THE INFLUENCE OF IRRIGATION INVESTMENTS AND R&D EXPENDITURES ON ENVIRONMENTAL QUALITY: EXPLORING THE EKC HYPOTHESIS FOR SUSTAINABLE DEVELOPMENT IN CONVENTIONAL RESOURCE-DEPENDENT AREAS OF CHINA

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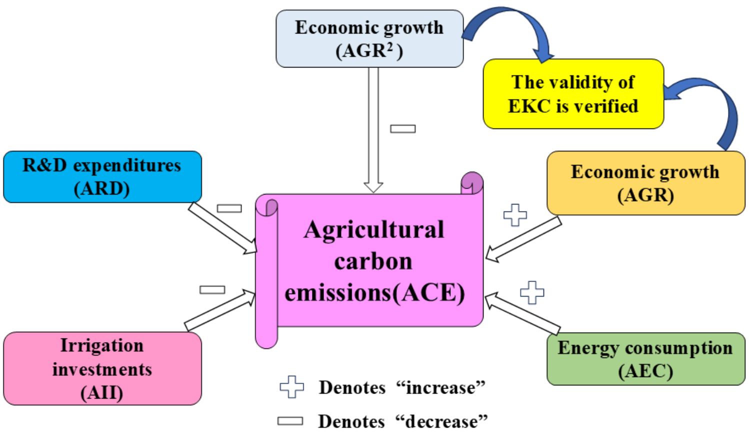
Abstract. This research aims to explore the validity of the Environmental Kuznets Curve (EKC) hypothesis and analyzes the roles of irrigation investments and research and development expenditures (R&D) expenditures in mitigating agricultural carbon emissions in the conventional resource-dependent areas of China from 2001 to 2021. A multivariable empirical framework is employed, incorporating the Lee and Strazicich (LS) and Fourier Lagrange multiplier (LM) unit root tests, Engle-Granger and Phillips-Ouliaris single equation cointegration tests, auto regressive distributed lag (ARDL)methodology, fully modified ordinary least squares (FMOLS) and dynamic ordinary least squares (DOLS) robustness estimators, and the Granger causality test to accomplish this objective. The research reveals that the EKC hypothesis is evident for carbon emissions related to agriculture across all provinces in the sample. Additionally, irrigation investments and R&D expenditures exhibit negative consequences for carbon emissions in the agricultural sector, both in the short and long term. Furthermore, there exists one-way causal relationships originating from irrigation investments and R&D expenditures to agricultural carbon emissions. Finally, this study highlights policy implications of digital and intelligent irrigation technology for local governments on both inhibiting carbon emissions and promoting sustainable agricultural development in China's conventional resource-dependent areas.
Keywords: *environmental Kuznets curve, irrigation investments, R&D expenditures, ARDL method, agricultural sustainable development*

Graphical abstract



Abbreviations. EKC, Environmental Kuznets Curve; R&D, Research and development expenditures; ACE, Agricultural carbon emissions; AII, Agricultural irrigation investments; ARD, Agricultural research and development expenditures; AEC, Agricultural energy consumption; AGR, Agricultural gross domestic product; GHG, Greenhouse gas; LS, Lee and Strazicich; LM, Lagrange multiplier; ARDL, Auto regressive distributed lag; FMOLS, Fully modified ordinary least squares; DOLS, Dynamic ordinary least squares; VECM, Vector error correction model

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Introduction

The growth of human economic activity has resulted in an unparalleled surge in worldwide energy usage, leading to noteworthy environmental issues such as global warming. The increasing emissions of greenhouse gas (GHG) is the primary reason behind the warming of the planet. Since the rapid development of agriculture is one of the main contributors to GHG emissions, its influence on the warming of the climate cannot be disregarded. As stated in the Sixth Assessment Report by IPCC (2022), during the period of 2010 to 2019, the agricultural sector and land use are responsible for 13% to 21% of total worldwide GHG emissions. If added in food processing, packaging, transportation, retail and consumption, the entire agricultural system accounts for up to 30% of global GHG emissions. This means that agricultural systems are critical to global climate security. Consequently, a global agreement has been reached to alleviate GHG emissions, particularly those generated by agricultural activities.

China is the world's leading agricultural market and has a considerable influence on worldwide agricultural development. Its impact extends to both global economic growth and the environment, particularly the worldwide atmospheric greenhouse effect. China has established a strategic objective to achieve its highest level of carbon emissions by 2030, followed by a commitment to attain carbon neutrality by 2060 (Zhao et al., 2023). This shows China’s commitment and resolve in reducing carbon emissions and taking responsibility for tackling climate change. Regarding this, the Chinese government has emphasized that resolving issues related to climate change ultimately hinges on technological advancements. Technological innovation is vital to accomplishing carbon emissions diminishment goals (Yin and Li, 2019). Allocation of government resources to research and development (R&D) expenditures could establish market conditions that encourage the private sector and scientific research institutions investments in the advancement of energy and irrigation technologies (Yu et al., 2023). Consequently, the deployment of renewable energy would increase, displacing other polluting energy sources. Likewise, with the support of irrigation investments, these modern irrigation technologies would be transferred to irrigated agriculture and used on a large scale, which would significantly curb carbon emissions in agricultural activities (Luo et al., 2022; Zhao al., 2023). In light of this intricate scenario, ensuring the sustainable advancement of agricultural practices has emerged as a vital concern. Hence, in order to guarantee the agricultural sustainability, it is crucial to analyze the connections among carbon emissions, government irrigation investments and R&D expenditures in the agricultural sector.

This research primarily concerns with the traditional resource-based regions of China, involving Shaanxi Province, Gansu Province, Ningxia Hui Autonomous Region, Inner Mongolia Autonomous Region and Shanxi Province. These provinces are rich in fossil energy (e.g., coal, oil and natural gas) and renewable energy (e.g., wind and solar). Besides, the five provinces are geographically adjacent to each other and closely linked in the field of economy. Drought and water shortage are common factors that restrain the economic growth in agriculture in these provinces. Therefore, developing water-saving irrigated agriculture is the main way to sustainably advance the agricultural economy in the region. The same endowment of resources determines that the economic development mode of these provinces also has a certain similarity, which guarantees that the final findings are trustworthy and that the policy suggestions are relevant and effective.

The following points highlight the significant insights made by this research. Firstly, it is the pioneering finding on the connections among the parameters in traditional resource-based areas of China, thereby bridging the gap in research questions on carbon

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emissions in the economic adjacent regions. Secondly, this paper recognizes the issue of structural breaks in the economic data and offers the novel Fourier Lagrange multiplier (LM) test of greater robustness with respect to all the selected variables. Thirdly, this research investigates the impacts of irrigation investments and R&D expenditures on carbon releases mitigation, facilitating the implementation of a more rational government financial infrastructure towards reducing agricultural carbon releases in the aforementioned five provinces.

The remaining four sections of the paper are as follows. Section two presents a summary of research findings in related fields. Section three introduces the data source and research concept. Section four elucidates the outcomes of the empirical investigation. In the end, section five provides a summary of the findings and puts forth suggestions for policy recommendations.

Review of literature

Irrigation investments and carbon emissions nexus studies of the agricultural sector

In recent years, benefited from increased government investments in irrigated agriculture, a variety of advanced irrigation technologies are emerging, which has encouraged the adoption of advanced irrigation methods and has had a positive impact on GHG emissions inhibition. Numerous new research achievements have demonstrated the variability in the consequence of different irrigation practices on curbing GHG releases. In contrast to flood irrigation, drip irrigation can reduce soil CO_2 emissions more effectively (Wei et al., 2021). Zhang et al. (2023) concluded that using subsurface drip watering along with adding straw had greatly reduced the release of greenhouse gases and improved the soil's ability to store carbon. This made it a workable and environmentally friendly way to run farms and encourage sustainable farming in the north of China. Guardia et al. (2023) discovered that subsurface irrigation is an effective method for water conservation that had the potential to diminish the net GHG releases of irrigated croplands by reducing CH_4 and respiration fluxes. Additionally, controlled irrigation was proved to have the best potential to depress GHG releases and increase crop productivity (He et al., 2024). Nie et al. (2023) detected that commanded irrigation distinctly decreased CH_4 emissions in mollisols by 70.2–79.7%, with the abatement being more apparent when incorporating 5-year straw incorporation. Jiang et al. (2023) demonstrated that the amalgamation of biochar with regulated irrigation not only curbs GHG emissions, but also preserves water supplies, minimizing negative effects on rice harvest. Moreover, Liao et al. (2023) presented empirical evidence showcasing the efficacy of alternate wet and dry (AWD) irrigation in curbing global warming potential. In contrast to conventional irrigation, AWD irrigation significantly decreased CH_4 and NO_2 emissions by 25% and 50%, respectively. In contradiction to the above researches, Gultekin et al. (2023) investigated the impact of deficit irrigation techniques on GHG releases in drip irrigation and discovered that such practices resulted in a notable increase in GHG releases.

The linkage between advancements in irrigation technologies, irrigation investments, and irrigation practices has been substantiated by academic findings. Dinar et al. (1997) found that, in Colombia, the climate impacted investments, regions with favorable climate conditions exhibited a lesser appeal for irrigation investments, while appropriate government crop-price and credit policies encouraged irrigation investments. Zhang et al. (2023) considered that promotion of water-saving irrigation technology had the potential to significantly enhance China's irrigation water-energy-GHG releases framework,

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thereby augmenting irrigation efficiency whilst maintaining irrigation energy consumption at current levels. The introduction of water-saving irrigation technologies needs to be executed in accordance with the respective local investment scenarios across the country. Chen et al. (2019) discovered environmental effects of various scenarios and their production benefits. Based on the findings, adopting drip irrigation over the long-run could boost crop yields and reduce water footprint, suggesting that the relevant government departments should put in place appropriate policies for technological investments in irrigation (Mushtaq et al., 2013).

R&D expenditures and carbon emission nexus studies of the agricultural sector

Some prior research findings have demonstrated that R&D expenditures would likely lead to carbon emissions abatement. Yu et al. (2023) examined the impact of China's emissions trading scheme (ETS) on carbon emissions and found that the intensity of carbon releases has been reduced by 4.3% and 7.5% as a result of the ETS pilots through increasing investments in R&D. Chen et al. (2023) suggested that public R&D spending policies could be effective in reducing carbon intensity. Taking the United States as an example, Kocak et al. (2022) considered that a positive shock in energy research and development expenditures curbed GHG emissions. Chang et al. (2023) also found that there existed the tenuous connections for the R&D strength and CO_2 releases. Similar studies also proved by Shahbaz et al. (2020) in the UK.

All of above studies are based on the aggregate data at single country level, if the study of carbon emission and R&D expenditure nexus is expanded to include multiple countries, the results change markedly. For instance, Gu et al. (2021) found that technology transfer had significant carbon emissions mitigation effects, developed countries attained substantial carbon abatements when low-carbon technologies were universally shared, whereas developing countries experienced predominantly limited abatements. Homoplastically, Li et al. (2020) conducted an empirical examination of the six largest worldwide carbon emitters to examine the impact of R&D expenditures on alleviating environmental challenges, indicating that developed countries displayed a better and more stable decoupling status compared to developing countries. Petrović et al. (2019) found that, higher R&D expenditures inhibited carbon releases, but this did not pertain to about 40% of OECD nations, the effect of R&D investments on carbon releases could not be characterized as negative in advance. Herzer (2022) examined data from the G7 nations from 1994 to 2018, confirming that both national and international government-sponsored initiatives for clean energy innovation were beneficial in curbing domestic CO_2 releases. However, Li et al. (2021) concluded that although R&D input remained a crucial strategy for reducing carbon emissions, the incremental benefits of technological improvements for cutting down carbon emissions are generally decreasing in 52 countries. Surprisingly, a game theory-based empirical analysis using the duopoly model proposed by Chen (2022) was expected to provide valuable perspective and method into existing literatures, supporting the creation and application of policies targeted in curbing carbon emissions.

Energy consumption, economic growth and carbon emissions nexus studies

Research on this topic is highly contested within the academic community and has generated a wealth of findings. Broadly, there are two prominent strands of research that focus on the connections among these three variates. The first strand is dedicated to the detailed investigations of the linkages between all the above variables. It is noted that

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some investigations are bound to specific countries, which may limit their generalizability. For instance, the studies by Wang et al. (2011), Dong et al. (2017a), Fang et al. (2017), Koondhar et al. (2021) and Yang et al. (2022) provided empirical evidences of China on the validity of a long-term cointegration links among carbon emission, economic development and energy consumption. Granger causalities were also found among these three variables. Similar studies conducted by Tang et al. (2016) in Vietnam, Alshehry et al. (2017) in Saudi Arabia, Cherni et al. (2017) in Tunisian and Raihan et al. (2023) in Egypt. There are also studies that focus on common problems that exist in multiple countries. Dong et al. (2018b) considered that carbon emissions had a negative impact on natural gas usage in Asia-Pacific nations, but not all Asia-Pacific countries approved that the increase in natural gas usage would cause a decrease in carbon emissions. Qiao et al. (2019) suggested that agricultural growth meaningfully increased CO_2 releases in the developing countries of G20. In contrast, the utilization of renewable energy restrained the CO_2 releases in developed countries of G20. From above analysis results, cointegrating regression, VEC model and Granger causality test were conventional approaches and frequently utilized (Yang et al., 2022; Raihan et al., 2023). It must be pointed out that in some previous studies, due to the neglect of the investigation into the deep connection among variables in the process of model construction, the endogenous problem among variables appeared, and finally affected the authenticity of empirical results, which should deserve our attention.

The second research trend involves evaluating the validity of the EKC hypothesis through the analysis of the three factors, i.e. to demonstrate whether a U-shaped inverse relationship exists between economic expansion and the environment deterioration. For instance, the research achievements by Ridzuan et al. (2020) in Malaysia, Zafeiriou et al. (2017) in Mediterranean countries, Dong et al. (2017a) in China presented empirical data supporting the credibility of the EKC hypothesis. Similar studies also conducted by Dogan et al. (2015) in the USA, Dogan (2016) in Turkey, Alamdarlo (2016) in Iran and Gokmenoglu et al. (2018) in Pakistan. However, Arouri et al. (2012) determined that the proof backing the EKC hypothesis is inadequate in twelve MENA countries. Liu et al. (2017) also considered that the findings of long-term estimations did not show the N-shaped connection in the countries concerned. Similarly, Jebli and Youssef (2016) discovered that the Tunisian data did not support the theory. Although these findings on EKC theory are abundant, they are incomplete and need to be analyzed and validated in depth and comprehensively.

There has been considerable research into the correlation of the three variables. However, there is a lack of studies delving into the precise methods through which both irrigation investments and R&D expenditures are influencing agricultural carbon emissions. Especially relevant when discussing carbon peaking and carbon neutrality, particularly within the resource-based regions of China. Thus, the purpose of this research is to evaluate the association of irrigation investments, R&D expenditures, and agricultural carbon emissions, addressing the limited research in this area.

Materials and methods

Estimation of carbon emissions from agriculture

To fully estimate agricultural carbon emissions, this part of discussion is based on the generalized activities of agricultural production, as informed by related research (Wang, 1999; Wu et al., 2007; Zhi and Gao, 2009; Duan, 2011; Tian et al., 2014). Agricultural

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carbon emissions can be mainly classified into four categories from which we can draw comprehensive conclusions. The initial category pertains to CO_2 emissions resulting from early agricultural production inputs, including fertilizers, pesticides, agricultural plastic films, machinery, irrigation, and soil ploughing. The second category comprises CH_4 emissions from paddy field cultivation. The third category encompasses CH_4 and NO_2 emissions emanating from livestock and poultry breeding during agricultural production activities. Lastly, the fourth category involves CO_2 emissions resulting from the incineration of crop straw during the ultimate stage of agricultural cultivation.

Based on the researches of Song and Lu (2009), Zhang et al. (2010) and Tian et al. (2014), the agricultural carbon emissions are calculated by the following formula:

$$ACE = \sum_{i=1}^{n} E_i \times \delta_i \qquad \text{(Eq.1)}$$

where ACE indicates all the carbon emissions generated through agriculture, E_i represents the consumption of various energy source i, δ_i means the corresponding carbon emission coefficient of source i , i is the different types of energy sources. The agricultural carbon emission coefficients are shown in *Table 1*. These coefficients are derived from authoritative literatures and scientific research institutions, ensuring their precision through rigorous validation processes.

Table 1. *Carbon emission coefficient of major carbon-based energy sources*

Carbon resources	Carbon emission coefficient	Data origin
Fertilizers	0.8956 (kg C/kg)	Tian et al., 2014
Pesticides	4.9341 (kg C/kg)	Zhi and Gao, 2009
Agricultural films	5.18 (kg C/kg)	Tian et al., 2014
Diesel oil	0.5927 (kg C/kg)	IPCC, 2014
Irrigation	266.48 (kg C/ hm^2)	Duan, 2011
Soil ploughing	312.6 (kg C/km^2)	Wu et al., 2007
Paddy field	3.136 (g C/(m^2·day))	Tian et al., 2014
Pig	34.091 (kg C/(head·year))	IPCC, 2014
Cattle	415.91 (kg C/(head·year))	IPCC, 2014
Sheep	35.1819 (kg C/(head·year)	IPCC, 2014
Horse	133.9448 (kg C/(head·year)	IPCC, 2014
Straw burning	1.247 (t c/t)	Wang, 1999

Note: For the convenience of analysis, according to the IPCC(2014), CH_4 and NO_2 are uniformly replaced into standard C, 1t CH_4 and 1t NO_2 are equivalent to that caused by 6.8182 t C and 81.2727 t C, respectively

Study area and data source

The scope of this investigation includes Shaanxi Province, Gansu Province, Ningxia Hui Autonomous Region, Inner Mongolia Autonomous Region and Shanxi Province, situated in the northern part of China. Five parameters are examined in the empirical analysis using the annual data from 2001–2021. ACE denotes per capita agricultural carbon emissions, expressed in metric tons per capita. AGR signifies per capita agricultural gross domestic product, measured in US$ per capita, normalized to 2001 prices. AEC stands for per capita energy usage, represented in tons oil equivalent per capita. AII denotes per capita irrigation investments, calculated in US$ per capita,

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normalized to 2001 prices. ARD refers to per capita R&D expenditures, calculated in US$ per capita, normalized to 2001 prices. The estimation of carbon emissions linked to agricultural activities is grounded in *Eq. 1*, the data on agricultural gross domestic product and agricultural carbon releases are collected from China Rural Statistical Yearbook. The original data on energy usage is selected from the China Energy Statistics Yearbook. The information about irrigation investments is acquired from the National Bureau of Statistics (NBS). The details regarding R&D expenditures are gathered from the Statistical Bulletin of National Science and Technology Investments. The data mentioned are transformed into natural logarithms to account for the variations in each unit of measurement and better adaptive testing. *Fig. 1* displays the Box and Whisker Plot of the natural logarithm of ACE, AGR, AEC, AII and ARD in the case of five resource-dependent provinces of China. Statistical descriptions of the five parameters can be found in *Table 2*, which illustrates a substantial characteristic in all the variates. These findings imply that each sequence of variables conforms to normal distributions.

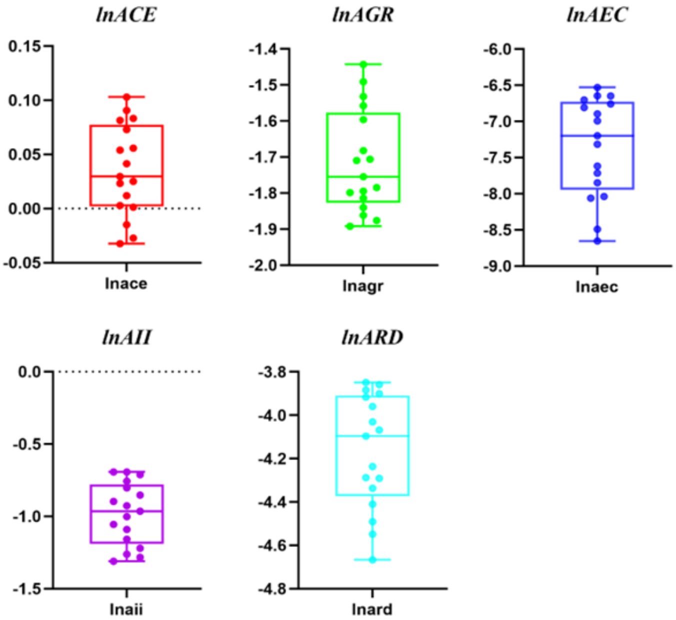

Figure 1. *Box and Whisker plots of the five variates during 2001-2021*

Table 2. *Descriptive statistics of the selected variables (after logarithm), 2001-2021*

	lnACE	lnAGR	lnAEC	lnAII	lnARD
Mean	0.035373	-1.713962	-7.348848	-0.981339	-4.167063
Median	0.029504	-1.754962	-7.199265	-0.964955	-4.097085
Maximum	0.102903	-1.443314	-6.531398	-0.693147	-3.849706
Minimum	-0.032361	-1.892170	-8.653191	-1.310230	-4.666675
Std. Dev.	0.042092	0.141745	0.685184	0.214051	0.263171
Skewness	-0.019452	0.555490	-0.517559	-0.124916	-0.378661
Kurtosis	1.858516	2.031879	1.970104	1.699171	1.885001
Jarque-Bera	0.924021	1.538170	1.510276	1.242822	1.286871
Probability	0.630016	0.463437	0.469946	0.537186	0.525484
Sum	0.601334	-29.13735	-124.9304	-16.68277	-70.84007
Sum Sq. Dev.	0.028348	0.321467	7.511624	0.733088	1.108141

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Empirical modeling

The primary aim of the research is to verified the dynamic impact of AGR, AEC, AII and ARD on ACE for the case of China's traditional resource-based regions. This paper utilizes the research methodologies of Dong et al. (2018b) and Zhang et al. (2019) by adding AII and ARD as new explanatory variables to construct a econometric model as follows:

$$ACE_t = f(AGR_t, AEC_t, AII_t, ARD_t) \quad \text{(Eq.2)}$$

After applying the natural logarithm, *Eq. 2* can be modified in the following manner:

$$lnACE_t = \alpha + \beta_1 lnAGR_t + \beta_2 lnAEC_t + \beta_3 lnAII_t + \beta_4 lnARD_t + \varepsilon_t \quad \text{(Eq.3)}$$

According to the EKC hypothesis, first introduced by Grossman and Krueger (1991), there is a non-linear correlation between economic growth and carbon emissions. With the intention of assessing the truth of the EKC hypothesis, we introduce the square of agriculture economic growth (AGR^2) as a predictor variable. This leads to the formulation of the extended EKC model, outlined below:

$$\begin{gathered} lnACE_t = \alpha_0 + \beta_1 lnAGR_t + \beta_2 (lnAGR)_t^2 + \beta_3 lnAEC_t \\ + \alpha\beta_4 lnAII_t + \beta_5 lnARD_t + \varepsilon_t \end{gathered} \quad \text{(Eq.4)}$$

where α_0 is the intercept term and $\varepsilon_t$is the error term, β_{1to5} indicate the undetermined coefficients of ACE, AGR, AGR^2, AEC,AII and ARD, respectively. For the EKC hypothesis to be proven, it is necessary for β_1 to be positive, β_2 to be negative, and for both coefficients to display statistical significance.

Methodology

The empirical investigation procedure illustrated in *Fig. 2* is utilized in the study to discover connections between variables and examine the EKC hypothesis in the five traditional resource-based provinces of China. The process begins with gathering data from various sources and conducting descriptive statistics on each variable. Next, Lee and Strazicich (LS) and Fourier Lagrange multiplier (LM) unit root tests are used to examine the stationarity of the variables. The third step involves conducting the Engle-Granger and Phillips-Ouliaris single equation cointegration tests to determine if a cointegration connection exists among the parameters. In the fourth step, the auto regressive distributed lag (ARDL) method is employed to investigate the short-run and long-run coefficients. Then, the fifth step is carried out to secure the stability of the estimation outcomes, with the use of dynamic ordinary least squares (DOLS) and fully modified ordinary least squares (FMOLS) as a robustness check for the ARDL approach. Ultimately, the Granger causality estimation is utilized to investigate the causality connection among the five parameters, as determining the direction of causality can aid in crafting targeted policies to address carbon emissions.

LS and Fourier LM unit root tests

First of all, we analyze whether the sequence of all selected series in this paper are stationary. It is noteworthy that the likelihood of a structural break in the economic series

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since the onset of the Asian economic and financial crisis is close to 50 per cent (Solarin and Shahbaz, 2015). Conventional unit root testing fails to address this concern, which may lead to inaccurate results. To solve this problem, we utilize the LS approach, recommended by Lee and Strazicich (2013), which can identify sharp structural breaks in the series. However, if structural breaks occur frequently and are relatively flat, the LS unit root test may have difficulty identifying them. To compensate for this, we also employ the Fourier LM unit root test, proposed by Gallant's (1981) and improved by Enders and Lee (2012) and King (2022).

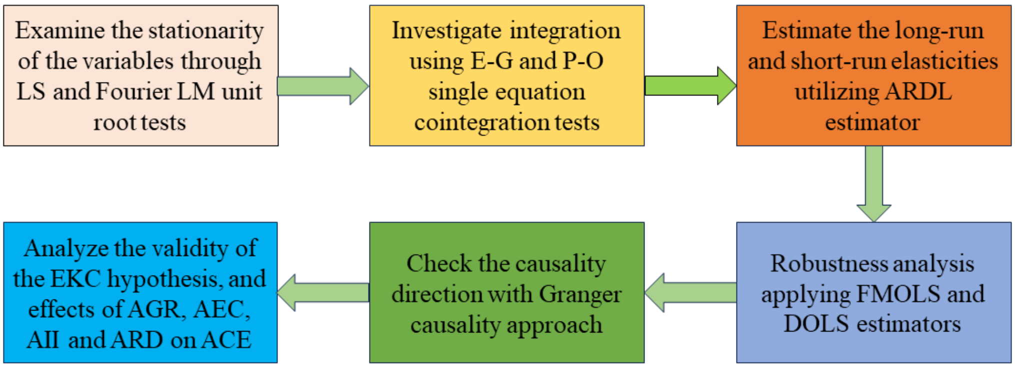

Figure 2. *Empirical analysis flowchart*

Cointegration test

The utilization of cointegration analysis can yield valuable and instructive revelations about the enduring equilibrium connections that may exist between variables, as well as the potential consequences that may arise from fluctuations in a single factor. The Engle and Granger single equation cointegration test is employed to assess the possibility of a sustained correlation among the determinants. This approach unites the moving average, autoregressive, and error correction methodologies for cointegrated systems and introduces a straightforward yet ultimately efficient two-step estimation technique (Engle and Granger, 1987). Furthermore, the testing for cointegration may be affected by potential serial correlation and heterogeneity in the residuals caused by certain macroeconomic time series. To address these potential problems, this research applies the Phillips and Ouliaris single equation cointegration assessment (Phillips and Ouliaris, 1988). The examination incorporated fixed trends, including both constant and linear trend components, within the framework of the cointegration analytical process. Such characteristics increase its versatility and suitability for scenarios characterized by these trends, which is especially significant for time series data.

ARDL bound test and short-run and long-run parameters approach

Utilizing the ARDL bound testing method allows for an investigation into the long-term cointegration of the designated parameters. The null hypothesis(H_0: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$) and the alternative hypothesis(H_1: $\beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq 0$) are formulated for the purpose of examining the cointegration, which is identified by the thorough evaluation of the F-statistic and T-statistic. In the event that the F-statistic and T-statistic surpass the upper threshold and fall within the 5% significance level, the null hypothesis is dismissed, and the long-term cointegration can be inferred. When the F-

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statistic and T-statistic are beneath the lower critical threshold, the null hypothesis is upheld, suggesting that there is no cointegration. When the values of the F-state and T-state fall within the range defined by the upper and lower critical thresholds, it signifies that the decision remains inconclusive (Koondhar et al., 2021). The formulation pertaining to bound test can be found in *Eq. 5* as below:

$$\begin{aligned} \Delta lnACE_t = \beta_0 + \beta_1 lnAGR_{t-1} + \beta_2 (lnAGR)^2_{t-1} + \beta_3 lnAEC_{t-1} + \beta_4 lnAII_{t-1} \\ + \beta_5 lnARD_{t-1} + \sum_{i=1}^{k} \alpha_1 \Delta lnGDP_{t-i} + \sum_{i=1}^{k} \alpha_2 \, \Delta (lnAGR)^2_{t-i} \\ + \sum_{i=1}^{k} \alpha_3 \Delta AEC_{t-i} + \sum_{i=1}^{k} \alpha_4 \Delta AII_{t-i} + \sum_{i=1}^{k} \alpha_5 \Delta ARD_{t-i} + \varepsilon_t \end{aligned} \qquad \text{(Eq.5)}$$

where Δ functions as the operator that calculates differences, β_0 is the intercept term, β_{1to5} are the long-run determinants, α_{1to5} are the short-run estimates, ε_t indicates the error term, k denotes the lag length, t represents the time, i signifies the best possible value for lag.

Once cointegration has been established for all chosen variables, the subsequent task involves deriving the long-run and short-run variables for *Eq. 4* by using ARDL approach. Three advantages of the ARDL approach make it the preferred method for this study over other approaches. On the one hand, the model requires a low sample size of data; on the other hand, it is applicable for assessing the long-term association among individual parameters and producing consistent outcomes, regardless of whether the variables under study are the same as I(0), the same as I(1), or a mixture of I(0) and I(1) processes. Additionally, if the model is subjected to a simple linear transformation, a vector error correction model (VECM) model can be obtained, thus facilitating the observation of the process of adjustment of variables from short-term fluctuations to long-term equilibrium, which can effectively explain the phenomenon of short-term fluctuations. The equation shown in *Eq. 6* outlines the fundamental principles of the ARDL method when applied to ACE, AGR, AGR^2, AEC, AII and ARD.

$$\begin{aligned} lnACE_t = \beta_0 + \sum_{t-1}^{l} \beta_1 \, lnAGR_{t-1} + \sum_{t-1}^{l} \beta_2 \, (lnAGR)^2_{t-1} + \sum_{t-1}^{l} \beta_3 \, lnAEC_{t-1} \\ + \sum_{t-1}^{l} \beta_4 \, lnAII_{t-1} + \sum_{t-1}^{l} \beta_5 \, lnARD_{t-1} + \sum_{t-1}^{n} \alpha_1 \Delta lnGDP_{t-1} \\ + \sum_{t-1}^{n} \alpha_2 \Delta \, (lnAGR)^2_{t-1} + \sum_{t-1}^{n} \alpha_3 \Delta AEC_{t-1} + \sum_{t-1}^{n} \alpha_4 \Delta AII_{t-1} \\ + \sum_{t-1}^{n} \alpha_5 \Delta ARD_{t-1} + ECT_{t-1} + \varepsilon_t \end{aligned} \qquad \text{(Eq.6)}$$

where l and n denote the lag length, ECT_{t-1} is the error correction term that measures the rate at which adjustments are made towards the long-term within a limited time frame.

Robustness analysis

After that, two distinct estimator techniques, FMOLS and DOLS, are utilized to test the robustness of the ARDL approach's long- and short-term estimates. FMOLS and

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DOLS approaches offer the advantage of correcting for any dynamic heterogeneity that may exist across the series. Besides, if cointegration exists, the vectors are averaged to get the regression coefficients, and the predicted t-statistics are tweaked to get rid of as many errors as possible (Jahanger et al., 2023; Su et al., 2023). These two methods incorporate specialized techniques to rectify the issue of autocorrelation between variables (Nguyen et al., 2021).

Furthermore, the research utilizes the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMQ) tests to examine potential endogeneity, stability in structural features, and durability of both long and short-term estimations. A stable regression is indicated when the CUSUM and CUSUMSQ plots remain within the key thresholds established at the 5% significance level, thus failing to dismiss the null hypothesis of parameter stability. By applying this approach, we can evaluate the dependability of the ARDL model estimation outcomes and ascertain the precision of the research findings.

Granger causality test

Granger causality test fundamentally employs the VECM to determine the importance of a collection of coefficients. Using this approach, one can determine if a variable's lagged term affects the values of other variables at the present time. If the impact is noteworthy, it signifies the existence of Granger causality between that variable and other variables. Conversely, if the effect is negligible, then such Granger causality is non-existent. The initial assumption of the Granger causality test is that the variable under examination is not causally linked to the dependent variable. However, if the probability (p-value) derived from the result is below a predetermined level of confidence, typically 5%, then this is deemed to indicate a causal linkage between the examined variate and the dependent variate. On the contrary, it is considered that the tested variable is not causality of the dependent variable. Based on above principles, testing the causal relationship between the five variables can assist in formulating more targeted measures to curb carbon emissions associated with farming activities. Thus, the VECM-based Granger causality method introduced by Engle and Granger is applied to inspect the interaction between the above parameters in this paper (Granger, 1969; Engle and Granger, 1987). The VECM can be written as following equation (Dong et al., 2017b, 2018c; Qiao et al., 2019):

$$\begin{bmatrix} \Delta lnACE_t \\ \Delta lnAGR \\ \Delta(lnAGR)_t^2 \\ \Delta lnAEC_t \\ \Delta lnAII_t \\ \Delta lnARD_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ \alpha_5 \\ \alpha_6 \end{bmatrix} + \begin{bmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \\ \delta_4 \\ \delta_5 \\ \delta_6 \end{bmatrix} \times (ECT_{t-1}) + \sum_{n=1}^{k} \begin{bmatrix} A_{11,n} & A_{12,n} & A_{13,n} & A_{14,n} & A_{15,n} \\ A_{21,n} & A_{22,n} & A_{23,n} & A_{24,n} & A_{25,n} \\ A_{31,n} & A_{32,n} & A_{33,n} & A_{34,n} & A_{35,n} \\ A_{41,n} & A_{42,n} & A_{43,n} & A_{44,n} & A_{45,n} \\ A_{51,n} & A_{52,n} & A_{53,n} & A_{54,n} & A_{55,n} \\ A_{61,n} & A_{62,n} & A_{63,n} & A_{64,n} & A_{65,n} \end{bmatrix} \times \begin{bmatrix} \Delta lnACE_{t-1} \\ \Delta lnAGR_{t-1} \\ \Delta(lnAGR)_{t-1}^2 \\ \Delta lnAEC_{t-1} \\ \Delta lnAII_{t-1} \\ \Delta lnARD_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \end{bmatrix} \quad \text{(Eq.7)}$$

where Δ represents the first-difference operator; ECT_{t-1} denotes the lagged error correction term; and ε_t represents the random error term.

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Empirical results

LS and Fourier LM unit root tests

Time series stationarity is often assessed through unit root tests, with the LS and Fourier LM unit root tests being typically employed in this study. The empirical outputs are illustrated in *Table 3* and *Table 4*, respectively. *Table 3* reveals that the P-value statistic of the initial data exceeds the critical value at the 5% significance level, denoting non-stationarity of variables at level. Nevertheless, at the 5% significance level, the P-value statistic is less than the crucial value when the first difference is obtained, suggesting no presence of unit root and confirming the stability of each series. Besides, the possibility of structural breaks is also detected. *Table 4* displays the findings of the Fourier LM test, verifying the outcomes of the LS test. Therefore, it can be proved that each variable is integrated, denoted as I(1), which can be utilized for subsequent cointegration tests.

Table 3. *LS unit root test, 2001-2021*

Variables	Level	Lags	Break date	First difference	Lags	Break date	Order of integration
lnACE	-2.843*	2	2008	-3.261**	3	2006	I(1)
lnAGR	-3.676*	1	2007	-4.325***	3	2009	I(1)
$\ln(AGR)^2$	-3.274*	1	2007	-4.462***	3	2009	I(1)
lnAEC	-4.827	0	2008	-3.162**	1	2010	I(1)
lnAII	-2.847	1	2006	-4.015***	2	2013	I(1)
lnARD	-3.848*	2	2012	-3.362**	3	2012	I(1)

Note: *, ** and *** indicate the rejection of the unit root hypothesis and the lag order according to the principle of minimum AIC and SC at the significance levels of 10%, 5% and 1%, respectively

Table 4. *Fourier LM unit root test, 2001-2021*

Variables	Level	Frequency	Lags	Break date	First difference	Frequency	Lags	Break date	Order of integration
lnACE	-3.173	2	0	2009	-2.724**	2	0	2008	I(1)
lnAGR	-4.332*	1	0	2009	-6.613***	2	0	2010	I(1)
$\ln(AGR)^2$	-4.826*	1	0	2009	-8.134***	2	0	2010	I(1)
lnAEC	-1.765	2	1	2010	-3.867**	2	1	2012	I(1)
lnAII	-1.252	2	0	2008	-4.117***	1	1	2009	I(1)
lnARD	-6.167*	1	1	2011	-5.353**	2	1	2008	I(1)

Note: *, ** and *** indicate the rejection of the unit root hypothesis and the lag order according to the principle of minimum AIC and SC at the significance levels of 10%, 5% and 1%, respectively

Cointegration estimation

The outcomes for cointegration using the Engle-granger single equation cointegration test and Phillips-ouliaris single equation cointegration test are demonstrated in *Table 5* and *Table 6*, respectively. *Table 5* illustrates that both the t- statistic and z-statistic for the ACE are p <0.05, which is also evident in *Table 6*. The data supports the rejection of the test's null hypothesis: series are not cointegrated. This implies that there is cointegration

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between ACE and its determinants. Accordingly, through the use of time series estimators and calculating determinants, the impact of AGR, AGR^2, AEC, AII and ARD on ACE can be measured in the five resource-based provinces of China.

Table 5. *Engle-granger single equation cointegration test, 2001-2021*

Dependent	T-statistic	Prob	Z-statistic	Prob
lnACE	-5.081**	0.028	-19.133**	0.012
lnAGR	-6.232*	0.072	-22.323*	0.059
$(lnAGR)^2$	-3.711*	0.061	-18.127*	0.072
lnAEC	-6.162**	0.018	-23.163**	0.015
lnAII	-5.856**	0.048	-23.152**	0.027
lnARD	-5.364*	0.035	-21.124**	0.031

Notes: * and ** show the significance at 10% and 5% levels

Table 6. *Phillips-ouliaris single equation cointegration test, 2001-2021*

Dependent	T-statistic	Prob	Z-statistic	Prob
lnACE	-5.176**	0.016	-19.342**	0.028
lnAGR	-5.367**	0.019	-19.163**	0.011
$(lnAGR)^2$	-2.9796*	0.0792	-11.8879*	0.080
lnAEC	-6.171**	0.013	-16.382**	0.036
lnAII	-2.176**	0.024	-19.325**	0.032
lnARD	-4.825**	0.012	-20.324**	0.029

Notes: * and ** show the significance at 10% and 5% levels

ARDL bounds test

Furthermore, the cointegration analysis is investigated using the bounds testing procedure as supplementary within the ARDL framework. The findings of ARDL bounds procedure is summarized in *Table 7*. The outcomes from *Table 7* reveal that the F-state value is 3.68 and T-test value is -3.89. The observed values surpass the upper limit at a 5% significance level, resulting in the dismission of the null hypothesis at a 1% significance level, which indicates a cointegration relationship among the variables. Therefore, the bounds test aligns with the Engle-Granger and Phillips-Ouliaris single equation cointegration tests, rejecting the null hypothesis of no levels of association. This again proves the existence of a long-term association among AGR, AGR^2, AEC, AII, ARD, and ACE, which cannot be disregarded. With the confirmed cointegration estimate, this paper moves forward to assess ARDL approach.

Table 7. *ARDL bounds test, 2001-2021*

	10%		5%		2.5%		1%		P-Value	
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
F-STAT 3.68***	2.2	3.09	2.56	3.49	2.88	3.87	3.29	4.37	0.003	0.005
T-TEST -3.89***	-2.34	-3.31	-2.76	-3.64	-3.12	-3.96	-3.43	-4.65	0.002	0.008

Notes: *** Represents the sign for 1% significant level, I(0) indicates to lower bound critical value, I(1) represents upper bound critical value

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Short-run and long-run ARDL simulations

After establishing the existence of cointegration estimation, the research calculates both the short-run and long-run coefficients using the ARDL approach, which are displayed in *Table 8*. As we can see, the coefficients for lnAGR and ln(AGR)^2 show significant positive and negative trends, respectively. This confirms that the EKC relationship may exists between AGR and ACE in the traditional resource-based regions of China. Additionally, the coefficients for lnAEC are notably positive, as illustrated in *Table 8*, suggesting that a percentage rise in AEC will lead to an increase of 0.024% in ACE over the long-term and 0.072% in the short-term. This suggests that ACE resulting from AEC will upsurge with the rise of AEC. This phenomenon arises due to the ongoing growth of AEC, driven by the robust advancement of agriculture, while traditional energy still accounts for a large proportion in this area. Conversely, the coefficients of lnAII and lnARD are substantially negative, suggesting that AII and ARD will mitigate ACE in the resource-dependent regions of China. More precisely, in the long term, a 1% rise in AII and ARD correlates with a drop of 0.056% and 0.032% in ACE, respectively; in the short term, a 1% increase in AII and ARD results in a reduction of 0.016% and 0.021% in ACE, respectively. The values of R^2, F-statistic and D-W statistic ensure the stationarity of the ARDL approach of this research.

Table 8. *Long-run and short-run ARDL simulation, 2001-2021*

Variables	Coefficient	Std. error	T-test	P-value
Long-run				
lnAGR	2.367**	0.016	6.243	0.023
(lnAGR)^2	-0.219*	15.811	5.203	0.062
lnAEC	0.024**	10.469	-1.972	0.025
lnAII	-0.056**	2.132	-0.287	0.016
lnARD	-0.032**	3.267	-0.192	0.029
Ect(-1)	-0.414***	2.287	-0.881	0.009
Short-run				
ΔlnAGR	26.176**	0.018	5.368	0.016
Δ(lnAGR)^2	-1.372**	14.361	8.172	0.032
ΔlnAEC	0.072*	11.338	-1.867	0.083
ΔlnAII	-0.016**	3.712	-0.268	0.027
ΔlnARD	-0.021**	4.179	-0.236	0.031
R^2	0.9987			
F-statistic	430.3082***			
D-W stat	3.2136			

Note: ***, **, and * correspond to the 1%, 5%, and 10% significance levels, respectively

Robustness test

The outcomes of the FMOLS and DOLS estimations are displayed in *Table 9*, which were conducted to assess the robustness of the ARDL approach. The estimators' coefficients have a similar direction when closely reviewed, although there are noteworthy differences in their statistical significance. A positive connection is evident between AGR and ACE in the five provinces of China. It denotes that the increase in AGR by 1% will trigger the level of ACE by 0.437% (FMOLS) and 0.425% (DOLS).

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Conversely, a negative interaction exists between $(AGR)^2$ and ACE, showing that 1% increase in $(AGR)^2$ will cause a decrease in ACE by 0.037% (FMOLS) and 0.028% (DOLS). Furthermore, AEC positively affects ACE, in which a 1% upsurge in AEC causes a surge in ACE by 0.049% (FMOLS) and 0.377 %(DOLS). However, an adverse association is uncovered between AII and ACE, indicating that a 1% surge in AII mitigates ACE by 0.049% (FMOLS) and 0.052% (DOLS). Likewise, between ARD and ACE, a negative interaction is uncovered. A rise in the amount of ARD by a percentage will result in a drop in ACE by 0.056% (FMOLS) and 0.039% (DOLS). Besides, the Jarque-Bera statistics for the FMOLS and DOLS models confirm the absence of normality concerns, while the high R^2 values indicate the strong explanatory power of the independent variables in relation to AEC.

Table 9. *FMOLS and DOLS analysis, 2001-2021*

Variables	**FMOLS**	**P-value**	**DOLS**	**P-value**
constant	16.623*	0.057	15.282*	0.063
lnAGR	0.437*	0.061	0.425**	0.021
(lnAGR)^2	-0.037*	0.051	-0.028*	0.069
lnAEC	0.239**	0.018	0.377*	0.058
lnAII	-0.049*	0.072	-0.052**	0.034
lnARD	-0.056**	0.046	-0.039**	0.037
Jarque-Bera	1.264	0.642	1.176	0.736
R^2	0.967		0.976	
Adjusted R^2	0.955		0.968	

Note: * and ** show the significance at 10% and 5% levels

Furthermore, to guarantee the accuracy of the findings, CUSUM and CUSUMQ estimations are performed on the recursive residuals to investigate the durability of the parameters. The boundary interval for the 5% significance level is indicated by the dotted line in *Fig. 3*, as demonstrated by the results of the test. The findings demonstrate that the residuals are contained within the defined threshold, implying that the model's coefficients remain steady throughout the study timeframe. In light of this, the results shown in the *Table 8* are suitable for informing policy decisions.

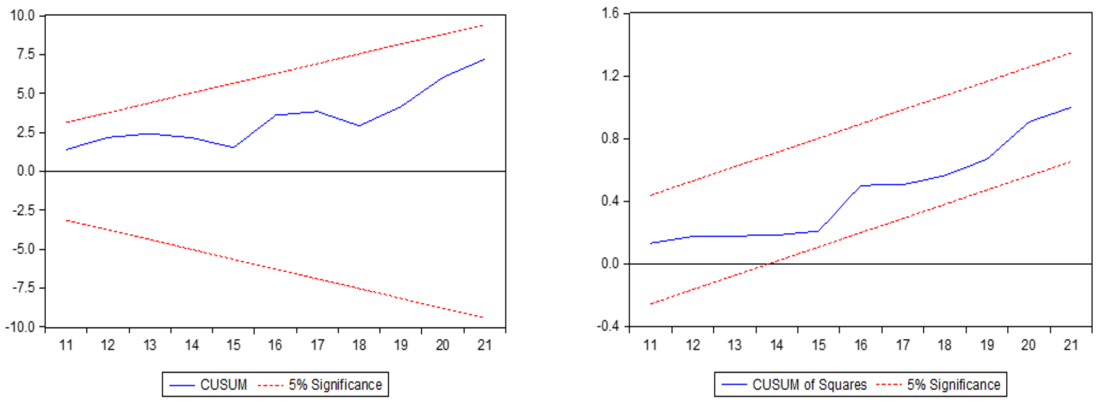

Figure 3. *CUSUM plots and CUSUM Squared plots for the ARDL model*

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Granger causality test

The above demonstration of long-term and short-term cointegration relationships serve as evidence that Granger causality may exist among the five variables. Even though, it still can't point out the relationship direction. Therefore, to further explore the interaction between these variates, we conduct a causal correlation test based on the VECM. Before conducting Granger causality tests, the normal distribution of VECM residuals is evaluated through the Jarque–Bera estimations for robustness, the outcomes of which are demonstrated in *Table 10*. The p-values in the four equations and the joint one are above 10%, which imply that the VECM is stationary. The findings from the Granger causality tests are presented in *Table 11*. Bidirectional causalities are detected to exist between ACE and AEC. Additionally, unidirectional Granger causalities are found to run from AGR to ACE. Expectedly, AII results in ACE and ARD result in ACE. We confirm that the connection of causality between ACE, AGR and AEC is somewhat consistent with the studies of Alshehry et al. (2017), Fang et al. (2017), Koondhar et al. (2021) and Yang et al. (2022). Additionally, the causal association of AII, ARD and ACE validates the speculations of Zhu et al. (2023) and Guardia et al. (2023).

Table 10. *VECM normality residual test, 2001-2021*

Component	**1**	**2**	**3**	**4**	**5**	**Joint**
Jarque–Bera statistic	0.4572	0.6832	6.1396	4.4461	4.6513	11.7261
P-value	0.7957	0.7106	0.1464	0.1083	0.2536	0.1638

Table 11. *Granger causality analysis - VECM approach, 2001-2021*

Dependent variable	**Short run**					**Long run**
	ΔlnACE$_t$	**ΔlnAGR$_t$**	**ΔlnAEC$_t$**	**ΔlnAII$_t$**	**ΔlnARD$_t$**	**ECT$_{t-1}$**
ΔlnACE$_t$	-	4.656** (0.032)	7.673** (0.027)	4.336*** (0.003)	6.554** (0.017)	-3.285** (0.041)
ΔlnAGR$_t$	3.346 (0.367)	-	6.124** (0.031)	6.172** (0.022)	4.179** (0.034)	-1.629* (0.061)
ΔlnAEC$_t$	6.322** (0.012)	5.124*** (0.002)	-	5.566** (0.031)	5.322** (0.016)	-2.162** (0.022)
ΔlnAII$_t$	4.173 (0.521)	3.231** (0.019)	5.322 (0.125)	-	5.336** (0.034)	-2.073** (0.033)
ΔlnARD$_t$	3.644 (0.151)	4.254*** (0.004)	5.123 (0.282)	4.333 (0.322)	-	-0.186** (0.042)

Note: ***, **, and * correspond to the 1%, 5%, and 10% significance levels, respectively. The P-values are indicated in brackets

Subsequent to the empirical demonstration process described above, the findings from the previous analysis are systematically organized and illustrated in *Fig. 4*.

The summary of results presented in *Fig. 4* clearly demonstrates that the EKC is indeed relevant to this particular region. In this context, it is evident that both AII and ARD serve as beneficial elements that positively influence environmental quality. Conversely, it appears that AGR and AEC are not conducive to the attainment of environmental objectives, thus presenting challenges in this domain. Hence, strategies aimed at the environment in resource-dependent areas of China should prioritize initiatives such as maintaining ecological advantages via substantially investing in irrigation and significantly boosting R&D spending, alongside efforts to enhance efficiency.

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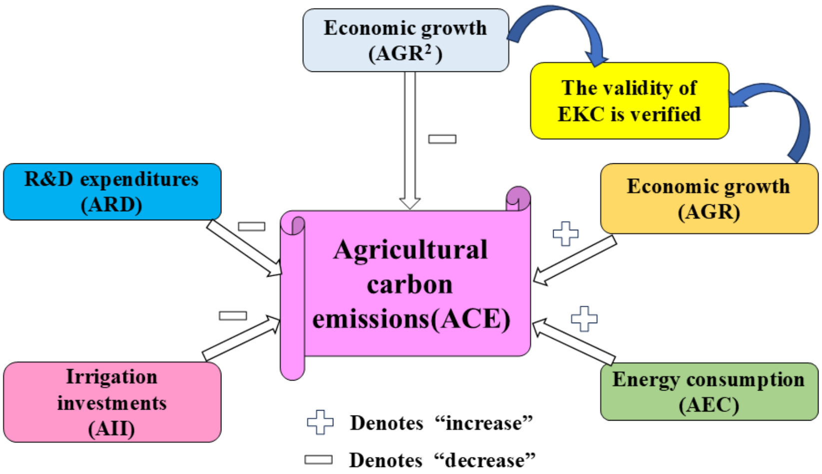

Figure 4. *Graphical representation of the findings during 2001-2021*

Discussion

Within the structure of irrigation investment, government investment serves as the predominant source, while contributions from enterprise and private investment constitute a smaller fraction, which is gradually increasing. Except from 2016 to 2019, government investment in irrigation accounted for more than 80%. From 2016 to 2019, government investment accounted for more than 74%. From 2007 to 2020, corporate and private investment also increased from 4.06% to 8.44%. In government investment, the central government's share has gradually decreased, while the local government's share has gradually increased. From 2007 to 2020, the proportion of central government funds in government investment dropped from 45.09% to 26.93%, while the proportion of local government funds increased from 54.91% to 73.07% (Lan, 2023). Since the Eighth Five-Year Plan period, the total amount of irrigation investment in northern China has shown a growing trend. Due to the reform of taxes and fees and the reform of the government's fiscal and taxation system, especially the central government is the main body of irrigation investment. Since the Twelfth Five-Year Plan period, investment in water-saving irrigation projects in northern China has intensified, accounting for more than half of the new irrigation investment (Wang et al., 2021).

Additionally, this study established a substantial and positive correlation between the ACE and AGR, indicating a deficiency of environmentally sustainable practices in the growth operations of traditional resource-dependent regions in northwestern China. Comparable outcomes are observed in other provinces of China (Zhang et al., 2019). This resemblance indicates that the rapid growth rate of AGR boosted the need for energy derived especially from coal and petroleum, hence augmenting carbon emissions. On a global scale, agricultural growth meaningfully increases carbon releases in the developing countries (Jebli et al., 2017; Qiao et al., 2019). The research implies that the agriculture industry may help reduce carbon emissions through appropriate farming methods. A decrease in the carbon footprint can result from agricultural operations that trap carbon emissions via the application of proper technology.

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Conclusions and policy implications

Utilizing data collected from 2001 to 2021, this research examines the validity of the EKC hypothesis and explores how AII and ARD contribute to the decrease of carbon emissions in the traditional resource-based regions of China. A multivariable empirical framework comprising of the LS and Fourier LM unit root tests, Engle-Granger and Phillips-Ouliaris single equation cointegration tests, ARDL approach, FMOLS and DOLS robustness estimators, and the Granger causality test is applied. The results of the unit root test demonstrate that these five variables are non-stationary, but stationary after the difference of the first order. Consequently, the ARDL bounds estimation is implemented. The findings affirm the presence of a cointegration link between the parameters. Additionally, the evidence from the estimates supports the EKC hypothesis, with the lnAGR coefficient showing a strong positive correlation and the $\ln(AGR)^2$ coefficient showing a significant negative correlation. Furthermore, according to the ARDL analysis, AEC plays a significant role in promoting ACE, with improvements in environmental quality observed as AII and ARD increase in both the short and long term. The Granger causality analysis results suggest that ACE and AEC appear a bidirectional causality. The unidirectional Granger causalities are demonstrated that AGR growth causes ACE. Expectedly, AII results in ACE, and ARD also result in ACE. In summary, AII and ARD contribute to carbon mitigation in the agricultural sector of the five traditional resource-based provinces within the estimated duration.

From the findings of this paper, several policy measures should be taken to restrain ACE and maintain the sustainable development of the AGR in China's traditional resource-based regions.

Firstly, after researching the various impacts of AGR growth on ACE, it is hypothesized that the conventional agricultural industrial structure somewhat contributes to the rise in ACE. In order to incentivize the advancement of low-carbon agriculture, local governments should offer pragmatic policy and financial assistance to upgrade the agricultural economy. For instance, the agricultural sectors should be encouraged to tackle the transformation and modernization of their industrial structure. Furthermore, low-carbon ecological agriculture, tourism-based agriculture, and leisure-focused agriculture should be developed vigorously.

Secondly, the advancement of the agricultural sectors results in increased reliance on fossil fuels, leading to a rise in ACE. Nevertheless, limiting the usage of fossil energy will inhibit AGR development. The scientific solution to resolve this contradiction lies in optimizing the structure of AEC and improving establishment of renewable energy supply system such as increasing the proportion of geothermal, wind, solar, tides, waves and other green and clean energy while substituting the use of traditional carbon-dependent energy.

Thirdly, these five geographically adjacent provinces suffer from a scarcity of water resources, which creates a resemblance in the agriculture development approach in the areas. In the agricultural production process, flooded irrigation not only leads to a considerable wastage of water, but also amplifies ACE. Therefore, the local government ought to enhance funding for agricultural irrigation while prioritizing the advancement of digital and intelligent irrigation technology within the water-conserving irrigation system (Saia, 2023). Meanwhile, active investments policies for irrigation should be implemented to encourage the implement of controlled irrigation techniques, such as drip irrigation, rather than conventional flooded irrigation techniques. This will effectively

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contribute to energy conservation and ACE abatement, while synchronously enhancing AGR growth.

Finally, the local government ought to improve its support for ARD, encourage companies to enhance technological innovation, and improve energy utilization efficiency. Currently, the R&D status of renewable energy in the five traditional resource-based provinces of China remains low, and the extent of renewable energy usage within the total energy consumption framework is comparatively minimal. Therefore, the government should take advantage of domestic renewable resources and implement favorable policies to boost the growth of the renewable energy industry. Furthermore, encourage companies to manufacture renewable energy sources to increase their uptake and decrease dependence on traditional fossil fuels, while simultaneously depressing carbon emissions.

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