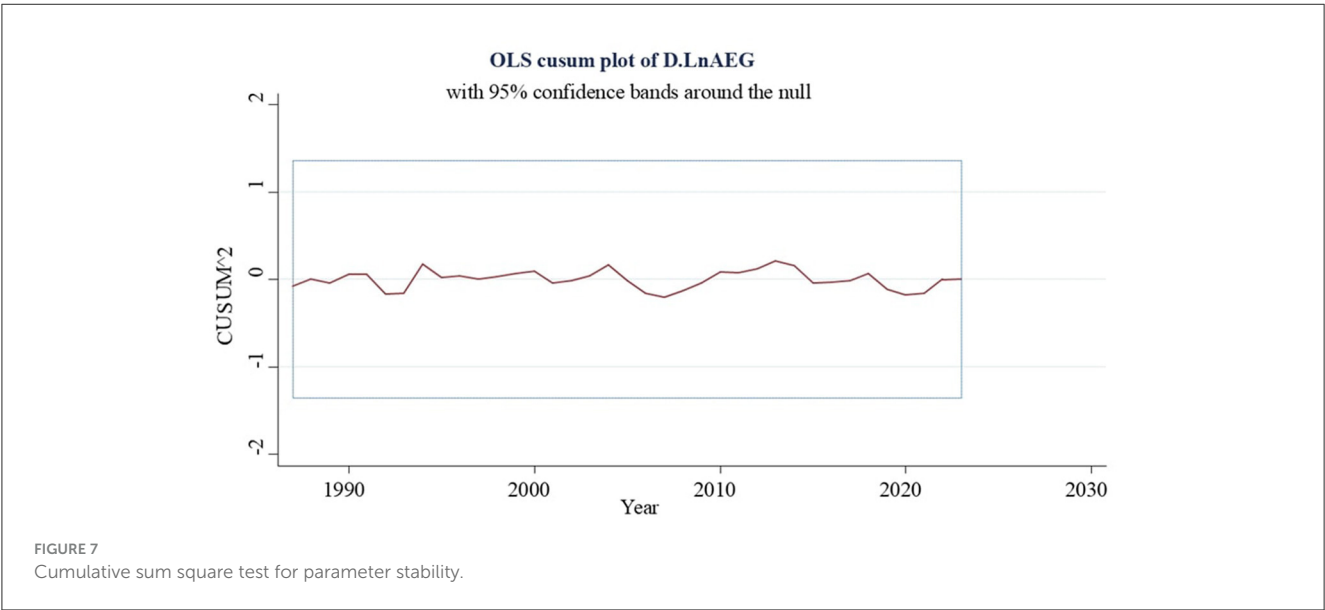
P-value < 0.05 indicates the presence of serial correlation; P-value > 0.05 indicates the absence of serial correlation. H₀: no serial correlation.

5 Conclusion and policy implications

Agriculture is often regarded as a key solution to alleviating poverty, particularly among the 80% of the world’s impoverished population residing in rural areas and dependent on farming. Recognized as a pivotal strategy, agricultural development is seen as essential for eradicating extreme poverty, promoting inclusive prosperity, and meeting the nutritional needs of an anticipated global population of 10 billion by 2050.

The Zero Hunger Challenge, initiated at Rio+20 in 2011, urges governments to double the productivity and income of smallholder farmers, establish sustainable food systems, and guarantee universal access to sufficient, nutritious food throughout the year. In the 14th Five-Year Plan period (2021–2025), the government of China issued a plan to advance agricultural and rural modernization to create a strong agricultural economy. Furthermore, the 14th Five-Year Plan (FYP) introduces a National Agriculture Green Development Plan aimed at transforming the agricultural sector to prioritize environmental sustainability. The key to achieving these goals relied on efficient utilization of agricultural input resources.

Therefore, this study conducted the association between agricultural mechanization, irrigated area, chemical fertilizer consumption, and crop sown area with agricultural economic growth in China from the onset of major rural reforms in 1983–2023, a period during which the Chinese government has actively promoted modern agriculture and rural revitalization as key strategies for future agricultural development. In recent years, the growth rate of China’s agricultural economy has declined, along with its contribution to the national economy. This trend may be attributed to dynamic changes in key agricultural input resources, driven by both anthropogenic and natural factors. Anthropogenic factors include unsustainable farming practices and excessive chemical fertilizer use, which causes nitrogen runoff soil/land degradation (Xu et al., 2023). Natural factors include natural disasters, including prolonged drought, temperature rise,



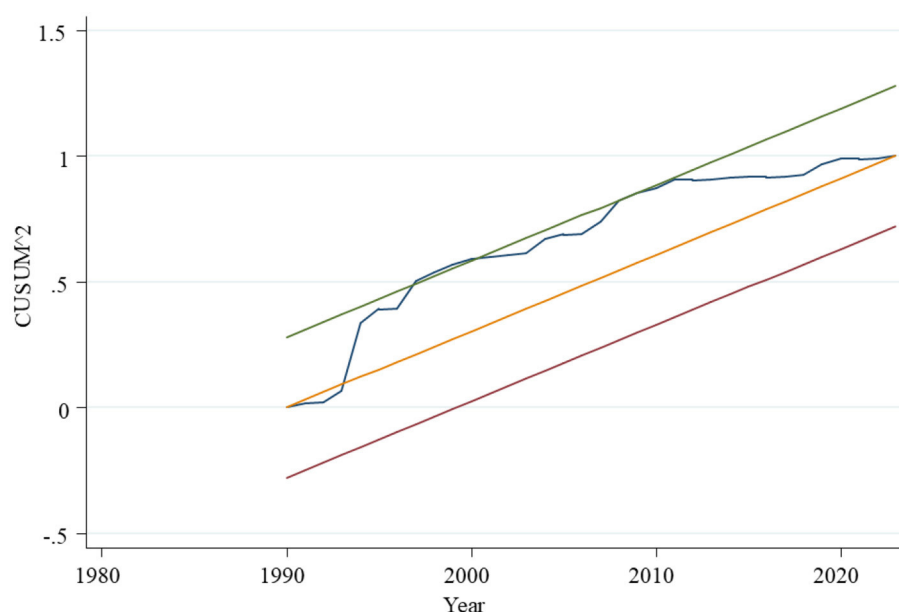


FIGURE 8
Cumulative sum test using OLS CUSUM plot for parameter stability.

biodiversity loss, and soil erosion (Lin and Wang, 2024; Yuan et al., 2022).

Annual data obtained from the Chinese statistical yearbook were used. The data were checked for the confirmation of stationarity and cointegration, as it is a requirement for further short- and long-run estimation. The ADF, PP, KPSS, and Zivot-Andrews unit root tests were conducted to confirm the stationarity of the variable at only the level or first difference. We used the ARDL bound test approach to examine the existence of cointegration in the long run among the study variables. Dynamic ARDL and novel dynamic simulation forecast were applied to estimate the effect in the long and short run. We further examine the existence of causality effect using Granger causality test approach.

The results of ADF, PP, KPSS, and Zivot-Andrews unit root tests with structural breaks confirms the stationarity of variables. The ARDL bound test result also verified the cointegration among the study variables, which validates the existence of a long-run relationship. The dynamic ARDL estimation shows that a 1% increase in agricultural mechanization slightly boosts agricultural economic growth in the short run, but may reduce it in the long run. An increase in irrigated land and chemical fertilizer consumption promotes agricultural development in both the short and long run. However, the relationship between crop sown area and agricultural growth is not significant in either the short or long run. The results from the novel dynamic ARDL model show that a 10% positive shock in agricultural mechanization, chemical fertilizer use, and crop sown area leads to a decrease in agricultural economic growth, while a 10% negative shock in these factors results in an increase in agricultural economic growth, both in the short and long run. However, a 10% shock in irrigated land remains insignificant. The strong Granger causality effects observed for irrigated area, chemical fertilizer consumption, and crop sown land

arise from their direct contributions to increasing productivity and total output in agriculture. These factors have an immediate and measurable impact on yields and farm incomes. On the other hand, agricultural mechanization shows a weaker causality effect because its benefits are more indirect, focused on efficiency improvements rather than direct yield enhancement, and are constrained by high costs and energy dependencies. Moreover, diagnostic tests show no issues with normality, heteroskedasticity (Cameron and Trivedi IM-test), or autocorrelation (Breusch-Godfrey LM test), and the CUSUM OLS test confirms the model's good fit at a significance level below 1%.

On account of the study's findings, several policy recommendations are proposed. *First*, the stunted association of agricultural mechanization and agricultural economic growth shows that the source of agricultural economic growth in China resulted mainly from rural-labor transfer/allocation instead of technological advancement, in particular, agricultural mechanization. Thus, a strategic shift to mechanized-oriented agricultural development is required in a more advanced way. It may be a challenge when the shift considers land transfer to create large-scale agriculture in the short term, but the outcome will be in line with the long-term agricultural modernization goal of the country by 2030.

Second, the strong relationship between agricultural economic growth and chemical fertilizer consumption suggests that a gradual strategy should be implemented to decouple chemical fertilizers from agricultural growth in China. Because urgent reduction of chemical fertilizer application may lead to uncertain outcomes on food security, the government should promote organic and regenerative farming, invest in precision agriculture technologies to optimize fertilizer use, and provide subsidies for sustainable practices. Additionally, reforming fertilizer subsidies and introducing environmental taxes on excessive fertilizer use

can incentivize efficiency. These measures will help reduce reliance on chemical fertilizers while maintaining productivity and sustainability in agriculture. Ultimately, a balanced approach combining technology, policy reforms, and sustainable practices will foster long-term agricultural growth.

Third, as the irrigation area shows a positive association with agricultural economic growth in China, the government should invest in advanced irrigation technologies, such as drip and sprinkler systems, to maximize water efficiency, enlarge irrigated areas, and improve agricultural productivity in China amid water scarcity. Policies should also focus on the modernization of existing irrigation infrastructure, promote the recycling of wastewater for agriculture, and encourage water-saving farming practices. Efforts should be made to develop water storage capacities through reservoirs and rainwater harvesting, along with incentivizing farmers to adopt water-efficient crops, to ensure more sustainable use of water resources. Moreover, a proper national water management strategy that balances agricultural needs with ecological preservation is essential to ensure long-term water availability.

Fourth, China's resource supply and demand balancing act requires prioritizing high-efficiency inputs (such as precision irrigation) to boost growth while minimizing resource waste (SDG 12), and redirecting subsidies from land expansion toward sustainable urban-rural food systems (SDG 11). *Finally*, top priority should be given to maintaining the quantity and quality of crop land for sustainable agricultural development. Policies should focus on reclaiming degraded and abandoned lands through sustainable land rehabilitation techniques, such as soil erosion control, reforestation, and the use of organic amendments to restore fertility and enlarge crop sown areas without resorting to the natural environment. More investment in technology is needed for precision land assessment and targeted reclamation projects to ensure efficient use of such areas. Incentives should be provided for farmers who adopt sustainable land management practices. This study also encourages policies, such as the farmland transfer policy and the cultivated land protection policy, to establish a long-term association between crop-land and agricultural development. This can prevent degradation and enhance long-term agricultural productivity.

Although we have examined the effect of agricultural input resources, mainly mechanization, irrigation, fertilizer, and farmland, on agricultural economic growth from dynamic vantage points, certain limitations still exist. *First*, although this study uses a novel dynamic ARDL estimation approach, the sample size used is limited. As a result, further research is needed with a larger and more comprehensive dataset (e.g., microdata at regional and county level) to provide a more accurate prediction of the impacts of agricultural input resources on the economic growth of the agriculture sector. *Second*, as China is a large agricultural country, future research needs to consider regional variation to further explore the associations in detail. While the diagnostic and stability tests validate the robustness of the models, further research is required to deepen our understanding of the relationship between the expansion of crop sown areas and agricultural economic development, as indicated by the simulation forecasts. *Third*, a more detailed analysis of specific variables, such as chemical fertilizer use, is necessary to investigate their sources and underlying mechanisms, given their environmental

connections with the agricultural sector. Finally, we recommend cross-country research on the relationship between agricultural input resources and sustainable agricultural development, which could provide valuable insights from a global perspective.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/[Supplementary material](#).

Author contributions

MA: Writing – original draft, Investigation, Writing – review & editing, Resources, Formal analysis, Software, Methodology, Data curation, Conceptualization, Validation, Visualization. BC: Supervision, Project administration, Validation, Writing – review & editing, Funding acquisition, Formal analysis, Visualization. TA: Validation, Writing – review & editing, Visualization. AW: Validation, Writing – review & editing, Visualization. RZ: Data curation, Validation, Conceptualization, Investigation, Methodology, Funding acquisition, Resources, Writing – original draft, Formal analysis, Software, Visualization. AKA: Investigation, Visualization, Validation, Formal analysis, Writing – review & editing, Supervision. WL: Visualization, Validation, Writing – review & editing. MM: Validation, Writing – review & editing, Visualization.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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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.2025.1619447/full#supplementary-material>

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