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Robotics, environmental regulation, and agricultural carbon emissions: an examination of the environmental Kuznets curve theory and moderating effects

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Introduction: Reducing carbon emissions from agriculture is essential to ensuring food security and human prosperity. As a country with approximately 20% of the global population, China has begun actively practicing the low-carbon agricultural development conception. Against the backdrop of disruptive technologies that continue to be integrated into various industries, the massive application of agricultural robots has opened the way to intelligent agriculture. This paper tries to answer whether there is some non-linear nexus between the application of agricultural robots and agricultural carbon emissions in China. As an essential tool for carbon emission reduction in China, does environmental regulation moderate the nexus between agricultural robot applications and agricultural carbon emissions? If so, how does this effect manifest itself?

Methods: This work takes China as an example by collecting macro-regional panel data from 30 provinces from 2006 to 2019. The environmental Kuznets curve theory is extended to agricultural carbon emissions, and we carried out empirical tests utilizing the panel fixed effects model and the moderating effects model.

Results: This study verifies the inverted U-shaped nexus between agricultural robotics applications and agricultural carbon emissions in Chinese provinces, i.e., the agricultural carbon emissions (ACE)-Kuznets curve holds. The higher the level of formal environmental regulation, the larger the peak of the ACE-Kuznets curve and the more the inflection point is pushed back. The higher the level of informal environmental regulation, the lower the peak of the ACE-Kuznets curve and the later the inflection point.

Discussion: The findings in this paper represent the first exploration of the environmental Kuznets curve in agricultural carbon emissions. It is noteworthy that the moderating effect of formal environmental regulation does not lower the peak of the curve as we expect. This appearance is attributed to the reality that China is still in a phase of rising agricultural carbon emissions, which is exacerbated by the overlapping positive effects of agricultural robotics applications and formal environmental regulations. Informal environmental regulation is more effective than formal environmental regulation in reducing agricultural carbon emissions at this stage.

KEYWORDS

agricultural robotics, agricultural carbon emissions, Kuznets curve, formal environmental regulation, informal environmental regulation

1 Introduction

Since 1970, agriculture has been responsible for around a quarter of global greenhouse gas emissions (Smith et al., 2014; Bennetzen et al., 2016), and at one point this share reached a third (Gilbert, 2012). In the long run, agricultural carbon emissions (ACE), such as black carbon from straw burning, impact the quantity and quality of cereal foods (Gupta, 2014). ACE are one of the most important influencing factors that cause harm to sustainable agricultural development (Koonthar et al., 2021). Whereas, reducing ACE can effectively guarantee the food system's sustainability, thus ensuring human beings' basic survival and sustainable development (Singh and Khanna, 2021; Costa et al., 2022; Opoku et al., 2022). China has about 21.5% of the global population size, but only 7% of the global arable land, and its arable land continues to shrink (Greenwood, 2022). Therefore, to cope with food security, China needs to achieve agricultural carbon reduction (Fu et al., 2022).

At present, Chinese agriculture has begun to step into the stage of high-quality evolution with low carbon as the keynote, but an unpromising phenomenon still exists (Chen and Xu, 2023). Due to the limitations of objective conditions such as population size and arable land area, China's agricultural carbon emission reduction must rely on the input of disruptive technologies to take advantage of the technological innovation effect to drive the agricultural green upgrading and transformation under the premise of guaranteeing food security. Digital technologies, including big data, blockchain, digital twin, artificial intelligence (AI), and the Internet of Things (IoT), can attract an influx of high-level production factors, including high-end talents, cutting-edge knowledge, advanced technological processes and production procedures, thereby optimizing the factor structure of conventional agriculture and expanding the scale and quality of agricultural technological innovation (Klerkx et al., 2019; Bolfe et al., 2020), and ultimately promote agricultural carbon emission reduction (Ali et al., 2021; Luo et al., 2023). Robots are loaded with AI (Rajan and Saffiotti, 2017), blockchain (Aditya et al., 2021), big data (Zhang, 2021), 5G (Sophocleous et al., 2022), digital twins (Hoebert et al., 2019) and a host of other digital technologies as physical carriers (Sodikjanov and Khayitboyev, 2023). Its unique potential for cutting carbon emissions. Robots can contribute significantly to reducing carbon emissions in electricity, gas, manufacturing, or agriculture (Li et al., 2022). The application of robots in agricultural production could ultimately reduce ACE by improving nitrogen utilization, accelerating plant breeding, promoting sustainable agricultural models, and reducing food waste (Pearson et al., 2022). However, to date, policies introduced in many countries to "promote the adoption of robots" still lack rigorous environmental assessments (Dusik et al., 2018), which has led to a heated debate in academia on how robots affect carbon emissions. Agricultural machinery, including harvesters, vans, tractors, trucks, etc., are used to perform various agrarian tasks and processes (Malik and Kohli, 2020). However, due to deficient maintenance and lack of strict

environmental regulation (ER) on these fossil fuel-power agricultural machinery, their increasing emission levels have led to pollution, environmental degradation, and significant carbon emissions (Zhang et al., 2017).

Research addressing the nexus between agricultural robotics and ACE is still in its infancy and currently focuses on the linear relationship between them (Oliveira et al., 2021). The relationship between other disruptive technologies, such as ICTs, or new economic models under the impact of disruptive techniques and carbon emissions has been discussed in greater depth by scholars (Melnyk et al., 2019). ICTs and the digital economy all have an inverted U-shaped nexus with carbon emissions (Higón et al., 2017; Sorrell, 2020; Bai et al., 2023; Lei et al., 2023; Li et al., 2023; Zheng et al., 2023). Can these findings be extended to robotic applications in agriculture? i.e., is there some nonlinear relationship, such as an inverted U-shaped relationship, between agricultural robotics applications (ARA) and ACE? To solve this hesitation, this paper takes the Chinese province as the research object and "dissects" the nonlinear nexus between the two variables.

In addition, ER has consistently been recognized as one of the crucial factors effecting carbon emissions (Dietzenbacher and Mukhopadhyay, 2007; Van der Ploeg and Withagen, 2015; Najm, 2019; Ouyang et al., 2019; Danish Ulucak et al., 2020; Neves et al., 2020), and is no exception for ACE (Jiang et al., 2018; Tang et al., 2019; Laborde et al., 2021; Du et al., 2023). Scholars' cognition of ER is evolving and deepening. Initially, the direct intervention, allocation and utilization of environmental resources by the government through administrative orders for the environment protection were regarded as direct regulation. With the participation and growth of market forces, the types of ER have become more and more abundant, including governmental command-and-control ER, market-incentive ER, and voluntary agreement ER, among others. Subsequently, the introduction of informal regulation (Pargal and Wheeler, 1996) expanded the meaning of ER. China is a vast country with various types of ER, combining statutory, local, informal, and other means. China's emphasis on ER has deepened significantly over the past few years (Green and Stern, 2017; Kostka and Nahm, 2017), e.g., the Chinese government has strengthened the formulation and improvement of environmental laws and regulations (Fang et al., 2021). Environmental protection departments' supervisory and enforcement capabilities have continued to improve, and investigations and prosecutions of environmental violations have become timelier and more effective (Hu et al., 2023). Chinese society's concern for environmental issues has gradually increased, and the public's willingness to partake in environmental protection actions has increased (Flatø, 2020). Therefore, this work tries to reply another query: How does the overlay of formal and informal ER and agricultural robotics applications act on ACE in China in the context of widespread regional ER? And how does the overlap between the two styles of ER and ARA differ? The practical implications of answering these questions are that they can help improve China's

agricultural management capacity to comply food security and sustainable agrarian development. Theoretically, placing agricultural robotics, ER, and ACE under the same research framework is essential, thus expanding the study of the interrelationships between modern agricultural production and sustainable agricultural development.

This work complements the existing corpus in the next three ways. First, it extends the findings of the traditional environmental Kuznets curve (EKC) to the field of ACE. It constructs a theoretical framework for the nonlinear nexus between ARA and ACE. Second, this paper takes the Chinese provincial area as the research object and verifies the inverted U-shaped nexus between ARA and ACE for the first time. Third, this paper incorporates formal and informal ER into the research framework and analyzes their direct effects on ACE and their moderating effects on the nexus between ARA and ACE, which, according to our knowledge, is a brand-new attempt and exploration.

2 Theory and hypotheses

2.1 Relationship between agricultural robotics applications and agricultural carbon emissions

There is no consensus among scholars on exactly how the use of agricultural robots will affect ACE. One view is that using robots increases agrarian green total factor productivity in the first place, suppressing agricultural carbon intensity (Lin and Li, 2023). For example, robotic tractors fitted with hybrid energy systems for weeding and pest control can reduce emissions by 50%, i.e., reducing substances emissions such as carbon monoxide, carbon dioxide, and nitrogen oxides (Gonzalez-de-Soto et al., 2016). Another view is that although the wave of agricultural automation has produced many agricultural robots, diesel-powered robots, which use diesel as an energy source, are the mainstay in all areas of agriculture (Bručienė et al., 2021; Niu et al., 2022; Jiang et al., 2023). The current widespread adoption of robots in agriculture still carries the risk of increasing carbon emissions, as solar- and electric-powered agricultural robots have not yet been able to fully replace those using traditional fossil fuels. Current research has showed solicitude for discussing the linear effects of ARA on ACE.

Only constructing a linear regression model to analyze the effect of ARA on ACE and ignoring the nonlinear relationship between the two can lead to the negative or positive effects being ignored, making the research conclusions unable to reveal the actual results (Wang et al., 2023a). This study leads into the idea of the EKC and constructs the influence mechanism of the nonlinear relationship between ARA and ACE based on scale, structure, and technology effects (Wang et al., 2023b). Overall, this work concludes that as ARA increase, ACE will show an inverted U-shaped tendency of increasing and then decreasing. The ARA-ACE theoretical link is as follows.

For one thing, when ARA starts to increase from a lower level, the scale effect causes the application of agricultural robots to change in the same direction as ACE. Therefore, It exhibits an upward movement on the curve's left side. First, ARA expand agricultural energy demand. Robotics, as a digital technology, has a clear dependence on electricity. With the popularization of ARA, agricultural electricity consumption will continue to rise (Song et al., 2023). China's electricity production currently relies on coal-fired power generation (Yang et al., 2022). To meet the electricity requirement insufficiency created by the ARA

rollout and to guarantee electricity supply, the high-carbon energy sources consumption will increase, inevitably leading to more ACE (Böhringer and Rivers, 2021). In addition, ARA will scale up agricultural production. The application of digital technology-based agricultural robots can transform traditional agricultural production methods and automate agriculture (Oliveira et al., 2021), which leads to extensive labor force replacements and significant increases in agricultural productivity. This advantage drives the scaling up of agriculture, i.e., more agricultural products can be produced when the production time remains the same as in the traditional way (Bechar and Vigneault, 2016, 2017). Increasing agricultural production consumes more resources and energy, which subsequently increases yield-based ACE (van Loon et al., 2019; Lamb et al., 2021). At this stage, since the level of ARA is still relatively limited, the decrease in ACE due to technological effects is not yet able to entirely neutralize the increase in ACE due to scale effects.

On the other hand, when ARA grows to a certain level and continues to grow, the technology effect and structural effect will lead to the application of agricultural robots and ACE reverse change, so it shows the characteristics of the right side of the curve down rise. First, ARA can improve the agrarian production efficiency. ARA will promote the realization of agrarian production automation and intelligence. For example, ARA can realize precise fertilizer application and irrigation (Oliveira et al., 2021), reduce resource waste and environmental pollution, and promote the agrarian development in the direction of being more environmentally friendly and sustainable. In addition, ARA can optimize the structure of agricultural production. Agricultural robots, equipped with advanced sensors and data analysis technologies, can monitor multiple factors such as soil, weather, and plant growth in real-time (Bručienė et al., 2021; Niu et al., 2022). Through the intelligent decision support system, farmers can make production plans more scientifically, select suitable crop varieties, and optimize the production structure to adapt to local soil, climate conditions, and market demand to reduce resource waste and environmental pollution.

In short, this work argues that the effect of ARA on ACE has a non-linear trend. First, the scale effect will dominate. Then, the other two effects dominate, thus forming an ACE-Kuznets curve (KC) shaped like an EKC. Based on this analysis, hypothesis 1 is proposed:

H1: The effect of ARA on ACE is characterized by an inverted U-shape, i.e., ACE initially increases with the increase in the application of agricultural robots and then gradually decreases after reaching the peak point.

2.2 Impact of environmental regulations on the ACE-Kuznets curve

ER is a prerequisite for the formation of the EKC (Wang et al., 2022), which is particularly evident in developed countries (Zhang et al., 2019) such as the United States (Pata, 2021), the United Kingdom (Yilanci et al., 2023), France (Ma et al., 2021), Germany (Pata et al., 2023) and Italy (Kalisvaart et al., 2023). This phenomenon may be because developed countries have more robust legal systems regarding environmental protection (Song et al., 2020). In addition to promoting the formation of the EKC, ER is also one factor that influences the shape of the EKC. Scholars deemed that if

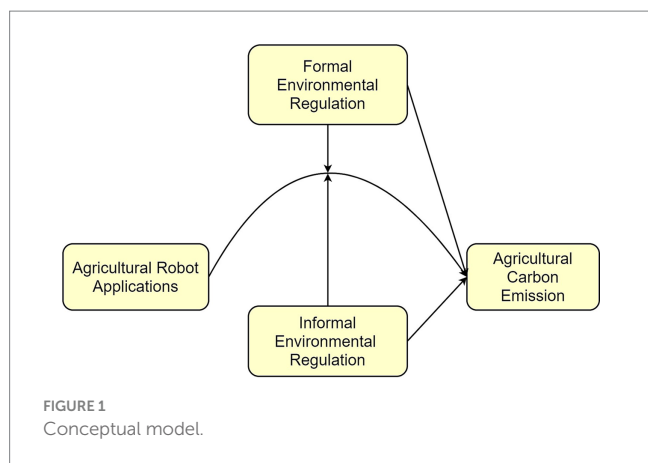


FIGURE 1
Conceptual model.

TABLE 1 Agricultural carbon emission sources and emission coefficients.

Carbon source	Carbon emission coefficients	Reference source
Diesel fuel	0.59 kg/kg	Stocker (2014)
Fertilizer	0.89 kg/kg	West and Marland (2002a,b)
Pesticide	4.93 kg/kg	West and Marland (2002a,b)
Agricultural film	5.18 kg/kg	Wang and Zhang (2016)
Irrigation	266.48 kg/hm2	Duan et al. (2011)
Tillage	312.60 kg/km2	Zhi and Gao (2009)

appropriate environmental policies are implemented, a horizontal path can be found, and even the inflection point can be reached earlier (Munasinghe, 1995; Dai et al., 2022). In terms of the intensity of ER, low-intensity ER can make the EKC flatter and the position of the inflection point lower. In contrast, high-intensity ER can make the inflection point of the EKC more advanced (more advanced compared to low-intensity), the position of the inflection point higher, and the shape of the curve steeper (Yin et al., 2015). After going through the experience of covering EKC in several countries, Dasgupta et al. (2002) found that the number of EKC thresholds based on a sample of developing countries is lower than that of developed countries. They suggested that ER in developing countries may be one of the most considerable grounds for this trend. Not coincidentally, Blackman et al. (2006) reached similar conclusions on environmental issues such as climate change, air quality, waste management, land degradation, and natural disasters. Zhang et al. (2009) used carbon dioxide, sulfur dioxide, industrial smog, and solid waste as indicators of environmental quality. They found that stringent and systematic ER can change the EKC pattern and its inflection point. These effects show the unique role of ER for EKC.

In addition, the causes of EKC formation can be decomposed into scale, structural, and technological effects (Grossman and Krueger, 1991). ER can promote industrial structure upgrading to enhance the structural effect, and industrial structure upgrading can further promote technological innovation to enhance the technical effect (Wen and Dai, 2021). ER can also increase total factor productivity (Peng et al., 2021), which is conducive to expanding production scale under the condition of ER.

In addition to formal environmental regulation (FER), the effects of informal environmental regulation (IER), i.e., individuals' environmental thoughts, concepts, awareness, attitudes, and perceptions of environmental protection, become more and more obvious (Whitburn et al., 2019; Torres et al., 2020; Peter et al., 2021; Smith, 2021; Kousar et al., 2022).

However, the current study does not address the impact of ER on EKC in agriculture. Does ER have a similar effect on the shape of the ACE-KC? Can ER positively impact the agrarian low-carbon development in China? Based on the above discussion, hypothesis 2 is proposed:

H2: ER (including FER and IER) changes the shape of the ACE-KC, and higher levels of regulation bring the curve's inflection point forward.

In conclusion, based on the EKC theory, we hypothesize an inverted U-shaped nexus between ARA and ACE and that the two moderating variables, formal and informal ER, moderated the relationship simultaneously. Therefore, the following conceptual model is developed to reflect these influences (see Figure 1).

3 Materials and methods

3.1 Variable selection

3.1.1 Explained variables: agricultural carbon emissions (ACE)

This study combines practical experience in production and relevant research results. Also, it takes into account that the decarbonization of agriculture mainly manifests itself in the reduction of inputs of high-carbon agricultural materials and high-carbon agricultural production activities, and concludes that the carbon emissions from agriculture mainly originate from the following aspects: (1) direct or indirect carbon emissions from the production and utilize of fertilizers, pesticides, and agricultural films (Long and Tang, 2021); (2) carbon emissions from the direct ordiesel fuel's indirect consumption by agrarian machinery (Mantoam et al., 2020); (3) carbon emissions from the use of electricity in irrigation (McCarthy et al., 2020); (4) carbon emissions from the destruction of soil organic carbon pools during agricultural ploughing, i.e., organic carbon loss (Mukumbuta and Hatano, 2020). Accordingly, this study mainly examines the carbon emissions directly or indirectly caused by six carbon sources touched upon the agricultural production procedure, such as fertilizers, pesticides, agricultural films, diesel fuel, irrigation, and ploughing, and adopts the IPCC Carbon Emission Coefficient Method to estimate the ACE. The estimation method for ACE is shown in Equation (1).

$$ACE = \sum ACE_i = \sum T_i \cdot \delta_i \tag{1}$$

Where ACE is the total amount of ACE, ACE_i is the amount of carbon emissions from each carbon source, T_i is the amount of each carbon source, and δ_i is the emission coefficient of the carbon source (In Table 1, there are agricultural carbon emission sources and emission coefficients). Fertilizer, pesticide, agricultural film, diesel

fuel, irrigation, and ploughing are calculated using the actual amount of use, irrigated area, and crops sown area in that year, respectively.

3.1.2 Explanatory variable: agricultural robot installations (ARI)

This paper uses the amount of agricultural robots installed as a proxy variable for ARA. Referring to the practices of existing studies (Cheng et al., 2019; Acemoglu and Restrepo, 2020), this study uses the Bartik instrumental variables method to estimate the installation of agricultural robots at the regional level. The robot stock data provided by the International Federation of Robotics (IFR) is at the country-industry level, and its industry classification standards are inconsistent with those of China. This work draws on Yan et al. (2020) to group and organize relevant industries and use the food and beverage industry as a proxy for agriculture. The formula for measuring the number of agricultural robots installed at the regional level is shown in Equation (2).

$$ARI_{it} = \frac{L_{it}}{L_t} \times ARI_t \quad (2)$$

where L_{it} is the number of people employed in the food and beverage industry in region i in year t ; ARI_t is the national stock of robots in the food and beverage industry in year t ; and L_t is the number of people employed in the national food and beverage industry in year t . The larger the value of ARI, the higher the level of application of agricultural robots.

3.1.3 Moderator variables

In this paper, ER is categorized into formal and informal ER. First, this work uses the amount of regional environmental laws as a proxy variable for FER (Yu and Wang, 2021). In addition, this paper draws on the methodology of Pargal and Wheeler (1996), which selects a range of indicators such as income level, educational attainment, population density, and age structure to synthesize a measure of the intensity of informal regulation in each region. Specific indicators are explained as follows: (1) Income level. The higher the income level, the stronger the public demand for a high-quality living environment. Compared with poorer areas, high-income areas are more concerned about the impact of environmental pollution (Nahar et al., 2023). In this paper, the average salary of urban workers is used to measure the income level of each region. (2) Education level. The higher the education level, the more intense the environmental protection awareness and the higher the degree of public concern for environmental quality (Al-Shidi et al., 2021). In this paper, the proportion of employed people with a tertiary education level or above in each region is chosen as an indicator to portray the more significant influence of higher education levels in informal regulation. (3) Population density. Higher population density means that the number of people affected by the negative externalities of environmental pollution is higher, and the number of people involved in informal regulation is also higher (Muktiwibowo, 2018). In this paper, the density of the resident population is selected to measure the population density of each region. (4) Age structure. Provinces with a high proportion of young people are more concerned about pollution and have a higher level of participation in environmental non-governmental organizations (NGOs) (Bi et al., 2010; Yapici et al., 2017). This paper

chooses the proportion of the population under 15 years old as the age structure variable. We use the entropy weight method to calculate the final comprehensive index.

3.1.4 Control variables

Referring to existing research (Rehman et al., 2019; He et al., 2021; Liu et al., 2021; Xu et al., 2023), this article chooses the intensity of financial support for agriculture (X_1), rural electricity consumption (X_2), total sown area of crops (X_3), the total power of agricultural machinery (X_4), agricultural disaster area (X_5) and agricultural industry structure (X_6) as control variables. Among them, the intensity of financial support for agriculture is measured by the amount of agriculture-related expenditure as a proportion of financial expenditure. The structure of the agricultural industry is measured by the value-added of primary industry/gross regional product.

3.2 Data sources

This work takes 30 provincial administrative regions in China (excluding Tibet, Hong Kong, Macao, and Taiwan region) as the study area, with a sample period of 2006–2019 (given the data availability). The raw data for measuring the ARI come from reports published by the IFR and the China Labor Statistics Yearbook. The remaining variables are from the National Bureau of Statistics of China, China Statistical Yearbook, CEIdata database, China Rural Statistical Yearbook, and the China Three Rural Areas (agriculture, rural areas, and peasants) Research Database. Table 2 presents the results of descriptive statistics for each variable.

3.3 Model and estimation

Based on the theoretical hypotheses of Section 2 and the variable selection of Section 3.1, this study first establishes a benchmark regression model to test the inverted U-shaped relationship between ARI and ACE, namely the ACE-KC hypothesis. The benchmark regression model setup is as follows:

$$ACE_{it} = \beta_0 + \beta_1 \cdot ARI_{it} + \beta_2 \cdot ARI_{it}^2 + \beta_3 \cdot Z_{it} + \mu_i + \varepsilon_{it} \quad (3)$$

Following this, to test the moderating effect of FER and IER on the inverted U-shaped relationship between ARI and ACE, this study adds the interaction term of FER (IER) with ARI and the interaction term of FER (IER) with ARI^2 to Equation (3). The constructed moderating effect model is as follows:

$$\begin{aligned} ACE_{it} = & \beta_0 + \beta_1 \cdot ARI_{it} + \beta_2 \cdot ARI_{it}^2 + \beta_3 \cdot FER_{it} \\ & + \beta_4 \cdot IER_{it} + \beta_5 \cdot Z_{it} + \beta_6 \cdot ARI_{it} \cdot FER_{it} \\ & + \beta_7 \cdot ARI_{it}^2 \cdot FER_{it} + \beta_8 \cdot ARI_{it} \cdot IER_{it} \\ & + \beta_9 \cdot ARI_{it}^2 \cdot IER_{it} + \mu_i + \varepsilon_{it} \end{aligned} \quad (4)$$

In Equations (3, 4), subscripts i and t denote province and year, respectively; Z is a matrix of control variables; β_0 is a constant term; β_i ($i \neq 0$) denotes the parameter to be estimated. μ_i denotes individual

TABLE 2 Descriptive statistics of variables.

Variable	Observations	Mean	Standard deviation	Minimum value	Maximum value
ACE	420	320.45	233.57	9.80	995.75
ARI	420	136.03	246.40	0.03	1842.58
FER	420	133.62	118.64	7	774
IER	420	0.20	0.11	0.07	0.84
X ₁	420	10.72	3.76	1.57	20.38
X ₂	420	253.51	385.51	0.60	2011
X ₃	420	3097.52	2840.92	93.97	13,353.02
X ₄	420	993.24	974.07	2	7,394
X ₅	420	0.11	0.06	0.003	0.33
X ₆	420	0.35	0.15	0.02	0.73

fixed effects, which control the inherent characteristics of provinces that do not change over time, and ε_{it} is the error term. In addition, ACE, ARI, and control variables are logarithmized before empirical analysis to reduce heteroskedasticity and non-stationarity.

We estimate Equations (3, 4) using fixed-effects (within) regression. The selection of the estimation method is accomplished in two steps. In the first step, a choice between pooled and random effects regression is made. The p -value of the Breusch and Pagan Lagrange Multiplier (BP-LM) test rejects the null hypothesis. There is evidence of substantial random effect. Therefore, we run a random effects model. In the second step, the Hausman test is utilized to select a fixed effects or random effects model. This paper uses robust Hausman with looser assumptions to conduct the test. We use fixed effects since the p -value is significant ($p < 0.05$).

4 Results

4.1 The impact of agricultural robot installation on agricultural carbon emissions

In this section, we make a preliminary judgment on the relationship between ARI and ACE to verify their nonlinear relationship. Columns (1)–(2) of Table 3 show the results of the direct impact of ARI on ACE. The coefficient of the linear term of ARI is 0.0738 ($p < 0.01$), and the coefficient of the quadratic term is -0.0048 ($p < 0.01$) when only the primary term of ARI, the secondary term, and the rest of the control variables are included. With the inclusion of the FER and IER variables, for the panel fixed-effects model with both individual (province) and time effects, the coefficient of the linear term of ARI is 0.0694 ($p < 0.01$), and the coefficient of the quadratic term is -0.0041 ($p < 0.01$). And they all pass the correlation significance test. Therefore, it can be inferred that ARI and ACE show an inverted U-shaped curve relationship. This result indicates that hypothesis 1 has been verified.

A possible explanation for this result is that in the early stages of introducing agricultural robotics, the amount of agricultural robots installed may be relatively low due to the time required for the public to accept and absorb new technologies. However, the demand for agricultural development will continue to increase as society develops,

and traditional agriculture is mainly dependent on fossil fuels and resources (Rosati et al., 2021; Sumberg and Giller, 2022), which may bring about a continued rise in ACE. However, as the amount of agricultural robots continues to increase, on the one hand, the automation of agrarian production increases, reducing the need for human labor, and how agriculture is practiced is likely to change during this phase (Marinoudi et al., 2019; Lowenberg-DeBoer et al., 2020). For example, the delicate management of agriculture and the reduction of pesticide and fertilizer use. For one thing, the greater the number of agrarian robots, the lower the cost of utilizing clean energy to power the robots due to scale effects. Therefore, as agricultural robots gradually become more common, the energy source of the robots will also use more clean energy. Both may lead to a gradual decline in ACE during this period. In addition, among the control variables, X₃, X₄, and X₅ always have significant positive effects on ACE, and the rest of the control variables do not have consistent effects on ACE in different models.

4.2 The impact of the interaction between the number of agricultural robots installed and environmental regulations on agricultural carbon emissions

The estimation result of adding the interaction terms ARI·FER and ARI²·FER is shown in column (3) of Table 3. In the individual-time fixed-effects model, the coefficient of FER is 0.0003; The coefficient of the interaction term of FER with the linear term of ARI is -0.0001 ($p < 0.1$); The coefficient of the interaction term of FER with the quadratic term of ARI is 0.00008 ($p < 0.05$). The estimation result of adding the interaction terms ARI·IER and ARI²·IER is shown in columns (4) of Table 3. In the individual-time fixed-effects model, the coefficient of IER is -1.3598 ($p < 0.01$); The coefficient of the interaction term of IER with the linear term of ARI is -0.2166 ($p < 0.01$); The coefficient of the interaction term of IER with the quadratic term of ARI is 0.0179 ($p < 0.05$). These results indicate that FER and IER both have independent significant moderating effect on the ACE-KC.

The estimation results of adding the interaction terms ARI·FER, ARI²·FER, ARI·IER, and ARI²·IER are shown in columns (5) and (6) of Table 3. The inverted U-shaped nexus between ARI and ACE still

TABLE 3 Empirical results on direct and moderating effects.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	ACE	ACE	ACE	ACE	ACE	ACE
ARI	0.0738*** (0.0066)	0.0694*** (0.0192)	0.0952*** (0.0222)	0.1127*** (0.0220)	0.1026*** (0.0099)	0.1086*** (0.0228)
ARI ²	-0.0048*** (0.0007)	-0.0041*** (0.0008)	-0.0055*** (0.0012)	-0.0061*** (0.0015)	-0.0042*** (0.0016)	-0.0054*** (0.0016)
FER		-0.000033 (0.0000)	0.0003 (0.0002)		0.0004* (0.0002)	0.0003 (0.0002)
IER		-2.8186*** (0.2803)		-1.3598*** (0.4738)	-1.2550*** (0.3671)	-1.5500*** (0.4866)
ARI-FER			-0.0001* (0.0001)		-0.0001** (0.0001)	-0.0001* (0.0001)
ARI-IER				-0.2166*** (0.0616)	-0.1906*** (0.0581)	-0.1809*** (0.0650)
ARI ² -FER			0.00008** (0.0000)		0.000014** (0.0000)	0.000012* (0.0000)
ARI ² -IER				0.0179** (0.0078)	0.0122 (0.0081)	0.0138* (0.0083)
X ₁	-0.0384** (0.0166)	0.0282 (0.0286)	-0.0071 (0.0320)	0.0349 (0.0283)	-0.0416*** (0.0148)	0.0344 (0.0284)
X ₂	-0.0255 (0.0204)	0.0283 (0.0199)	-0.0350 (0.0214)	0.0545*** (0.0208)	0.0821*** (0.0207)	0.0555*** (0.0211)
X ₃	0.2773*** (0.0234)	0.2303*** (0.0229)	0.2924*** (0.0249)	0.2249*** (0.0223)	0.1893*** (0.0223)	0.2161*** (0.0229)
X ₄	0.0145** (0.0057)	0.0094* (0.0050)	0.0132** (0.0057)	0.0112** (0.0050)	0.0106** (0.0050)	0.0102** (0.0050)
X ₅	0.2718*** (0.0289)	0.1127*** (0.0303)	0.2735*** (0.0307)	0.1145*** (0.0305)	0.1465*** (0.0290)	0.1231*** (0.0310)
X ₆	0.0959*** (0.0363)	0.0144 (0.0329)	0.0789** (0.0371)	-0.0046 (0.0326)	0.0294 (0.0330)	0.0045 (0.0332)
Constant	4.0843*** (0.2175)	4.1315*** (0.2024)	3.9690*** (0.2302)	3.8252*** (0.2141)	4.1219*** (0.2171)	3.9326*** (0.2237)
Year fixed effects	No	Yes	Yes	Yse	No	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	413	413	413	413	413	413
R-squared	0.7080	0.7911	0.7356	0.7990	0.7837	0.8011
F_value	186.81***	181.97***	142.57***	184.89***	234.41***	184.18***
BP-LM test statistic	1582.38***	1563.18***	1570.94***	1643.22***	1515.64***	1605.64***
Hausman test statistic	177.19***	172.70***	168.72***	179.88***	182.51***	181.11***

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

holds, suggesting the relationship is robust. The coefficients on FER are 0.0004 ($p < 0.1$) in the individual fixed-effects model and 0.0003 in the individual-time fixed-effects model. This result suggests that FER does not have a significant inhibitory effect on ACE. The coefficients of the interaction term of FER with the linear term of ARI are -0.0001 ($p < 0.05$) in the individual fixed-effects model and -0.0001 ($p < 0.1$) in the individual-time fixed-effects model; the coefficients of the interaction term of FER with the quadratic term of ARI are 0.000014 ($p < 0.05$) in the individual fixed-effects model and 0.000012 ($p < 0.1$) in the individual-time fixed effects model. This result indicates that FER has a significant moderating effect on the ACE-KC. The coefficients for IER are -1.2550 ($p < 0.01$) in the individual fixed-effects model and -1.5500 ($p < 0.01$) in the individual-time fixed-effects model. This result indicates that IER has a significant inhibitory effect on ACE. The coefficients of the interaction term of IER with the liner term of ARI are -0.1906 ($p < 0.01$) in the individual fixed-effects model and -0.1809 ($p < 0.01$) in the individual-time fixed-effects model; the coefficients of the interaction term of IER with the quadratic term of ARI are 0.0122 in the individual fixed-effects model and 0.0138 ($p < 0.1$) in the individual-time fixed-effects model. This result suggests that IER has the same significant moderating effect on the ACE-KC.

At this point, hypothesis 2 is halfway confirmed, i.e., ER (both formal and informal ER) changes the shape of the ACE-KC, and exactly how the shape changes will be discussed in Section 4.3. In

addition, the control variables X₂, X₃, X₄, and X₅ have significant positive effects on ACE, while the rest have insignificant effects on ACE.

4.3 Robustness test and endogeneity test

4.3.1 Robustness test

To ensure the reliability of the above conclusions, we draw on the practices of existing studies (Liu P. et al., 2024) and further conduct robustness tests on the benchmark regression model and the moderating effects model. The specific approach is as follows: We use the first-order lag terms of ARI, FER, and IER as new variables to re-estimate each model in Table 3, respectively. The results are displayed in Table 4. The results of the robustness test show that the direction and significance of the coefficients in the re-estimate model and the original model remain the same, indicating that the empirical findings of this study are robust.

4.3.2 Endogeneity test

To prevent model estimation errors caused by endogeneity problems, we use the two-stage least squares (2SLS) method for re-estimation in this study. Drawing on the idea of Huang et al. (2019) selecting historical data from the time dimension as a viable instrumental variable, this study uses the number of agricultural small

TABLE 4 Robustness test results on direct and moderating effects.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	ACE	ACE	ACE	ACE	ACE	ACE
ARI	0.0631*** (0.0057)	0.0570*** (0.0191)	0.0788*** (0.0229)	0.0814*** (0.0221)	0.0783*** (0.0077)	0.0753*** (0.0228)
ARI ²	-0.0039*** (0.0007)	-0.0031*** (0.0008)	-0.0046*** (0.0012)	-0.0044*** (0.0014)	-0.0019* (0.0011)	-0.0040*** (0.0015)
FER		-0.00003 (0.0000)	0.0003 (0.0002)		0.0002 (0.0002)	0.0002 (0.0002)
IER		-3.0630*** (0.2741)		-2.3279*** (0.4952)	-2.0977*** (0.3883)	-2.5091*** (0.5128)
ARI·FER			-0.0001* (0.0001)		-0.0001** (0.0001)	-0.0001* (0.0001)
ARI·IER				-0.1042* (0.0552)	-0.0984* (0.0502)	-0.0699* (0.0482)
ARI ² ·FER			0.00001* (0.0000)		0.00001* (0.0000)	0.00001* (0.0000)
ARI ² ·IER				0.0104 (0.0073)	0.0051 (0.0074)	0.0059 (0.0077)
X ₁	-0.0770** (0.0313)	0.0163 (0.0304)	-0.0544 (0.0348)	0.0184 (0.0303)	-0.0084 (0.0273)	0.0226 (0.0305)
X ₂	-0.0287 (0.0211)	0.0437** (0.0198)	-0.0367* (0.0218)	0.0572*** (0.0213)	0.0820*** (0.0213)	0.0573*** (0.0217)
X ₃	0.2592*** (0.0240)	0.2191*** (0.0228)	0.2724*** (0.0260)	0.2122*** (0.0223)	0.1731*** (0.0219)	0.2039*** (0.0231)
X ₄	0.0135** (0.0057)	0.0076 (0.0049)	0.0104* (0.0057)	0.0085* (0.0049)	0.0087* (0.0049)	0.0073 (0.0050)
X ₅	0.2827*** (0.0302)	0.1031*** (0.0306)	0.2859*** (0.0316)	0.1111*** (0.0316)	0.1320*** (0.0300)	0.1157*** (0.0319)
X ₆	0.1021*** (0.0370)	0.0031 (0.0326)	0.0876** (0.0377)	-0.0014 (0.0324)	0.0235 (0.0326)	0.0091 (0.0330)
Constant	4.4142*** (0.2395)	4.2297*** (0.2185)	4.3224*** (0.2558)	4.0765*** (0.2289)	4.3180*** (0.2302)	4.1725*** (0.2406)
Year fixed effects	No	Yes	Yes	Yes	No	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	384	384	384	384	384	384
R-squared	0.6599	0.7759	0.6952	0.7782	0.7625	0.7805
F_value	188.60***	189.93***	143.07***	188.94***	247.71***	187.36***
BP-LM test statistic	1445.83***	1310.33***	1316.49***	1414.21***	1359.83***	1374.32***
Hausman test statistic	168.52***	177.75***	175.74***	191.78***	188.05***	183.47***

Standard errors in parentheses; *p < 0.1, **p < 0.05, ***p < 0.01.

TABLE 5 2SLS regression results.

Variables	(1)	(2)
	ARI	ACE
IV	0.3665*** (0.0433)	
ARI		0.0245* (0.0134)
Control variable	Yes	Yes
Year fixed effects	Yes	Yes
Individual fixed effects	Yes	Yes
Observations	391	391
R-squared	0.9122	0.6093
F_value	40.59***	161.26***

Standard errors in parentheses; *p < 0.1, **p < 0.05, ***p < 0.01.

tractors in each province from 1978 to 1991 as an instrumental variable (IV) for regional ARI. The instrumental variable satisfies both the correlation and exogenous conditions.

The 2SLS estimation results are shown in Table 5. In column (1), both the F-statistic and instrumental variables show significant results at the 1% level. This result confirms the validity of the selected instrumental variables, i.e., no weak instrumental variables exist. The

regression results in column (2) show that ARI contributes significantly to ACE, confirming that the results of the benchmark regression are robust.

4.4 Analysis of the moderating effect

We already know that FER and IER have significant moderating effects on the ACE-KC. Next, this paper further analyzes how the two styles of ER affect the shape of the ACE-KC. After concluding that the coefficients of both interaction terms of FER with ARI and ARI² are significant, we extract the corresponding estimated regression equation (see Equation 5) based on the estimation results demonstrated by columns (6) in Table 3 (the estimated coefficients of FER are not significant, so they are deleted).

$$\hat{ACE} = \hat{\beta}_1 \cdot ARI + \hat{\beta}_2 \cdot ARI^2 + \hat{\beta}_6 \cdot ARI \cdot FER + \hat{\beta}_7 \cdot ARI^2 \cdot FER + \hat{\beta}_0 \tag{5}$$

Where \hat{ACE} represents the estimated value of ACE. $\hat{\beta}_1$ is 0.1086, $\hat{\beta}_2$ is -0.0054, $\hat{\beta}_6$ is -0.0001, $\hat{\beta}_7$ is 0.000012, and $\hat{\beta}_0$ is 3.9326.

Figure 2 shows the Kuznets plots of ACE and ARI for different levels of FER at low, medium, and high. FER(0) represents the relation diagram

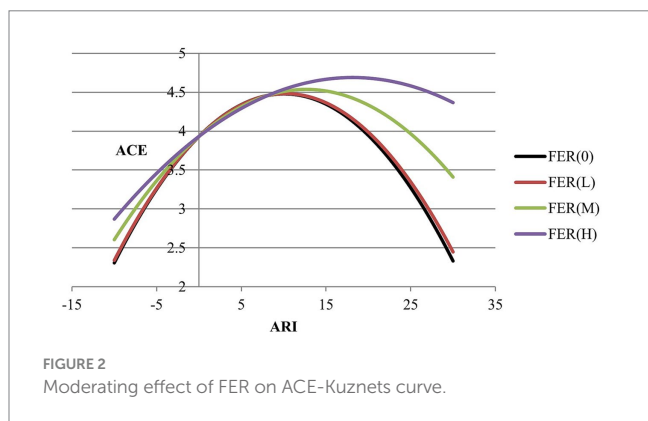


FIGURE 2 Moderating effect of FER on ACE-Kuznets curve.

between ARI and ACE when FER is taken as 0, i.e., when there is no FER. As a continuous variable, FER was divided using a generalized method (Aiken et al., 1991). The mean was used to represent the medium level (M). The mean plus one standard deviation represents a high level (H). The mean minus one standard deviation represents a low level (L). The results of the delineation are shown below:

$$FER(L) = 14.9817, FER(M) = 133.619, FER(H) = 252.2563$$

As shown in Figure 2, at lower levels of FER, the ACE-KC almost overlaps with the absence of FER, suggesting that lenient FER barely alters the relationship between ARI and ACE. The slope of the ACE-KC is smaller (in absolute value) under strict FER than under loose FER. The curve rises more slowly in the rising phase and falls more slowly in the falling phase. In addition, the higher the level of FER, the peak of the ACE-KC rises gradually, and its inflection point becomes more delayed. In conclusion, FER does not improve the relationship between ARI and ACE, while the higher the FER level, the worse the situation perhaps becomes. Therefore, the second half of hypothesis 2 was not tested. One possible reason for this is that ER itself may lead to a “green paradox” effect (Liu et al., 2018), which can occur especially in developing countries (Dietzenbacher and Mukhopadhyay, 2007; Van der Ploeg and Withagen, 2015). Some studies have found an inverted U-shaped relationship between ER and carbon emissions (Chen et al., 2020). The positive coefficient of FER in our results indicates that the current FER in China is in the increasing stage for ACE. Since the sample maximum value of ARI is 7.5189 (ARI is logarithmic value for consistency with the regression results), the black curve in Figure 2 shows that ARI is in an increasing stage before 7.5189, which indicates that the current ARI on ACE in China is also positive. When the positive effect of FER on ACE is superimposed on the positive effect of ARI on ACE, the phenomenon of the peak of the ACE-KC increasing with the increase of the FER level is shown in Figure 2.

After concluding that the coefficients of both interaction terms of IER with ARI and ARI² are significant, we extracted the corresponding estimated regression equations (see Equation 6) based on the estimation results exhibited by columns (6) in Table 3.

$$\begin{aligned} \hat{ACE} = & \hat{\beta}_1 \cdot ARI + \hat{\beta}_2 \cdot ARI^2 + \hat{\beta}_4 \cdot IER + \hat{\beta}_8 \cdot ARI \cdot IER \\ & + \hat{\beta}_9 \cdot ARI^2 \cdot IER + \hat{\beta}_0 \end{aligned} \quad (6)$$

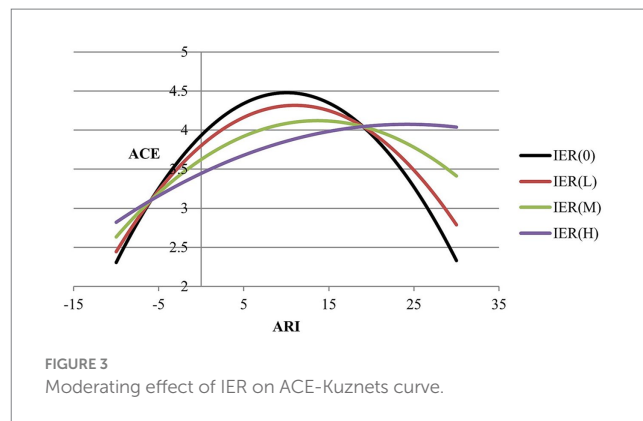


FIGURE 3 Moderating effect of IER on ACE-Kuznets curve.

Where \hat{ACE} represents the estimated value of ACE. $\hat{\beta}_1$ is 0.1086, $\hat{\beta}_2$ is -0.0054, $\hat{\beta}_4$ is -1.5500, $\hat{\beta}_8$ is -0.1809, $\hat{\beta}_9$ is 0.0138, and $\hat{\beta}_0$ is 3.9326.

Kuznets plots of ACE and ARI at different levels of IER at low, medium, and high levels are shown in Figure 3. IER was divided in the same way as FER. The division results are as follows:

$$IER(L) = 0.0841, IER(M) = 0.1989, IER(H) = 0.3137$$

Figure 3 shows that the ACE-KC’s slope (in absolute value) is smaller under strict IER pieces than under loose IER. The curve rises more slowly in the rising phase and falls more slowly in the falling phase. Also, the higher the level of IER, the peak of the ACE-KC gradually decreases, but its inflection point becomes more pushed back. Alternatively, the inverted “U” shaped nexus between the number of ARI and ACE becomes closer to a linear relationship as the level of IER increases. In short, the relatively strict IER is more conducive to realizing the decline of ACE peak than the relatively lenient FER, but the emission reduction process is not accelerated. Therefore, the second half of hypothesis 2 was not tested. However, compared to FER, IER did not advance the inflection point of the ACE-KC, but it reduced the peak of the ACE-KC. This result suggests that IER has a more significant effect on improving the relationship between ARI and ACE compared with FER. The main reason may be that the current ARI in China positively affects ACE. In contrast, IER has a negative effect on ACE (the coefficient of IER is significantly negative in Table 3). The superposition of both positive and negative effects makes the ACE-KC’s slope (absolute value) smaller, i.e., the curve becomes flatter. It also indicates that the positive effect of ARI on ACE is stronger than the negative effect of IER on ACE.

4.5 Heterogeneity analysis

There are “gradient differences” in agricultural development and AI levels in China’s eastern, central, and western regions, leading to regional heterogeneity in ARA. In addition, ARA may have a heterogeneous impact on the ACE due to differences in regional natural conditions and digitalization bases. Therefore, this study explores the moderating effects of FER and IER on the ACE-KC in China’s eastern, central, and western regions.

TABLE 6 Heterogeneity analysis results on moderating effects.

Variables	Eastern region	Central region	Western region
ARI	0.1560*** (0.0474)	0.0376 (0.0352)	0.0638 (0.0451)
ARI ²	-0.0148*** (0.0035)	0.0010 (0.0035)	-0.0015 (0.0055)
FER	-0.0003 (0.0003)	0.0007*** (0.0002)	0.0008* (0.0004)
IER	-0.8779 (0.7427)	-0.1641 (0.8960)	2.2750* (1.3702)
ARI·FER	-0.0001 (0.0001)	-0.0002*** (0.0001)	-0.0001 (0.0002)
ARI·IER	-0.2155*** (0.0737)	-0.5835*** (0.1236)	-0.6397** (0.2640)
ARI ² ·FER	0.00003*** (0.0000)	0.00002*** (0.0000)	-0.00001 (0.0000)
ARI ² ·IER	0.0306*** (0.0101)	0.0365** (0.0172)	0.0212 (0.0400)
X ₁	-0.0766* (0.0403)	0.1880*** (0.0319)	-0.1116* (0.0580)
X ₂	0.0233 (0.0242)	-0.1138** (0.0518)	-0.0287 (0.0479)
X ₃	0.2386*** (0.0479)	0.0448** (0.0185)	0.3014*** (0.0701)
X ₄	0.0115** (0.0057)	-0.0064 (0.0061)	0.0278*** (0.0101)
X ₅	0.2503*** (0.0691)	0.0051 (0.0266)	0.1872*** (0.0701)
X ₆	-0.0686* (0.0377)	-0.0073 (0.0476)	0.0012 (0.0666)
Constant	4.2659*** (0.4721)	5.7269*** (0.2811)	2.9735*** (0.5178)
Year fixed effects	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes
Observations	147	112	154
R-squared	0.8849	0.9572	0.8880
F_value	30.62***	273.35***	245.57***

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The results of the heterogeneity regressions for the eastern, central, and western regions are shown in Table 6. In the eastern region, the estimated coefficient of ARI is 0.1560; ARI² is -0.0148; ARI·FER is -0.0001; ARI²·FER is 0.00003; ARI·IER is -0.2155; and ARI²·IER is 0.0306. All coefficients except ARI·FER pass the significance test. These results indicate that the inverted U-shaped relationship between ARI and ACE holds in the eastern region and that FER and IER have significant moderating effects on ACE-KC. In the central region, the estimated coefficient of ARI is 0.0376; 0.0010 for ARI²; -0.0002 for ARI·FER; 0.00002 for ARI²·FER; -0.5835 for ARI·IER; and 0.0365 for ARI²·IER. The ARI and ARI² coefficients are insignificant, while the interaction term coefficients all pass the significance test. This suggests that the inverted U-shaped relationship

between ARI and ACE does not hold in the central region, but FER and IER have significant moderating effects.

In contrast, the inverted U-shaped relationship between ARI and ACE and the moderating effects of FER and IER are insignificant in the western region. The heterogeneity results suggest that ACE-KC is particularly pronounced in the relatively economically developed eastern region, consistent with the finding that EKC is particularly pronounced in developed countries (Kalisvaart et al., 2023). The moderating effects of FER and IER in the western region are not significant, perhaps because the region is sparsely populated, the level of economic development and environmental pollution is low, and the strength of ER is relatively small, so there are no significant moderating effects.

5 Discussion and conclusion

This study uses the Chinese provincial areas as the objects of study to explore the nonlinear effect of the application of agricultural robots on ACE in the context of various disruptive technologies that shape the outlook for changes in agricultural production. We also explore the moderating effects of FER and IER on the nexus between the application of agrarian robots and ACE, based on the context that China has been prioritizing environmental and climate issues in recent years and incorporating both formal and informal ERs into the research framework. It is found that there is an inverted U-shaped relationship between the application of agricultural robots and ACE, i.e., as the application of agricultural robots increases, ACE first increases and then decreases. The results obtained in this paper are like those of Liu B. et al. (2024), except that their study was on the nonlinear nexus between the extent of application of all industrial robots in the region and regional carbon emissions. On the other hand, this paper focuses on the agricultural sector, making our study a novel exploration of academia.

According to the moderating effects analysis of the study, both formal and informal ER changed the shape of the ACE-KC. Specifically, FER increased the peak of the ACE-KC and delayed the inflection point. IER decreased the peak of the ACE-KC but delayed the inflection point. The current literature studying the effect of ER on CO₂ KC focuses on FER. The research by Yin et al. (2015) found that higher levels of ER, while causing the peak of CO₂ KC to rise, also had a more advanced inflection point, which is inconsistent with the results obtained in this paper. The possible reasons for this discrepancy are the different fields of study, where our study is focused on agriculture. Secondly, the independent variable used in this paper is ARI, while Yin et al. (2015) use gross regional product. Again, the period of the study sample is different. Our sample interval is from 2006 to 2019, while Yin et al. (2015) adopted the sample interval from 1999 to 2011. Some of the reasons FER makes the peak of the ACE-KC higher are discussed in depth next.

First, the spillover effects of environmental justice and environmental governance make it imperative that environmental protection, including carbon emission reduction, be carried out in the context of efficient synergies within the region (Gunningham, 2009; Holley and Sinclair, 2013). Although China's Beijing-Tianjin-Hebei and Yangtze River Delta regions are already engaged in collaborative legislation on regional environmental governance, collaborative legislation is a "new sprout" from China's traditional legislative system.

Therefore, China's Constitution, the Legislative Law, and other relevant laws on the legal effect of regional environmental governance collaborative legislation are not yet clear, which often leads to China's regional environmental governance collaborative legislation being faced with the problem of constitutionality, legislative conflicts and other problems (Van Rooij, 2006; Li, 2019; Zhu, 2019). Insufficient synchronization of regional environmental governance collaborative legislation will directly affect regional environmental governance synergistic law enforcement and reduce the effectiveness of law enforcement. Inadequate supporting policies and measures are not conducive to enhancing the efficiency of collaborative legislation on regional environmental governance. For example, the legal effect of different local normative documents on environmental protection issues varies greatly (Zhang and Fu, 2008). In practice, in the same region, various local normative documents are formulated by different subjects for the same environmental governance issues, which leads to local laws in some places and local government regulations in others (Shen et al., 2017). The difference in legal effect will directly affect the enforcement behavior of regional environmental law enforcement subjects, which will have a certain adverse effect on the future regional environmental collaborative governance, making the input of ER and governance effects often disproportionate.

Second, even without considering collaborative environmental governance, environmental laws established in different regions often contradict legislation and enforcement (Marquis et al., 2011), undermining their actual regulatory effect in curbing carbon emissions. For example, Shanghai has relatively clear provisions for local cooperative governance for air pollution prevention and control. However, some local legislation, such as Jiangsu's, is more general. The Tianjin Water Pollution Prevention and Control Regulations, compared with the water pollution prevention and control regulations of Beijing and Hebei, have a particular chapter on "Regional Water Pollution Prevention and Control Collaboration." Hebei Province stipulates the specific procedures for determining the list of enterprises participating in mandatory cleaner production audits. In contrast, Beijing and Tianjin only generally stipulate that the competent authorities in charge of cleaner production and the environmental protection authorities shall determine the list following the law without stipulating the specific procedures. The incomplete harmonization of legislative content is not only reflected in the inconsistency of substantive provisions but also includes procedural provisions that are not uniform. The inconsistency of the legislation makes regional environmental governance less effective (Lo et al., 2006) and weakens the inhibiting effect of environmental laws on carbon emissions.

Finally, FER (FER), such as strict environmental laws, may lead to escalating compliance costs for firms in STI activities (Delmas and Marcus, 2004; Shi et al., 2018; Chen and Qian, 2020), thereby weakening firms' technological innovation capabilities (Ramanathan et al., 2017; Jiang et al., 2021), limited R&D funds being used for environmental compliance and reducing R&D investment in non-environmental areas (Rubashkina et al., 2015), resulting in the technological value added declining in non-environmental areas of the robots, affecting its function of curbing carbon emissions. On the other hand, strict environmental laws may lead to an increasing number of agribusinesses engaging in greenwashing or carbon credit speculation, i.e., avoiding their current environmental responsibilities through differences in the price of carbon offsets between different

enterprises, purchasing green bonds, and purchasing carbon emission quota through the carbon trading mechanism (Kalesnik et al., 2020; Gao and Schmittmann, 2022), and increasing their emissions from agricultural activities (Kalesnik et al., 2020; Gao and Schmittmann, 2022).

Because of these reflections, in the future, we will focus on some issues related to ARA and synergistic carbon emission reduction in China's regional agriculture and thus continue to enrich the findings of this paper.

According to our knowledge, no literature examines the effect of IER on the KC. IER is more like a soft external constraining force than FER. For example, environmental media reports, as IER, can promote industrial structure upgrading by monitoring the government and guiding public opinion (Chen et al., 2020), thus protecting the environment and reducing carbon emissions. In addition, other variables that can be used as proxies for IER include the number of petition visits (Ren et al., 2018), community pressure (Féres and Reynaud, 2012), neighborhood income inequality (Moser and Zwickl, 2014), Pollution Information Transparency Index (PITI) (Zhang and Huang, 2023), etc., all have positive effects on environmental protection and carbon emission reduction. In agriculture, the PITI, an IER, can similarly increase total factor productivity and reduce ACE (Liu et al., 2022). In addition to the PITI, village rules, as a kind of IER, can likewise promote cleaner production behaviors among farmers and reduce ACE (Du et al., 2023). It follows that IER can effectively lower ACE. That is why we included IER in our model. In future research, we can continue to explore how different measures of IER differ in their impact on ACE and how the effect on the relationship between ARA and ACE differs, which would be a further extension of this study.

6 Policy implications

To realize "Agricultural Zero-Carbonism," our work can furnish the following recommendations to administrations.

The first suggestion. Although there is a significant ARA-ACE inverted U-shaped curve, China is still in the left half of the curve. At this stage, an increase in ARA leads to an increase in ACE. Since this trend is problematic to avoid before the inflection point, the government should vigorously promote agricultural robots and reach the inflection point as soon as possible. Meanwhile, the government should exploit and release numerous national, industry, and association-level standards for green agricultural robots, covering all agrarian corners with green agricultural robot standards, encouraging the manufacture of more clean energy-powered agrarian robots and minimizing the environmental damage brought about by the scale effect of agricultural robot applications.

The second recommendation. Since FER is insignificant for ACE, the government should adopt a lean governance approach by proposing a lean FER for agriculture to reduce the rising regulatory costs associated with policy redundancy. The government only needs to set more disbursements into the censor procedure. Being an all-around nanny in policy design, formulation, censor, implementation, and feedback is unnecessary. The government should adopt a scientific and elastic lean FER to replace the rigid and traditional FER.

The third recommendation. Since IER can limit and suppress ACE, the government should gradually delegate various powers of IER to the public, instructing the public to actively participate in the standard design, formulation, censoring, implementation, and feedback of IER and ultimately establish a system that is shared and governed by everyone. of “pro-environmental civil society.”

The fourth recommendation. Due to the regulatory effect of FER, the peak value of the inverted U-shaped curve rises, and the inflection point is pushed back. Plus, FER is not significant on ACE. Therefore, the government should reduce the FER for the agricultural sector or provide exemptions to qualified agricultural enterprises and self-employed agricultural workers and allow them to carry out agricultural operations under the prerequisites of “weak FER” or even “zero FER” under the premise of complying with the constitution.

The fifth recommendation. Due to the regulating effect of IER, the peak value of the inverted U-shaped curve decreases, and the inflection point is pushed back. Plus, IER can significantly reduce the ACE; therefore, the government should further promote IER and integrate it with the ARA’s development strategy, encourage more societal forces to partake in the investigation and application promotion of ARA, and customize the corresponding IER, increase the suitability between ARA and IER, reduce the internal consumption and increase the resonance effect, so that the superposition of IER and ARA can make the inflection point earlier.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: the raw data for measuring the ARI come from reports published by the IFR and the China Labor Statistics Yearbook. The remaining variables are from the National Bureau of Statistics of China, China Statistical Yearbook, CEIdata database, China Rural

Statistical Yearbook, and the China Three Rural Areas (agriculture, rural areas, and peasants) Research Database.

Author contributions

YL: Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Project administration, Software, Writing – original draft. YC: Conceptualization, Investigation, Resources, Supervision, Validation, Visualization, Writing – review & editing.

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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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