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Research article

From awareness to Action: How climate attention drives the low-carbon transition in Chinese agriculture

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A R T I C L E I N F O

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A B S T R A C T

The agricultural low-carbon transition is essential to achieving China's dual carbon goals. Utilizing provincial panel data (2001–2021), this study analyzes the influence of climate attention on agricultural low-carbon transition and investigates underlying mechanisms. Additionally, leveraging the establishment of the carbon trading market—a key indicator of societal climate attention—as a quasi-natural experiment, this study applies DID and PSM-DID models to assess its role in promoting the agricultural low-carbon transition. The findings reveal that increasing climate attention significantly enhances the agricultural low-carbon transition, with more pronounced effects in the western region and major grain-producing areas. These results remain robust across multiple robustness checks. Mechanism analysis from the perspectives of agricultural enterprises, consumers, and governments indicates that disruptive and breakthrough technological innovations, increasing consumer demand for eco-agricultural products, and environmental regulation policies are key drivers of the agricultural low-carbon transition. Furthermore, using the carbon trading market as an exogenous shock, this study confirms its significant positive impact on the agricultural low-carbon transition. Therefore, increasing climate attention prompts agricultural enterprises, consumers, and governments to adopt proactive measures, thereby accelerating the agricultural low-carbon transition.

1. Introduction

As the global population continues to grow and food security pressures mount, the high emissions associated with agricultural expansion and extensive production methods have become increasingly evident. Agriculture, a significant source of greenhouse gas emissions, contributes substantially through practices such as fertilizer application, livestock farming, and rice paddy cultivation (Sharma et al., 2021). This high-emission model not only exacerbates global climate change but also triggers a range of cascading effects, including more frequent extreme weather events, fluctuations in crop yields, and deteriorating conditions for food production. In response to these challenges, the agricultural low-carbon transition has emerged as a global consensus and an essential path toward sustainable development. Notably, this pressure for transition stems not only from international organizations and domestic policies but is also increasingly driven by the public's heightened climate attention. As scientific research increasingly highlights the link between climate change and food security, societal attention over climate issues has grown significantly, profoundly influencing agricultural production through shifts in market demand, consumer behavior, and public opinion (Wei et al., 2022). Consequently, climate attention, acting as an intrinsic pressure mechanism, is driving the agricultural sector toward a more sustainable and low-carbon model. Against this backdrop, China, the world's largest developing country, formally introduced its dual carbon goals in 2020, offering clear guidance for the green and low-carbon transition of its economy and society, including the agricultural sector (Huang, 2023). However, the extent to which rising climate attention can effectively drive the agricultural low-carbon transition, as well as the underlying mechanisms at play, remains a critical yet underexplored question.

The literature on agricultural development in the context of climate change has advanced along two principal trajectories. The first focuses

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on the direct effects of climate change on agricultural production, particularly yield shocks and corresponding adaptation strategies. The increasing frequency and intensity of extreme weather events pose significant and growing risks to agricultural systems worldwide (Zhang and Wu, 2025). For instance, Chen and Gong (2021) found that extreme temperatures significantly reduce total factor productivity (TFP) and alter input use, resulting in lower crop yields. Wang et al. (2024) further showed that while climate change diminishes agricultural output, adjustments to irrigation policies can effectively offset these losses. Notably, temperature-induced yield declines have slowed considerably since 1996 compared to earlier periods. These studies highlight the broad economic consequences of climate change in agriculture, with some extending the analysis to its effects on transportation, trade, shifting demand patterns, and regulatory responses (Dell et al., 2012; Burke and Emerick, 2016). The second strand of literature focuses on the factors driving the transition of agricultural production in response to climate change. Existing studies, adopting diverse perspectives, have explored how environmental policies, technological innovation, and market demand facilitate shifts in agricultural practices and the emergence of new production models. (De Leijster et al., 2020; Fytili and Zabaniotou, 2022; Li et al., 2022; Li et al., 2023; Chen et al., 2024; Ji et al., 2024; Chen et al., 2025). Meanwhile, a growing body of research is examining the influence of broader, external socio-economic factors. For instance, a recent study by Zhou et al. (2024) explores the complex effects of tourism agglomeration on low-carbon agriculture from an industrial perspective, underscoring the role of adjacent industries in shaping the pathways of agricultural transformation. However, these analyses often center on individual economic actors. In practice, the transition—particularly from traditional to low-carbon agriculture—requires broad societal engagement and collective concern across all sectors. Behavioral economics research highlights attention as a competitively scarce resource with significant externalities, influencing economic decisions across finance, consumer behavior, and organizational practices (Allcott, 2011; Fishbane et al., 2020; Hartzmark et al., 2021). While non-economic literature has examined how climate attention shapes individual cognition (Hart et al., 2015), the economic consequences of rising climate awareness—particularly its role in aligning multiple stakeholders to drive agricultural transition—remain insufficiently explored. Addressing this gap requires investigating how climate attention, as a reflection of societal attention allocation, functions as a coordinating mechanism among governments, research institutions, and the public to accelerate the agricultural low-carbon transition.

To answer this question, this study uses provincial panel data from China spanning 2001 to 2021, employing OLS, DID, and PSM-DID models to conduct a systematic empirical analysis of the impact of climate attention on the low-carbon transition of Chinese agriculture, measured by agricultural eco-efficiency, and its underlying mechanisms. In contrast to previous studies that primarily examined specific manifestations of climate change—such as yield losses due to extreme weather events (Yang et al., 2022; Song et al., 2022) or behavioral shifts among individual agents (Lankoski and Thiem, 2020; Ehlers et al., 2021)—this study addresses a broader and more systemic question: Can a heightened level of climate attention at the societal scale effectively enhance agricultural eco-efficiency and drive the agricultural low-carbon transition? This inquiry is both theoretically and practically significant. On one hand, climate attention reflects the attention paid to climate issues by agricultural enterprises, consumers, and governments, yet their effects and pathways in the agricultural sector remain largely unexplored. On the other hand, agricultural eco-efficiency, as a key metric for low-carbon transition, directly reflects the rationality of resource allocation and the effectiveness of environmental protection efforts. Exploring the relationship between climate attention and agricultural eco-efficiency will not only deepen theoretical understanding of agricultural low-carbon transition but also provide valuable insights for policy design in the agricultural sector under the dual carbon goals.

This study makes several important contributions to the literature. First, we introduce a novel and more direct measure of societal climate attention by constructing an original index based on textual analysis of approximately 1.75 million articles from mainstream Chinese newspapers spanning 2001 to 2021. This approach overcomes limitations in existing research on measuring societal climate attention and offers a more robust methodological framework for identifying how external societal focus drives the Chinese agricultural low-carbon transition. Second, our methodology strengthens causal inference by employing a quasi-natural experimental design. We exploit the rollout of China's pilot carbon trading markets as an exogenous shock and implement rigorous DID and PSM-DID models, supported by extensive robustness checks, including a joint randomization placebo test. Third, we provide empirical evidence on the mechanisms through which climate attention translates into concrete action. Specifically, we identify and systematically test three key channels: enterprise-led technological innovation, consumer demand for eco-agricultural products, and the role of formal environmental regulation. Together, these contributions offer a more nuanced understanding of the "awareness-to-action" pathway and establish a stronger theoretical foundation for the development of targeted policy interventions.

The structure of the study is as follows: Section 2 constructs the theoretical framework and presents theoretical hypotheses. Section 3 outlines the models, data, and methods. Section 4 presents the empirical regression results and conducts a series of robustness checks, including a heterogeneity analysis. Section 5 offers extended analyses. The final section concludes with a summary of the findings and directions for future research.

2. Theoretical framework and hypotheses

The theory of limited attention, emerging from the intersection of cognitive psychology and economics, posits that economic agents face cognitive constraints in processing information and making decisions, necessitating the selective allocation of scarce attention resources (Broadbent, 1957; Kahneman, 1973). The scarcity and selective distribution of attention profoundly influence how agents acquire, process, and act on information. On one hand, limited attention prevents agents from simultaneously considering all relevant information, requiring trade-offs in attention allocation. On the other hand, selective attention determines which information is prioritized in decision-making. This process systematically shapes economic behavior across various actors, providing a crucial perspective for understanding decision-making in information-rich environments. Peng et al. (2022), using firms as their research sample, found that unexpected events disrupt existing attention allocation patterns, influencing how managers perceive external environmental attributes and prompting strategic and resource reallocation adjustments. These shifts in attention allocation triggered by sudden events not only reshape firm behavior but also extend to consumer and government responses. A growing body of research indicates that attention allocation influences consumer utility assessments and purchasing decisions. When specific product attributes receive greater attention, consumer preferences and willingness to pay undergo systematic changes (Jerath and Ren, 2021; Niu et al., 2022). At the government level, attention allocation affects policy priorities and resource distribution (Dai, 2025). Du et al. (2024), using city-level panel data, found that increasing government attention for environmental issues significantly enhances green total factor productivity.

In recent years, the escalating challenges of global climate change have intensified international attention over sustainability. The signing of the Paris Agreement and the establishment of national carbon reduction targets underscore the growing global commitment to addressing climate issues. Against this backdrop, climate attention, as a distinct form of attention allocation, not only reflects societal awareness of climate change but also generates significant economic consequences by shaping the behavior of multiple actors—particularly within the climate-sensitive agricultural sector. Translating widespread climate attention into effective, large-scale action in agriculture requires a co-ordinated response. As Xu (2025) emphasizes, this demands a systematic governance model that integrates efforts across disciplines, institutions, and scales—mobilizing governments, enterprises, and consumers as joint stakeholders in the transition. Heightened climate attention can play a pivotal role in accelerating the agricultural low-carbon transition by:First, increased climate attention reflects a deeper societal understanding of climate change risks, which enhances the intrinsic motivation for agricultural transition (Turhan, 2016). Second, heightened climate attention is often accompanied by stronger social oversight and pressure, prompting agricultural producers to adopt more environmentally friendly practices (Quang and De Wit, 2020). Third, higher levels of climate attention are typically associated with increased information dissemination and knowledge sharing, which can reduce the cognitive and learning costs of adopting low-carbon technologies in agriculture (Coquil et al., 2018). The research framework is illustrated in Fig. 1.

Based on this theoretical framework, we propose the following hypothesis.

H1. An increase in climate attention will promote the agricultural low-carbon transition.

2.1. Agricultural enterprises

Technological innovation is a key driver of total factor productivity growth and the agricultural low-carbon transition. Climate attention influences the innovation behavior of agricultural R&D entities through both supply-side and demand-side mechanisms. On the supply side, climate attention stimulates innovation in two ways. First, R&D entities respond to strategic shifts driven by societal attention over climate change, resulting in supply-side innovations. Second, shared societal climate attention affects agricultural producers' demand for technology, thereby generating demand-driven innovation effects for R&D entities. Market forecasting and foresight are critical factors for the success of innovators (Dosi, 1982; Christensen, 1997), and R&D decisions are often shaped by media coverage, public discourse, and other informational sources. For instance, Cheng and Liu (2018) found that public attention improves the environmental performance of high-pollution industries, with the effect intensifying based on the influence and credibility of the media coverage. Public and governmental climate attention signals a shift in market demand, prompting innovative entities to capture these signals and pursue targeted innovation.

On the demand side, climate attention expands both the extensive and intensive margins of demand for climate-friendly technologies, thereby stimulating R&D activity. On one hand, societal focus on climate change enhances awareness of eco-friendly technologies among agricultural producers and the broader public, accelerating the adoption of these technologies (Deng et al., 2025). This expansionary demand effect creates new market opportunities that incentivize agricultural R&D entities to pursue green innovations (Horbach and Rammer, 2025). On the other hand, climate attention increases the demand for eco-friendly technologies on the intensive margin, shifting their relative prices compared to conventional technologies. According to induced technical change theory, R&D entities are more likely to innovate in areas where the relative price of a technology is higher. Thus, demand shifts driven by climate attention directly influence the direction of technological change. Moreover, venture capital is highly responsive to government and public attention. Joëlle Noailly et al. (2024) demonstrated that higher levels of environmental and climate policy indices, based on news data, increase the likelihood of clean-tech startups attracting venture capital, while stock market returns for high-emission firms tend to decline. This suggests that climate attention channels capital from high-emission sectors to environmentally friendly startups, further driving eco-friendly technological innovation.

Thus, we propose the following hypothesis.

H2. An increase in climate attention will drive agricultural enterprises to innovate, thereby facilitating the agricultural low-carbon transition.

2.2. Consumers

Markets play a critical role in resource allocation, effectively transmitting shifts in consumer preferences and guiding production adjustments (Schäufele and Hamm, 2017; De Marchi et al., 2019). As public awareness of climate change grows, consumer purchasing behavior is changing, particularly with a rising demand for environmentally friendly agricultural products. This shift is driven by two key factors: first, an increase in environmental awareness, as consumers recognize the significant food safety risks posed by climate change. Extreme weather exacerbates the risks of crop diseases, declining irrigation water quality, and the proliferation of harmful substances, prompting consumers to focus not only on climate change but also on its impact on food safety. As a result, there is a stronger demand for eco-agricultural products (Jeschke, 2016; Agrimonti et al., 2021). Second, the growing food safety attention driven by climate change has raised doubts about traditional high-input agricultural practices.

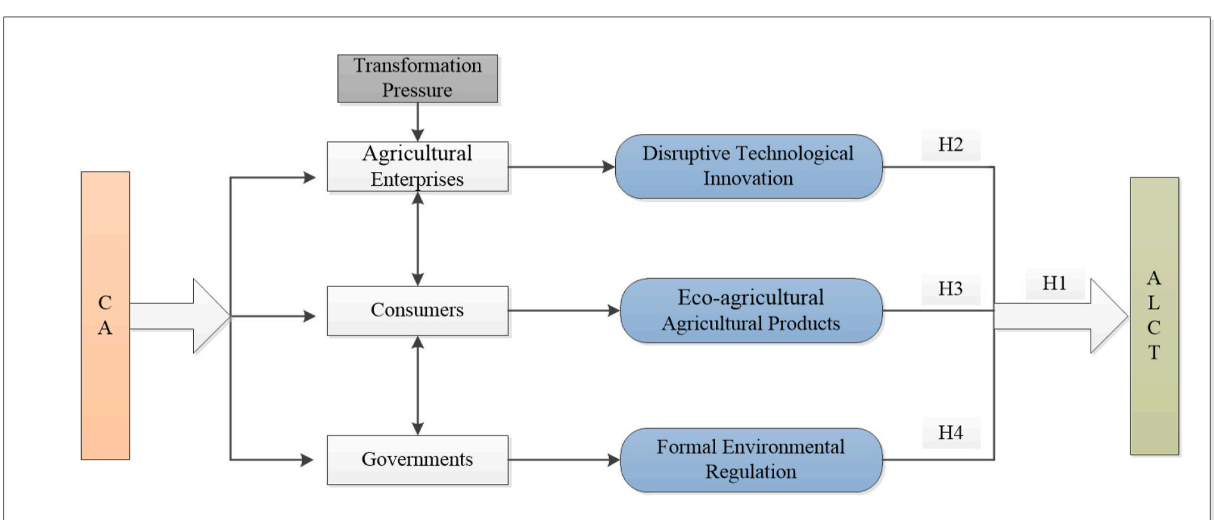

Fig. 1. Research framework of climate attention (CA) impacting the agricultural low-carbon transition (ALCT).

The unique advantage of market mechanisms is their ability to efficiently transmit changes in consumer preferences through price signals. The market premium for eco-agricultural products incentivizes producers to adjust their production methods. This self-driven adjustment, motivated by individual interests, is more sustainable and intrinsically motivated than government-imposed regulations. Furthermore, quality certifications—such as green, organic, and geographical origin certifications—serve as a bridge between consumer preferences and producer behavior. By reducing information asymmetry and setting production standards, these certifications improve market efficiency (Mancuso et al., 2024). For example, Xiang et al. (2020) found that price-sensitive consumers in China's dairy market favored green certifications, while environmentally conscious consumers preferred organic certifications and traceability labels, using price as a signal of quality. As demand for eco-agricultural products continues to increase, market competition drives the optimization of agricultural product structures. The growing market share of environmentally friendly products fosters the coordinated development of the entire industry, creating a positive feedback loop that promotes the agricultural low-carbon transition.

Thus, we propose the following hypothesis.

H3. An increase in climate attention will drive market demand for eco-agricultural products, thereby accelerating the agricultural low-carbon transition.

2.3. Governments

A key consideration in government policy-making is responding to public attention, with societal climate attention acting as a driving force behind the implementation of climate regulation policies (El Benni et al., 2024). Numerous studies have examined the influence of public climate engagement, including pressure from public opinion, on government environmental regulations through bottom-up processes (Björkman and Svensson, 2009; Buntaine et al., 2024). Notably, Buntaine et al. (2024) found that public demands for accountability, particularly through social media platforms, significantly reduced corporate non-compliance and pollution emissions. This effect was especially pronounced in firms exceeding emissions standards, while private demands had a more limited impact on environmental improvements. These findings suggest that public demands, by increasing regulatory attention to public dissatisfaction, can effectively prompt local governments to reassess the balance between environmental protection and economic growth, thereby strengthening the enforcement of environmental regulations.

Thus, public climate attention often translates into public demands for action on climate issues, which, in turn, places pressure on governments to implement environmental protection measures, including the formulation of climate-related regulatory policies and the enhancement of oversight. In the absence of environmental constraints, farmers typically focus on profit maximization, prioritizing output without considering the negative externalities of production. Government regulations can shift farmers' objectives, encouraging them to balance production yields with environmental costs, ultimately improving overall agricultural eco-efficiency.

Thus, we propose the following hypothesis.

H4. An increase in climate attention stimulates the formulation of government environmental regulation policies, thereby supporting the agricultural low-carbon transition.

3. Research design

3.1. Sample selection and data sources

Given the pivotal role of provincial governments in China in both implementing national agricultural policies and formulating local agricultural regulations, this study uses panel data from 30 Chinese provinces spanning 2001 to 2021 to investigate the impact and mechanisms of climate attention on agricultural low-carbon transition, measured by Agricultural Eco-Efficiency (AEE). Due to significant missing data from Hong Kong, Macau, Taiwan, and Tibet, and to ensure the validity and reliability of the empirical results, these regions were excluded. Furthermore, the signing of the Kyoto Protocol in 1998 marked a significant milestone in global climate change efforts. Considering time lags and data availability, the study focuses on the period from 2001 to 2021.

This study introduces two key innovations in measurement. First, we compiled a dataset comprising the full text of over 1.75 million articles from mainstream Chinese newspapers published between 2001 and 2021. Based on a self-developed climate attention lexicon, we applied **jieba** for word segmentation and conducted geography-specific Named Entity Recognition (NER) to construct a variable capturing climate attention terms. Second, A key innovation of this study is the inclusion of indicators related to disruptive technological innovation, utilizing the Google Patents Public Datasets and Google Patent Research Data. These patent databases, provided by IFI CLAIMS Patent Services, contain over 150 million records from more than 100 patent offices worldwide, covering virtually all recorded patents. The input-output variables for calculating agricultural eco-efficiency in China, along with other relevant economic, environmental, and social variables, are primarily sourced from the China Rural Statistical Yearbook, China Statistical Yearbook, China Urban Statistical Yearbook, China Agricultural Yearbook, China Rural Management and Operations Yearbook, and China Agricultural Machinery Industry Yearbook. Missing values for specific years were imputed using linear interpolation to ensure the accuracy and reliability of the results.

3.2. Empirical model

In the baseline regression, this study employs a fixed-effects panel model to examine the relationship between AEE and CA, controlling for both individual and time-fixed effects. The model specification is as follows:

$$AEE_{it} = \beta_0 + \beta_1 CC_{it} + \beta_2 X_{it} + u_i + \lambda_t + \varepsilon_{i,t} \tag{1}$$

In the model, i and t represent provinces and time, respectively. AEE_{it} is the provincial AEE, and CC_{it} is the core explanatory variable in this study, reflecting climate attention. The control variables include a series of economic, social, and environmental factors, such as: Agricultural Economic Development Level($AEDL_{it}$)、Urbanization Rate(UR_{it})、Disaster Incidence Rate(DIR_{it})、Extreme Climate Index(ECI_{it})、Agricultural Industrial Structure(AIS_{it})、Fiscal Support for Agriculture (FSA_{it})、Urban-Rural Income Ratio($URIR_{it}$) and Rural Residents' Engel Coefficient(REC_{it}). u_i and λ_t represent the individual fixed effects and time fixed effects, respectively. These are used to control for unobserved, province-level invariant characteristics and the common trends that might exist across all provinces at specific points in time, helping to better isolate a range of potential confounding factors. $\varepsilon_{i,t}$ is the random disturbance term. β_1 is the parameter of interest, which indicates how agricultural ecological efficiency in China changes as climate attention increases. Based on the earlier hypotheses, we expect β_1 to be positive.

3.3. Definition of key variables

3.3.1. Agricultural eco-efficiency

The dependent variable in this study is agricultural low-carbon transition, measured by AEE. To address the limitations of the traditional radial Data Envelopment Analysis (DEA) model—such as its inability to account for slack variables and undesirable outputs—we adopt the Slacks-Based Measure (SBM) model proposed by Tone (2001). AEE reflects the coordinated development of resource conservation, environmental protection, and agricultural economic growth. Accordingly, we construct an AEE measurement index system based on the "resources–energy–environment–agricultural economy" framework. The model includes capital, land, labor, and water resources as input variables, while output variables comprise both desirable and undesirable outputs. The following sections detail the input and output variables, along with the data processing methods.

Input Variables: (1) Capital Input. Measured using mechanical power, draft animal power, fertilizer usage, pesticide usage, and agricultural film input. Specifically, we use total agricultural machinery power, the number of large livestock, fertilizer application (adjusted for purity), pesticide usage, and agricultural film consumption. Since this study focuses on crop farming (small-scale agriculture), total agricultural machinery power is adjusted by the ratio of agricultural output value to the total output value of agriculture, forestry, animal husbandry, and fishery. (2) Land Input. Measured by the total planted crop area. (3) Labor Input. Following Ma and Tan (2021), labor input is calculated by multiplying the number of workers in the primary industry by the proportion of agricultural value-added in the total value-added of agriculture, forestry, animal husbandry, and fishery. (4) Irrigation Input. Measured by the total agricultural water usage.

Output Variables: (1) Desirable Output. Represented by total agricultural output value, adjusted for inflation with 2000 as the base year. (2) Undesirable Output. To align input-output statistics with small-scale agriculture and assess green agricultural transition under global climate change, agricultural carbon emissions are selected as the undesirable output. Following Li et al. (2011), we measure carbon emissions from six major agricultural production activities:

$$C = \sum C_i = \sum T_i \cdot \delta_i \tag{2}$$

Among these variables, C represents the total agricultural carbon emissions, while C_i、 T_i、 δ_i represent the carbon emission amount, carbon emission source volume, and carbon emission coefficient of the i-th carbon source, respectively. The carbon emission coefficients for each source are provided in Table 1 below.

3.3.2. Climate attention

The independent variable in this study is climate attention (CA). This index is constructed through textual analysis of approximately 1.75 million articles published in mainstream Chinese newspapers between 2001 and 2021. We began by developing a comprehensive climate attention dictionary, initially based on existing literature and substantially expanded using a Large Language Model (LLM) to analyze a random sample of 5000 full-text articles. The entire corpus was then processed using word segmentation techniques (jieba) and Named Entity Recognition (NER) to identify climate-related content and associated geographic references. These geographical entities were subsequently mapped to their respective provinces using the jionlp library. This allowed us to aggregate the frequency of climate-related reports into a province-year panel dataset, which serves as our final measure of CA.

Table 1
Carbon sources, carbon emission coefficients, and reference sources.

Emission Source Volume	Carbon Emission Coefficient	Reference Sources
Pesticides	4.9341 kg kg^{-1}	Oak Ridge National Laboratory (USA)
Tillage	312.6 kg kg^{-1}	College of Biological and Agricultural Engineering, China Agricultural University
Fertilizer	0.8956 kg kg^{-1}	Oak Ridge National Laboratory (USA)
Irrigation	20.476 kg/hm^2	Referring to Dubey's research findings
Agricultural Films	5.18 kg kg^{-1}	Institute of Agricultural Resources and Ecology, Nanjing Agricultural University
Diesel	0.5927 kg kg^{-1}	Intergovernmental Panel on Climate Change (IPCC), United Nations

Notes: The carbon emission coefficient for agricultural irrigation is adjusted based on the average coal-fired power generation coefficient in China from 2004 to 2008.

3.3.3. Mechanism variables

This study investigates the underlying mechanisms from three perspectives: agricultural enterprises, consumers, and governments. We provide a brief introduction to the mechanism variables selected for analysis.

(1) We use agricultural technological innovation to capture the response strategies adopted by agricultural enterprises. To precisely evaluate the impact of climate attention on agricultural technology innovation, we construct three patent-based indicators to measure high-quality technological innovation output: total citations of agricultural patents (TIC), disruptive technology innovation (DTI), and radical technology innovation (RTI). To define agricultural patents, we follow the approach of Guo et al. (2021), who identified 399 IPC codes related to agricultural patents. These IPC codes underwent multiple rounds of selection and data quality verification, covering the primary categories of agricultural patents. Based on this classification, we extracted approximately 1.7 million agricultural patents from China, including granted invention patents, published invention patents, and utility model patents.

To assess regional innovation output, we use the number of highly cited agricultural patents rather than relying solely on patent quantity. This approach accounts for China's unique patent policies, where policy-driven incentives often lead to a surge in patent applications that do not necessarily reflect genuine innovation. Many patents are strategically filed to capitalize on policy benefits, resulting in a "patent quantity boom" but a concurrent "quality decline" (Chen et al., 2024). These strategic patents are typically low-quality, highly similar, and lack substantive technological advancement. Since patent citation counts are widely used as a proxy for patent quality, we apply a threshold of five or more citations to filter out low-quality patents and more accurately capture substantive technological innovation.

However, relying solely on citation counts as a quality criterion has been criticized due to the prevalence of citation manipulation, which can undermine reliability (Chen et al., 2024). To enhance robustness, we introduce breakthrough and disruptive innovation indicators as additional quality measures. In innovation economics, technological innovation is typically classified into two types: incremental innovation, which consolidates existing technological trajectories, and radical innovation, which breaks away from existing trajectories and redefines the direction of technological progress. The latter, also known as breakthrough technological innovation, effectively captures a patent's or publication's contribution to technological advancement. To quantify breakthrough innovation, we adopt the RTI Index, developed by Russell and Owen-Smith (2017), which employs a dynamic patent network approach. The specific calculation formula is as follows:

$$RTI_t = \frac{1}{n_t} \sum_{i=1}^{n} \left(-2 f_{it} b_{it} + f_{it} \right) \tag{3}$$

f_{it} is a dummy variable, indicating whether the i-th patent cites a focal patent at time t; if it does, $f_{it} = 1$; otherwise, $f_{it} = 0$. Similarly, b_{it} is a dummy variable, indicating whether the i-th patent cites a subsequent patent (predecessor) of the focal patent at time t; if it does, $b_{it} = 1$; otherwise, $b_{it} = 0$. n_t represents the total number of reference patents of the focal patent and its subsequent patents within the time window t (Fig. 2 illustrates this calculation process). This method produces an index ranging from -1 to 1, widely used by scholars to classify patents as breakthrough (radical) or incremental (consolidative) based on their relationship to zero. The core intuition is that a breakthrough patent establishes a new technological benchmark, leading subsequent patents to cite it rather than its predecessors. Expanding on this idea, we posit that the greater the impact of a breakthrough innovation on subsequent technologies, the more disruptive it is. Accordingly, we define the DTI as

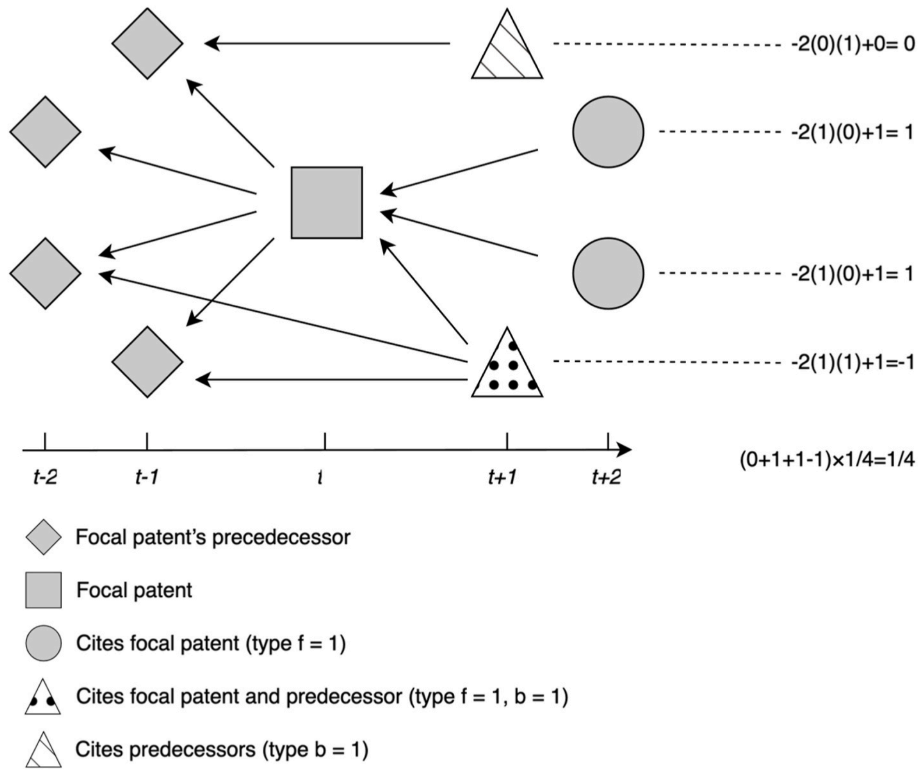

Fig. 2. Illustrative calculation of the RTI Index.

the product of the RTI Index and the number of citations the focal patent receives within the time window t (denoted as m_t):

$$DTI_t = \frac{m_t}{n_t}\sum_{i=1}^{n}(-2f_{it}b_{it} + f_{it}) \tag{4}$$

Using the above formula, we computed the RTI_5 and DTI_5 indices over a five-year time window using Google's global patent database, which comprises 150 million patents. This approach aligns with Bornmann et al. (2020), who identified t = 5 as the optimal time frame for capturing innovation impact. Moreover, utilizing a global patent dataset mitigates regional and temporal truncation biases in RTI_t and DTI_t indices, as noted by Macher et al. (2024). Consequently, we adopt RTI_5 and DTI_5 as quality thresholds, providing a more accurate and reliable measure of innovation output.

(2) We use the eco-agricultural products to represent the mechanism variable from the consumer perspective. To quantify eco-agricultural products, we use green agricultural product certification (GAP), organic agricultural product certification (OAP), and geographical indication agricultural product certification (GIAP) as proxy variables. Due to data limitations, these indicators are available only from 2012 onward. To more accurately reflect market demand dynamics, we employ the cumulative annual count of certifications for statistical analysis. we construct a composite eco-agricultural product index (EAP) by integrating these three indicators to provide a comprehensive measure of market demand for superior agricultural products.

(3) Recognizing that environmental policies are a critical governmental response to climate change, we use formal environmental regulations (FER) as a proxy variable, measured by the frequency of environment-related keywords in local government work reports on agriculture. Since chemical fertilizers are a primary input that enhances grain yields while also contributing to agricultural pollution, their usage is expected to remain high in the absence of strict and targeted environmental regulations. To further assess the effectiveness of government regulations, we substitute the dependent variable with chemical fertilizer usage (AF), evaluating whether stricter environmental policies lead to a reduction in its application.

3.3.4. Control variables

To improve the reliability of causal identification, this study incorporates a range of control variables spanning economic, social, and environmental dimensions. Agricultural economic development level is measured by the share of primary industry output in total GDP. Urbanization rate is defined as the proportion of urban population to total population, while disaster incidence rate is assessed as the ratio of crop disaster-affected area to total sown area. Agricultural industrial structure is represented by the share of value-added from planting in the total value-added of agriculture, forestry, animal husbandry, and fishery. Financial support for agriculture is measured by the proportion of agriculture-related expenditures in local general public budget spending. Urban-rural income disparity is calculated as the ratio of per capita disposable income of urban residents to that of rural residents. The Engel coefficient of rural households reflects household consumption expenditure as a share of total expenditure. Lastly, to account for regional climatic variability—an important factor influencing agricultural systems (Wang et al., 2025)—we include a composite extreme climate index, constructed from the frequency of extreme low-temperature days, high-temperature days, heavy rainfall events, and drought occurrences.

3.3.5. Descriptive statistics

Table 2 presents the descriptive statistics of the study variables. At the provincial level, AEE ranges from 0.14 to 1.00, with an average of 0.67. A three-dimensional kernel density plot generated using MATLAB (Fig. 3) illustrates its distributional evolution, showing a slight rightward shift over time, indicating a gradual increase in overall AEE. The density curve initially peaks higher before declining, while its width narrows, and a right-skewed tail with increasing extension suggests

Table 2
Summary statistics of variables.

Variables	Definition	Sample size	Mean	Sd	Max	Min
AEE	Agricultural eco-efficiency	630	0.67	0.30	1.00	0.14
CA	Climate attention	630	7.40	1.25	10.52	4.01
TICZ	Technological Innovation with More Than 0 Citations	630	2557.00	4438.00	27,541.00	4.00
TICF	Technological Innovation with More Than 5 Citations	630	192.10	319.10	1919.00	0.00
DTITF	Disruptive Technological Innovation Index Greater Than 2.5	630	268.20	412.10	2688.00	0.00
DTIF	Disruptive Technological Innovation Index Greater Than 5	630	78.71	123.20	942.00	0.00
DTIT	Disruptive Technological Innovation Index Greater Than 10	630	17.66	29.71	271.00	0.00
RTIZF	Radical Technological Innovation Index Greater Than 0.5	630	76.01	118.10	901.00	0.00
RTIZ	Radical Technological Innovation Index Greater Than 0	630	184.60	307.10	1851.00	0.00
GAP	Green Agricultural Product Certification	300	1614.84	1984.73	6.50	12,476.00
OAP	Organic Agricultural Product Certification	300	1095.78	1188.04	3.00	7249.00
FER	Formal Environmental Regulation	630	3.31	1.15	6.51	0.00
GIAP	Geographical Indication Agricultural Product Certification	300	69.18	55.84	0.00	297.00
EAP	Eco-agricultural Product Index	300	0.65	0.14	0.15	0.92
AF	Agricultural Fertilizer	630	3362.00	2020.00	11,649.00	257.40
AEDL	Agricultural Economic Development Level	630	0.20	0.10	0.58	0.01
UR	Urbanization Rate	630	0.52	0.16	0.90	0.14
DIR	Disaster Incidence Rate	630	0.21	0.15	0.94	0.002
ECI	Extreme Climate Conditions	630	43.97	8.61	84.34	19.08
AIS	Agricultural Industrial Structure	630	0.52	0.07	0.75	0.34
FSA	Fiscal Support for Agriculture	630	0.09	0.05	0.20	0.01
URIR	Urban-Rural Income Ratio	630	2.26	0.55	3.75	1.11
REC	Rural households' Engel Coefficient	630	0.79	0.10	0.96	0.42

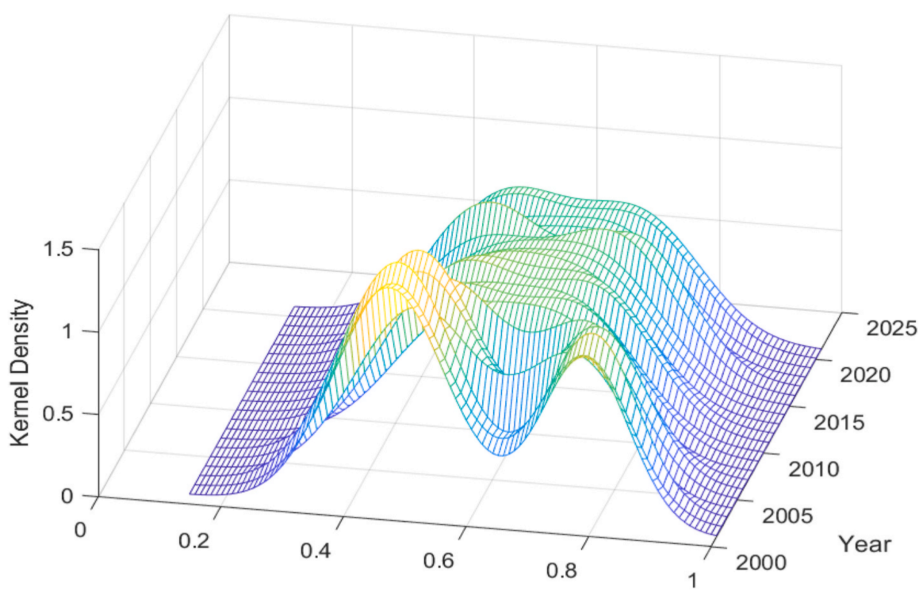

Fig. 3. Kernel density distribution of AEE.

persistent regional disparities. The distribution exhibits a bimodal pattern, with shifting peaks and a broadening side peak, highlighting multipolarization and significant regional differences, where AEE declines progressively from eastern to central to western regions. Similarly, the CA index, ranging from 4.01 to 10.52, demonstrates a significant upward trend from 2001 to 2021, reflecting growing climate awareness. Fig. 4 further validates this trend, showing that key climate-related events—such as the Kyoto Protocol, the Copenhagen Accord, China's carbon trading policies, and the dual carbon goals—have triggered short-term spikes in climate attention, aligning well with real-world developments.

Table 3 lists the correlation coefficients for the key variables. The correlation coefficient between AEE and CA is approximately 0.266, and to formally assess the potential for multicollinearity, we calculated the VIF for our primary regression model. The mean VIF was 4.07, well below the conventional threshold of 10, indicating that multicollinearity is unlikely to pose a significant concern in our analysis.

4. Empirical results and discussion

4.1. The impact CA on AEE

We use Model (1) to analyze the impact of CA on AEE. Table 4 presents the baseline regression results. In the first column, where only time and individual fixed effects are controlled, the coefficient of CA on AEE is positive and statistically significant at the 1 % level. As additional control variables are incorporated, the coefficient remains stable and consistently significant at the 1 % level, indicating that increased CA enhances China's AEE. Column (8), which includes all control variables, reveals that a one-unit increase in CA leads to a 0.092 increase in AEE. These results confirm that CA has a significant positive effect on China's AEE. Thus, improvements in provincial-level AEE are driven not only by factors such as agricultural economic development, industrial structure, and government financial support for agriculture but also by climate attention, reflecting the commitment of local governments and the

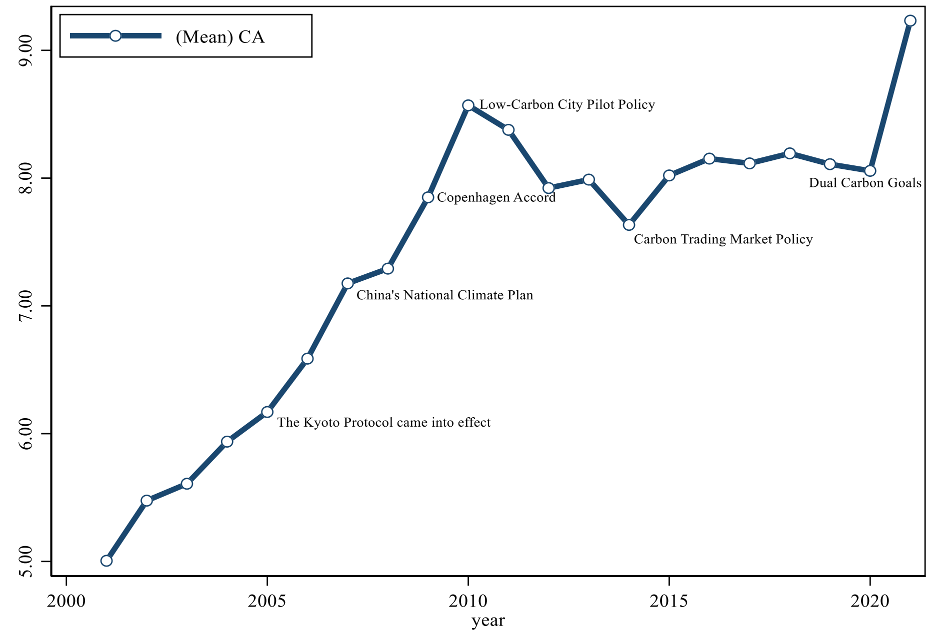

Fig. 4. Evolution trend of CA.

Table 3
Correlation coefficients.

VARIABLES	AEE	CA	AEDL	AIS	DIR	REC	URIR	ECI	UR	FSA
AEE	1									
CA	0.266***	1								
AEDL	−0.278***	−0.478***	1							
AIS	−0.523***	−0.108**	0.203***	1						
DIR	−0.265***	−0.474***	0.274***	0.048	1					
REC	−0.379***	−0.474***	0.354***	0.084*	0.409***	1				
URIR	−0.362***	−0.409***	0.294***	0.010*	0.379***	0.849***	1			
ECI	−0.020	0.264***	0.057	0.021	−0.001	0.014	0.001	1		
UR	0.327***	0.596***	−0.668***	−0.261***	−0.382***	−0.514***	−0.419***	0.054	1	
FSA	−0.157***	0.584***	0.063	0.204***	−0.204***	−0.052	−0.033	0.382***	0.134***	1

This table shows the correlation coefficients of key variables used for baseline analysis. Variable definitions are explained in detail in Table 1. The symbols ***, **, and* indicate significance at the 1 %, 5 %, and 10 % confidence levels, respectively.

public to sustainable agricultural development. Thus, H1 is confirmed.

4.2. Endogeneity treatment and robustness

We conduct a series of robustness tests to validate the reliability of the baseline regression results and account for potential confounding factors. These tests include addressing endogeneity, incorporating lagged effects, modifying the model specification, adjusting fixed effects, and substituting the dependent variable.

(1) **Addressing Endogeneity.** The baseline regression results may be subject to endogeneity attention. First, reverse causality could exist, as regions with higher AEE and stronger commitments to sustainable agriculture may exhibit greater CA. Second, omitted variable bias may arise from unobservable factors that vary over time at the macro-regional level or from province-specific shocks such as economic cycles or unexpected events. To address these issues, we employ an instrumental variable (IV) approach, using the lagged value of CA as an instrument and conducting two-stage least squares (2SLS) regression. Table 5, column (1), presents the first-stage regression results, where lagged CA significantly predicts current CA. The first-stage Cragg-Donald Wald F-statistic exceeds the Stock-Yogo weak instrument critical value, rejecting the null hypothesis of weak instruments. Column (2) shows that after addressing endogeneity, CA remains a significant positive determinant of AEE, confirming the robustness of our baseline findings.

(2) **Incorporating Lagged Effects.** As CA reflects both government policies and public sentiment, its impact on AEE may exhibit a time lag. To account for this, we re-estimate the model by incorporating lagged CA as the key explanatory variable. Columns (3) and (4) of Table 5 present results for one-period and two-period lagged CA, respectively. Both coefficients remain positive and statistically significant at the 1 % level, reinforcing the conclusion that CA enhances AEE even when delayed effects are considered. However, the impact diminishes over time, suggesting that sustained policy efforts are necessary to maintain improvements in AEE.

(3) **Modifying the Model Specification.** Agricultural sustainability follows a dynamic trajectory, with past developments influencing present and future levels of AEE. To account for this persistence and mitigate time-variant omitted variable bias, we extend the static model into a dynamic panel model. Specifically, we introduce the first-order lag of AEE as an explanatory variable and employ the two-step system Generalized Method of Moments (GMM) estimator with Windmeijer's finite-sample correction. Column (5) of Table 4 reports the results. The AR(1) and AR(2) tests indicate the presence of first-order autocorrelation but not

Table 4
Baseline results.

VARIABLES	Dependent variable: Agricultural Eco-efficiency (AEE)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CA	0.079***	0.093***	0.091***	0.092***	0.091***	0.091***	0.090***	0.091***	0.092***
	(0.020)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
AEDL		0.719***	0.687***	0.682***	0.669***	0.667***	0.683***	0.665***	0.625***
		(0.147)	(0.147)	(0.147)	(0.148)	(0.149)	(0.151)	(0.151)	(0.153)
AIS			0.392**	0.388**	0.367**	0.367**	0.370**	0.432***	0.456***
			(0.156)	(0.156)	(0.159)	(0.159)	(0.159)	(0.162)	(0.162)
DIR				−0.041	−0.042	−0.042	−0.038	−0.038	−0.039
				(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
REC					−0.208	−0.225	−0.187	−0.243	−0.423
					(0.258)	(0.270)	(0.278)	(0.280)	(0.294)
URIR						0.032	0.032	0.039	0.040
						(0.160)	(0.160)	(0.159)	(0.159)
ECI							−0.020	−0.021	−0.034
							(0.035)	(0.035)	(0.035)
UR								−0.136*	−0.108
								(0.076)	(0.078)
FSA									0.620*
									(0.316)
Constant	0.078	−0.165	−0.349**	−0.341*	−0.157	−0.214	−0.168	−0.103	0.005
	(0.154)	(0.159)	(0.175)	(0.175)	(0.288)	(0.403)	(0.410)	(0.411)	(0.414)
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.868	0.873	0.875	0.875	0.875	0.875	0.875	0.876	0.877
Observations	630	630	630	630	630	630	630	630	630

Notes: This table shows regression results for the effect of climate attention on Agricultural eco-efficiency. Variable definitions are explained in detail in Table 2. The dependent variable is the Agricultural eco-efficiency (AEE), and the independent variable is the climate attention (CA). The standard errors are reported in the parentheses. The symbols ***, **, and* indicate significance at the 1 %, 5 %, and 10 % confidence levels, respectively.

Table 5
Endogeneity treatment and robustness.

VARIABLES	2SLS		Lag effect		Dynamic effect	Adjusting fixed effects		Changing dependent variable
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IV	0.446***							
	(0.040)							
L.CA			0.096***					
			(0.022)					
L2.CA				0.109***				
				(0.023)				
L.AEE					0.415***			
					(0.134)			
CA		0.216***			0.078***	0.074***	0.079***	0.055***
		(0.051)			(0.026)	(0.021)	(0.022)	(0.024)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE × Year FE	No	No	No	No	No	Yes	No	No
Agricultural Region FE × Year FE	No	No	No	No	No	No	Yes	No
Cragg-Donald Wald F	123.554							
	[16.38]							
AR(1)					0.032			
AR(2)					0.971			
Adjusted R-squared	0.970		0.862	0.862		0.871	0.868	0.913
Observations	600	600	600	570	600	630	630	630

Notes: This table reports the results of Endogeneity Treatment and Robustness Checks. Variable definitions are reported in Table 2. The standard error reported in the parentheses. The symbols ***, **, and* indicate significance at the 1 %, 5 %, and 10 % confidence levels, respectively.

second-order autocorrelation, confirming the validity of the system GMM approach. The Hansen test fails to reject the null hypothesis, supporting the appropriateness of the instrumental variables. Even after accounting for dynamic effects, CA remains positively associated with AEE (coefficient = 0.078) and statistically significant.

(4) **Adjusting Fixed Effects.** Given China's vast geographical and economic diversity, regional disparities in resource endowment, economic development, and agricultural structure may lead to heterogeneous responses to climate change. For instance, eastern region, with more advanced technological capabilities, may adopt green innovations more rapidly. To control for these regional heterogeneities in economic policies, institutional changes, and external shocks (e.g., globalization, technological transition), we introduce region-specific time interactions into the model. Specifically, we incorporate fixed effects for eastern, central, and western regions interacted with time, as well as fixed effects for major grain-producing, grain-consuming, and balanced areas interacted with time. Columns (6) and (7) of Table 4 show that after accounting for these heterogeneous regional and temporal dynamics, the coefficient and significance

of CA remain unchanged, further validating the robustness of the baseline results.

(5) **Changing the Dependent Variable.** In agricultural production, undesirable outputs extend beyond CO_2 emissions to include non-point source pollution. To provide a more comprehensive measure of AEE, we redefine the undesirable output by incorporating both agricultural non-point source pollution and carbon emissions. Additionally, to address the issue that traditional DEA-SBM models often result in multiple efficient decision-making units, preventing meaningful differentiation and ranking, we adopt the Super-SBM model proposed by Tone (2002). This model retains the advantages of the SBM framework while allowing efficiency values greater than one, thus overcoming the limitation where all efficient units receive an identical score. Column (8) of Table 4 reports the results after substituting the dependent variable, showing that the coefficient of CA remains positive and statistically significant, reaffirming the validity and reliability of our baseline findings.

4.3. Heterogeneity analysis

China's vast territory encompasses regions with diverse economic foundations, resource endowments, and agricultural structures, leading to potential heterogeneity in the impact of CA on AEE. To investigate this heterogeneity, we divide the sample into subsamples based on economic development levels and agricultural planting structures and re-estimate the baseline regression model.

To assess the role of economic development, we adopt the standard regional classification in the literature, dividing the sample into eastern, central, and western regions. The left side of the vertical dashed line in Fig. 5 presents the estimated coefficients of CA on AEE, along with 95 % confidence intervals for each region. The results indicate that CA has a stronger positive effect on AEE in the western region compared to the central and eastern regions. This regional divergence can be attributed to two main factors. First, the western region, starting from a lower baseline of sustainable agricultural development, benefits from a catch-up effect, whereby increased CA serves as a powerful driver of marginal improvements. Second, the central region's limited response may result from a dual constraint: it lacks the technological and capital advantages of the east that facilitate green innovation, and its historical role as an industrial and energy hub may lead local governments to prioritize industrial decarbonization over agricultural greening. This intermediate status—neither underdeveloped enough to leverage catch-up gains nor advanced enough to lead innovation—combined with the eastern region's likely proximity to an efficiency ceiling, helps explain the weaker impact of CA outside the west.

We further examine the heterogeneity of CA's effects through the lens of agricultural production structure, classifying the sample into major grain-producing, grain-consuming, and grain-balanced areas. The right side of the vertical dashed line in Fig. 5 displays the corresponding regression results. CA has a more pronounced positive effect on AEE in major grain-producing and grain-balanced areas than in major grain-consuming areas. As core zones for national food security, major grain-producing and grain-balanced areas face considerable pressure to maintain both high yields and environmental sustainability. These areas tend to receive stronger policy support, including incentives for technological innovation, enhanced agricultural extension services, and public awareness campaigns around sustainability. Such measures have helped reconcile agricultural growth with environmental protection. In contrast, major grain-consuming areas—primarily located in China's southeastern coastal areas—benefit from higher levels of economic development and infrastructure but are constrained by limited arable land. With a stronger emphasis on secondary and tertiary industries, these areas exhibit a weaker and less persistent response to CA in terms of improving AEE.

4.4. Channels analysis

How does CA influence the AEE? This section empirically examines the underlying mechanisms. Drawing on theoretical insights, we analyze this relationship from three key perspectives: agricultural enterprises, consumers, and governments.

4.4.1. Pathways of agricultural technological innovation

Technological innovation plays a crucial role in transforming traditional agricultural practices, advancing sustainable agriculture, and enhancing AEE. Previous studies typically assess agricultural technological innovation by the number of patents. However, some patents arise from strategic innovation driven by incentive policies that prioritize quantity over quality. These strategic innovations, aimed at securing policy benefits, result in a "quantity leap" but often lead to a significant "quality decline," which does not effectively foster high-quality agricultural development (Chen et al., 2024). To better capture meaningful technological innovation, this study introduces three patent quality indicators—TIC, RTI, and DTI indices—as thresholds to construct authentic patent output measures for the mechanism test. Following Jiang Ting's recommendations (2022), we directly examine the relationship between the dependent variable and mechanism variables to

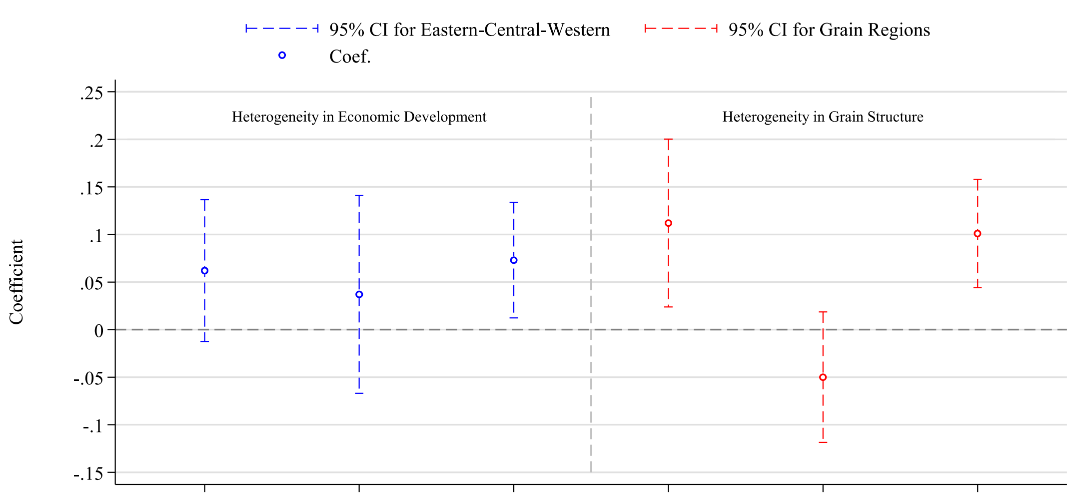

Fig. 5. Coefficients and 95 % confidence intervals for the effect of CA on AEE in different travel time.

investigate the underlying mechanisms.

Table 6 reports the regression results for the impact of CA on high-quality agricultural technological innovation, controlling for a comprehensive set of covariates and fixed effects. Columns (1) and (2) use the number of agricultural patents with forward citations exceeding zero (TICZ) and five (TICF), respectively, as proxies for innovation output. Columns (3) and (4) employ the number of patents with RTI values greater than 0 and 0.5, respectively, while columns (5), (6), and (7) use the number of patents with DTI values exceeding 2.5, 5, and 10. Across all specifications, the coefficient for CA remains positive and statistically significant at the 5 % level or better, consistently indicating that CA plays a robust role in promoting substantive, high-quality innovation in agriculture. These findings suggest that CA significantly drives substantial innovation output, thereby validating H2. A plausible explanation for this finding is that increased climate attention intensifies regulatory pressure and market demand for sustainability, thereby incentivizing agricultural producers to adopt high-quality innovations. These innovations go beyond conventional productivity-enhancing technologies to encompass advanced management practices that support ecosystem services—central to AEE. For example, practices that improve soil health to enhance carbon sequestration become more economically viable under such conditions. Empirical evidence from studies like Du et al. (2024), which shows that sustainable land management can significantly strengthen ecosystem carbon sinks, reinforces the ecological value of this innovation pathway. Thus, CA likely accelerates the low-carbon transition by fostering an environment in which ecologically beneficial innovations are more readily developed and adopted.

4.4.2. Pathways of eco-agricultural products

As extreme weather events become more frequent, public attention of climate issues has intensified, influencing consumer decision-making. Climate change poses significant threats to food safety by increasing pest infestations, degrading irrigation water quality, and accelerating the proliferation of harmful substances. Consequently, consumers are becoming more attentive to food production methods and safety, demonstrating a greater willingness to pay a premium for environmentally friendly and health-conscious products. This shift in consumer preferences has driven increased demand for organic, green, and geographical indication agricultural products, which adhere to sustainable production practices, minimize chemical inputs, protect biodiversity, and mitigate both carbon emissions and food safety risks. These evolving market dynamics send clear price signals to producers, incentivizing the adoption of low-carbon technologies.

Building on this analysis, we replace the dependent variable with four indicators—EAP, GAP, OAP, and GIAP—and re-estimate the model. As shown in Table 7, CA significantly increases EAP, indicating a strong positive impact on overall demand for eco-agricultural products. The results for GAP, OAP, and GIAP likewise show positive coefficients for CA, with statistical significance achieved for both GAP and GIAP. These findings suggest that increasing CA strengthens consumer preferences for environmentally sustainable agricultural products. This shift in demand sends a clear market signal to agricultural producers, encouraging reductions in chemical inputs, improvements in production efficiency, and lower carbon emissions. Consequently, these dynamics help accelerate the transition toward low-carbon agriculture. The evidence provides empirical support for Hypothesis H3.

Table 7
Channels analysis through eco-agricultural product.

VARIABLES	EAP	GAP	OAP	GIAP
	(1)	(2)	(3)	(4)
CA	0.025***	0.201**	0.077	0.302***
	(0.007)	(0.059)	(0.065)	(0.099)
Control Variables	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.983	0.983	0.980	0.912
Observations	300	300	300	300

Notes: This table reports the results of mechanism analysis through eco-agricultural product demand (Green Certification of Agricultural Products, organic Certification of Agricultural Products, and Geographical Indication Agricultural Products). Variable definitions are reported in Table 2. The standard error reported in the parentheses. The symbols ***, **, and* indicate significance at the 1 %, 5 %, and 10 % confidence levels, respectively.

4.4.3. Pathways of agricultural government regulation

China's agricultural production remains largely dependent on traditional smallholder farming, where economic considerations often take precedence over environmental attention. Virginia et al. (2013) argued that achieving sustainable agricultural development requires strengthening government environmental regulations and implementing comprehensive policy measures. Formal environmental regulations, particularly those codified in legal statutes, impose constraints and penalties on farmers who fail to meet pollution control standards and technological requirements. Under regulatory pressure, farmers may respond by increasing spending on pollution control, restructuring operations, or ceasing agricultural activities altogether. To examine this government-level mechanism, we introduce the variable of FER in agriculture. Following Saurabh Singhal (2024), we employ group comparisons to validate this mechanism.

First, we categorize the sample into high and low environmental regulation groups based on the median FER value and re-estimate the baseline regression model. As shown in Columns (1) and (2) of Table 8, CA significantly enhances AEE at the 1 % significance level in the high-regulation group, whereas its effect in the low-regulation group is not statistically significant. This suggests that stronger environmental regulations amplify the positive impact of CA on AEE, highlighting government regulation as a critical transmission channel. Thus, H4 is validated. To further validate this mechanism, we conduct an additional empirical analysis. Chemical fertilizers play a crucial role in boosting

Table 6
Channels analysis through agricultural technology innovation.

VARIABLES	TIC		RTI		DTI		
	TICZ	TICF	RTIZ	RTIZF	DTITF	DTIF	DTIT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CA	0.394***	0.215**	0.209**	0.228**	0.363***	0.241**	0.384***
	(0.068)	(0.089)	(0.090)	(0.096)	(0.080)	(0.095)	(0.100)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.964	0.956	0.955	0.929	0.953	0.932	0.884
Observations	630	630	630	630	630	630	630

Notes: This table reports the results of channels analysis through agricultural innovation. Variable definitions are reported in Table 2. The standard error reported in the parentheses. The symbols ***, **, and* indicate significance at the 1 %, 5 %, and 10 % confidence levels, respectively.

Table 8
Channels analysis through government environmental regulation.

VARIABLES	Agricultural Eco-efficiency (AEE)		Fertilizers for Agriculture		
	High-Regulatory Standards	Low-Regulatory Standards	Eastern Region	Central Region	Western Region
	(1)	(2)	(3)	(4)	(5)
CA	0.093***	0.028	−0.802*	0.083	0.412
	(0.032)	(0.023)	(0.421)	(0.515)	(0.361)
Control Variables	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.883	0.928	0.302	0.222	0.090
Observations	316	314	231	168	231

Notes: This table reports the results of channels analysis through government environmental regulation. Variable definitions are reported in Table 2. The standard error reported in the parentheses. The symbols ***, **, and* indicate significance at the 1 %, 5 %, and 10 % confidence levels, respectively.

grain yields but are also a major source of agricultural pollution. We expect that in regions with stronger environmental regulations, fertilizer use would be significantly reduced. Based on regional characteristics, we divide the sample into eastern, central, and western regions, which display a clear gradient of regulatory intensity, decreasing from east to west. We therefore hypothesize that the impact of CA on reducing fertilizer use exhibits regional heterogeneity. To test this, we replace the dependent variable with the logarithm of fertilizer application in pure nutrient terms and perform subsample regressions for the three regions. Columns (3), (4), and (5) of Table 7 report the results. In the eastern region, where environmental regulation is more stringent, CA significantly reduces fertilizer use. In contrast, its effect in the central and western regions is not statistically significant. These findings provide further evidence that government environmental regulation is a key channel through which CA improves AEE.

5. Further analysis

In the baseline regression analysis, we confirmed a significant positive relationship between CA and AEE. Climate change has heightened public attention about environmental issues, influencing agricultural production practices and technological choices. However, we may have overlooked common factors affecting both CA and AEE. Although we addressed endogeneity attention through an instrumental variable approach in previous sections, such factors could still impact the robustness of our results. To further elucidate the relationship between CA and AEE, we exploit the establishment of China's carbon trading market as an exogenous shock. This event, reflecting the nation's commitment to its dual carbon goals, underscores the growing societal focus on climate change.

The establishment of China's carbon trading markets offers a valuable quasi-natural experiment to identify the causal impact of heightened climate attention on AEE. A critical aspect for the validity of the DID approach is the exogeneity of the policy's timing and the exogeneity of its regional assignment with respect to the pre-existing trends in AEE. The selection of the initial regions for China's carbon trading market pilots was primarily guided by a set of criteria distinct from agricultural sector performance. These criteria, as indicated by policy documents and existing literature (NDRC, 2011; Liu et al., 2015), primarily included (a) Regions with a significant industrial base and high energy consumption, leading to substantial carbon emissions predominantly from non-agricultural sectors. Provinces or cities with a sound working foundation for climate change mitigation, including existing capacity for emissions data management and a robust legal framework. (c) Areas with prior experience in energy conservation, emissions reduction, and climate change response, indicating a certain level of preparedness. Crucially, the agricultural sector was not a primary target for direct emissions regulation, nor was its specific eco-efficiency trajectory a key determinant in the site selection process for these initial carbon trading market pilots. The overwhelming emphasis was on mitigating emissions from major industrial sources. Therefore, it is reasonable to argue that the decision to implement carbon trading market pilots in these specific provinces was largely exogenous to the pre-existing or anticipated trends in AEE of these regions relative to non-pilot provinces. Furthermore, while the initial carbon trading market did not directly regulate agricultural emissions, China's broader policy discourse signals an intent to integrate agriculture into carbon mitigation. Notably, a 2019 Ministry of Ecology and Environment directive encouraged agricultural participation in emissions trading. Recent studies (Ren and Fu, 2019; Yu et al., 2022) indicate that China's carbon trading market can positively influence agricultural green development. This evolving context and emerging evidence underscore the importance of investigating how heightened climate attention, partly driven by the carbon market, may spill over to promote agricultural low-carbon transition, a key motivation for our mechanistic inquiry.

We employ a DID approach to assess the impact of carbon trading pilots on AEE in selected provinces, comparing the AEE differences between the treatment group (provinces initially adopting the pilot programs) and the control group before and after implementation. The treatment group comprises Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, while the remaining provinces form the control group. After the implementation of the carbon trading pilots, AEE levels in the treatment group showed an upward trend. The DID regression model is specified as follows:

$$AEE_{it} = \beta_0 + \beta_1 DID_{it} + \beta_2 X_{it} + u_i + \lambda_t + \varepsilon_{i,t} \tag{5}$$

Among these, i and t represent the province and time, respectively. AEE_{it} is the Agricultural Ecological Efficiency (AEE) for province i at time t. DID_{it} is the core explanatory variable, the DID variable: $DID_{it} = Treatment_{it} \times Post_{it}$, $Treatment_{it}$ indicates whether the province belongs to the treatment group. $Post_{it}$ indicates the time after the implementation of the carbon trading pilot (0 before 2014, 1 after 2014). The other variables are control variables, consistent with the baseline regression model discussed earlier. u_i and λ_t represent individual and time fixed effects, respectively. $\varepsilon_{i,t}$ is the random error term. The impact of the carbon trading pilot on AEE is captured by the coefficient β_1 of DID_{it}. One additional benefit of using Equation (5) for estimation is that we can perform the event study analysis that examines the treatment effects dynamics and the presence of potential pre-trends, which can provide further support to our identification assumption. The event study is specified as follows:

$$AEE_{it} = \beta_0 + \beta_1 \sum_{\tau} \beta_\tau Post_{it}^{\tau} + \beta_2 X_{it} + u_i + \lambda_t + \varepsilon_{i,t} \tag{6}$$

$$s.t.\ \tau \in \{-6+, -5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5, 6, 7\}$$

Where we replace $Post_{it}$ with a series of year-specific dummy variables relative to the policy implementation. If the parallel trends assumption holds, we should observe that the coefficients for the years prior to policy implementation are not significantly different from zero. Considering the sample's time span and to avoid multicollinearity, the period t-1 (the year immediately preceding policy implementation) is set as the reference period.

Table 8 presents the regression results for model (5). Column (1) report the empirical findings with and without control variables, respectively. The coefficient for the core explanatory variable, DID, remains stable and statistically significant at the 1 % level in both cases. This suggests that the carbon trading pilot, as a key indicator of climate attention, significantly contributes to improving AEE in China. In other words, as climate change intensifies, increased climate attention plays a crucial role in enhancing AEE.

Fig. 6 displays the results of the dynamic effects test, examining the period-by-period impact surrounding the implementation of China's carbon trading market pilots. The solid black line with circular markers represents the point estimates of the policy effect for each period relative to the implementation, while the dashed grey lines indicate the corresponding 90 % confidence intervals. Prior to the implementation of the carbon trading pilot in 2014, none of the coefficients were statistically significant, indicating no discernible pre-treatment trend between the treatment and control groups. However, after 2014, with the commencement of the carbon trading pilot, national awareness of low-carbon production deepened, and the coefficients shifted from negative to positive, becoming statistically significant. This suggests that the carbon trading pilot had a lasting impact throughout the sample period.

To rigorously evaluate the robustness of our primary findings regarding the impact of China's carbon trading market pilots on agricultural eco-efficiency, we implement a comprehensive battery of validation procedures. First, we employ a PSM-DID methodology to address potential selection bias arising from pre-treatment observable heterogeneity across provinces; results are presented in Table 9, Column (2). Second, we examine the stability of our estimates by incorporating interaction terms between key provincial baseline characteristics and time trends, thereby controlling for potentially divergent pre-existing trajectories conditional on initial provincial attributes (Table 9, Column 3). Third, we conduct a stringent placebo test involving the joint randomization of both treatment assignment and policy implementation timing to verify our identification strategy; graphical evidence for this test is presented in Fig. 7. The consistency of results across these diverse and methodologically rigorous analytical procedures provides strong empirical support for our main conclusion that carbon trading pilots exert a positive effect on agricultural eco-efficiency.

6. Research conclusions and prospects

6.1. Research conclusions

With the intensification of climate change and associated risks, alongside the demand for high-quality economic development, the rise in societal climate attention presents an opportunity to drive Chinese agricultural low-carbon transition. To investigate this relationship, we constructed a provincial panel dataset spanning 2001 to 2021 and empirically tested the impact of CA on AEE using an OLS model.

Table 9
The effect of carbon trading on AEE.

VARIABLES	Dependent variable: Agricultural Eco-efficiency (AEE)		
	DID	PSM + DID	Controls × Year FE
	(1)	(2)	(3)
DID	0.071***	0.141***	0.110***
	(0.025)	(0.037)	(0.027)
Control Variables	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adjusted R-squared	0.874	0.871	0.875
Observations	630	356	630

Notes: This table reports the results of the difference-in-differences (DID) approach surrounding the implementation of the carbon trading on AEE. The t-statistics are in the parentheses. The standard error reported in the parentheses. The symbols ***, **, and* indicate significance at the 1 %, 5 %, and 10 % confidence levels, respectively.

Additionally, we designed a quasi-natural experiment based on the establishment of China's carbon trading market, a key indicator of societal climate attention, and employed DID and PSM-DID models to assess its contribution to AEE improvements. The main findings are as follows:

CA exerts a significant positive impact on AEE. Heterogeneity analysis indicates that this effect is more pronounced in western region than in the central and eastern regions, and stronger in major grain-producing and grain-balanced areas compared to major grain-consuming regions. Second, mechanism analysis from the perspectives of agricultural technological innovation, market demand, and government regulation identifies high-quality agricultural innovations (particularly disruptive and breakthrough technologies), market demand for eco-agricultural products, and government environmental regulations as key channels through which CA fosters AEE growth. Lastly, the establishment of the carbon trading market—an exogenous shock aligned with China's dual carbon goals —was shown to significantly promote AEE, thereby further validating and enriching the baseline regression results.

6.2. Recommendations

(1) Enhance societal climate attention to improve agricultural eco-efficiency. As climate attention has a significant positive impact on AEE, increasing societal awareness of climate issues is crucial

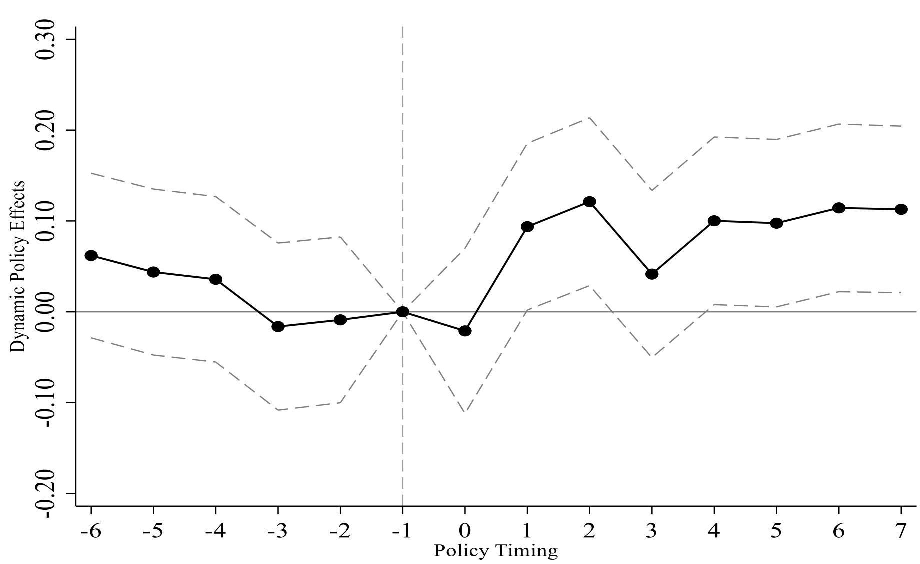

Fig. 6. AEE in treatment group (the carbon trading was implemented in 2014).

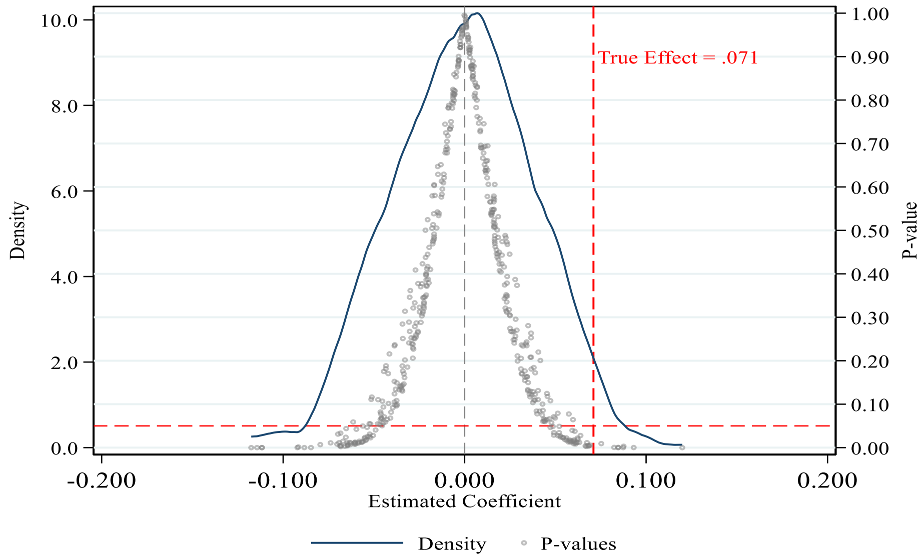

Fig. 7. Placebo test.

for supporting sustainable agricultural development. The government should continue to raise awareness of climate change through policy guidance, media campaigns, and educational initiatives. Additionally, the public should be encouraged to participate in climate action through green consumption and low-carbon lifestyles. Given regional disparities, special attention should be given to central and western regions and major grain-producing areas. Policies should optimize resource allocation to enhance climate attention in these areas, strengthening their capacity to address climate change and ensuring a more balanced improvement of agricultural eco-efficiency across the country.

(2) Strengthen agricultural technological innovation and institutional frameworks to unlock the potential of climate attention. Research indicates that technological innovation and mechanized production are key mechanisms through which climate attention drives AEE. The government should increase support for agricultural R&D, particularly for disruptive and breakthrough technologies. This includes developing tailored green finance mechanisms, as evidence from other sectors suggests that instruments like green bonds can effectively promote innovation by alleviating financing constraints (Dong and Yu, 2024). Special research funds should be established to facilitate collaboration between universities, research institutions, and enterprises, accelerating the application of technological innovations. Additionally, a robust agricultural technology extension system should be developed to introduce advanced machinery and techniques to farmers, improving productivity and resource utilization efficiency. A multi-party collaboration mechanism involving the government, farmers, and the market should be established to enhance policy implementation and oversight, ensuring that technological and managerial innovations effectively translate into improved agricultural eco-efficiency.

(3) Leverage the policy effects of the carbon trading market to promote agricultural green transition. The carbon trading market, as a key policy tool for achieving the dual carbon goals, has been shown to significantly enhance AEE. The government should further strengthen the carbon trading market framework, including expanding its coverage, optimizing market rules, and reinforcing the regulatory system. In the agricultural sector, efforts should be made to integrate agricultural carbon sinks into the carbon trading system, encouraging producers to adopt ecological farming practices and low-carbon technologies to earn carbon credits. Additionally, targeted subsidies or tax incentives should be introduced to lower the barriers for agricultural stakeholders to participate in the carbon market. Ongoing research and monitoring of the carbon market's operation should be conducted to adjust policies based on actual performance, ensuring that the market continues to support agricultural green development.

6.3. Research limitations and prospects

While this study provides a comprehensive analysis of the impact of climate attention on China's agricultural eco-efficiency and its underlying mechanisms, several limitations remain that future research could address. Methodologically, despite using various empirical techniques, such as OLS regression, DID, and PSM-DID, along with extensive robustness checks, the potential issue of endogeneity cannot be fully ruled out. From a research perspective, due to challenges in obtaining granular data on climate attention and agricultural eco-efficiency, this study primarily relies on provincial-level panel data. The lack of micro-level data on farmers' behavior limits the ability to fully capture the micro-mechanisms through which climate attention influences individual decision-making. Future research could combine household survey data to construct a multi-level analytical framework, enabling more accurate identification of the pathways through which climate attention impacts agricultural producers' behavior. Similarly, an important avenue for future work lies in the use of advanced, high-resolution environmental datasets—such as the stable isotope records compiled by Chen et al. (2024)—to investigate the environmental dimensions of agricultural transition with greater specificity. Finally, this study analyzes the carbon trading market as an exogenous shock to climate attention, but its effects may exhibit time-lag effects or path dependencies, which may not be fully captured in short-term analysis. Future research could utilize extended panel data and dynamic panel models to investigate these long-term effects more thoroughly. Additionally, the application of spatial econometric techniques would offer a valuable extension, as policies implemented in one region may produce spillover effects in neighboring areas—a dynamic observed in related domains, such as the influence of tourism on regional carbon emissions (Zhou et al., 2023).

CRediT authorship contribution statement

Yi Shi: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Zenghui**

Li: Writing – review & editing, Formal analysis, Data curation. **Li Lin:** Resources, Methodology, Formal analysis. **Huangxin Chen:** Supervision, Data curation. **Linjie Feng:** Investigation, Formal analysis. **Wencong Lu:** Visualization, Supervision, Project administration.

Declaration of generative AI in scientific writing

The authors did not use any AI tools in any process of this study.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

References

Agrimonti, C., Lauro, M., Visioli, G., 2021. Smart agriculture for food quality: facing climate change in the 21st century. Crit. Rev. Food Sci. Nutr. 61 (6), 971–981. https://doi.org/10.1080/10408398.2020.1749555.
Allcott, H., 2011. Consumers' perceptions and misperceptions of energy costs. Am. Econ. Rev. 101 (3), 98–104. https://doi.org/10.1257/aer.101.3.98.
Björkman, M., Svensson, J., 2009. Power to the people: evidence from a randomized field experiment on community-based monitoring in Uganda. Q. J. Econ. 124 (2), 735–769. https://doi.org/10.1162/qjec.2009.124.2.735.
Bornmann, L., Devarakonda, S., Tekles, A., Chacko, G., 2020. Are disruption index indicators convergently valid? The comparison of several indicator variants with assessments by peers. Quantitative Science Studies 1 (3), 1242–1259. https://doi.org/10.1162/qss_a_00068.
Broadbent, D.E., 1957. A mechanical model for human attention and immediate memory. Psychol. Rev. 64 (3), 205–215. https://doi.org/10.1037/h0047313.
Buntaine, M.T., Greenstone, M., He, G., Liu, M., Wang, S., Zhang, B., 2024. Does the squeaky wheel get more grease? The direct and indirect effects of citizen participation on environmental governance in China. Am. Econ. Rev. 114 (3), 815–850. https://doi.org/10.1257/aer.20221215.
Burke, M., Emerick, K., 2016. Adaptation to climate change: evidence from US agriculture. Am. Econ. J. Econ. Pol. 8 (3), 106–140. https://doi.org/10.1257/pol.20130025.
Chen, S., Gong, B.L., 2021. Response and adaptation of agriculture to climate change: evidence from China. J. Dev. Econ. 148, 17. https://doi.org/10.1016/j.jdeveco.2020.102557.
Chen, L.H., Wang, Q.Q., Zhu, G.F., Lin, X.R., Qiu, D.D., Jiao, Y.Y., Wang, Y.H., 2024. Dataset of stable isotopes of precipitation in the Eurasian continent. Earth Syst. Sci. Data 16 (3), 1543–1557. https://doi.org/10.5194/essd-16-1543-2024.
Chen, Q.Y., Zhao, H.Y., Lin, S.T., Shen, Y., 2024. High-quality technological innovation in China: situational narration and measurement system. Manag. World 5, 23–41. https://doi.org/10.19744/j.cnki.11-1235/f.2024.0061.
Chen, Y.S., Sun, Z.F., Zhou, Y.W., Yang, W.L., Ma, Y., 2024. The future of sustainable farming: an evolutionary game frame work for the promotion of agricultural green production technologies. J. Clean. Prod. 460, 13. https://doi.org/10.1016/j.jclepro.2024.142606.
Chen, H.X., Zhao, X., Smutka, L., Henry, J.T., Barut, A., Shahzad, U., 2025. Exploring the impact of China's low carbon energy technology trade on alleviating energy poverty in Belt and Road Initiative countries. Energy 318, 10. https://doi.org/10.1016/j.energy.2025.134604.
Cheng, J., Liu, Y.Y., 2018. The effects of public attention on the environmental performance of high-polluting firms: based on big data from web search in China. J. Clean. Prod. 186, 335–341. https://doi.org/10.1016/j.jclepro.2018.03.146.
Christensen, C.M., 1997. The Innovator's Dilemma: when New Technologies Cause Great Firms to Fail. Harvard Business Review Press.
Coquil, X., Cerf, M., Auricoste, C., Joannon, A., Barcellini, F., Cayre, P., Prost, L., 2018. Questioning the work of farmers, advisors, teachers and researchers in agro-ecological transition. A review. Agronomy for Sustainable Development 38 (5), 12. https://doi.org/10.1007/s13593-018-0524-4.
Dai, J.P., 2025. Is policy pilot a viable path to sustainable development? Attention allocation perspective. Int. Rev. Financ. Anal. 98, 15. https://doi.org/10.1016/j.irfa.2025.103923.
De Leijster, V., Verburg, R.W., Santos, M.J., Wassen, M.J., Martínez-Mena, M., de Vente, J., Verweij, P.A., 2020. Almond farm profitability under agroecological management in southeastern Spain: accounting for externalities and opportunity costs. Agric. Syst. 183, 11. https://doi.org/10.1016/j.agsy.2020.102878.
De Marchi, E., Cavaliere, A., Bacenetti, J., Milani, F., Pigliafreddo, S., Banterle, A., 2019. Can consumer food choices contribute to reduce environmental impact? The case of cisgenic apples. Sci. Total Environ. 681, 155–162. https://doi.org/10.1016/j.scitotenv.2019.05.119.
Dell, M., Jones, B.F., Olken, B.A., 2012. Temperature shocks and economic growth: evidence from the last half century. Am. Econ. J. Macroecon. 4 (3), 66–95. https://doi.org/10.1257/mac.4.3.66.
Deng, J.J., Li, Y., Ding, Y., Liu, F.Q., 2025. Effect of media attention on corporate green technology innovation: mechanism and evidence from China. Empir. Econ. 68 (2), 697–727. https://doi.org/10.1007/s00181-024-02660-6.
Dong, X., Yu, M.Z., 2024. Green bond issuance and green innovation: evidence from China's energy industry. Int. Rev. Financ. Anal. 94, 14. https://doi.org/10.1016/j.irfa.2024.103281.
Dosi, G., 1982. Technological paradigms and technological trajectories: a suggested interpretation of the determinants and directions of technical change. Res. Pol. 11 (3), 147–162. https://doi.org/10.1016/0048-7333(82)90016-6.
Du, C.C., Bai, X.Y., Li, Y.B., Tan, Q., Zhao, C.W., Luo, G.J., Li, M.H., 2024. The restoration of karst rocky desertification has enhanced the carbon sequestration capacity of the ecosystem in southern China. Global Planet. Change 243, 12. https://doi.org/10.1016/j.gloplacha.2024.104602.
Du, J.X., Zhong, Z.Z., Shi, Q.L., Wang, L.K., Liu, Y.R., Ying, N., 2024. Does government environmental attention drive green total factor productivity? Evidence from China. J. Environ. Manag. 366, 10. https://doi.org/10.1016/j.jenvman.2024.121766.
Ehlers, M.H., Huber, R., Finger, R., 2021. Agricultural policy in the era of digitalisation. Food Policy 100, 14. https://doi.org/10.1016/j.foodpol.2020.102019.
El Benni, N., Irek, J., Finger, R., Mack, G., Ammann, J., 2024. Citizens' perceptions of agricultural policy goals-evidence from Switzerland. Food Policy 125, 21. https://doi.org/10.1016/j.foodpol.2024.102643.
Fishbane, A., Ouss, A., Shah, A.K., 2020. Behavioral nudges reduce failure to appear for court. Science 370 (6517), 682. https://doi.org/10.1126/science.abb6591.
Fytili, D., Zabaniotou, A., 2022. Organizational, societal, knowledge and skills capacity for a low carbon energy transition in a circular waste bioeconomy (CWBE): observational evidence of the Thessaly region in Greece. Sci. Total Environ. 813, 21. https://doi.org/10.1016/j.scitotenv.2021.151870.
Guo, X.C., Wang, Y.F., Lu, Y., Ma, X., 2021. A Comparative Study on the Agricultural Scientific and Technological Innovation Capabilities of Major Countries and Regions in the World Based on Patents. China Agricultural Science and Technology Press.
Hartzmark, S.M., Hirshman, S.D., Imas, A., 2021. Ownership, learning, and beliefs. Q. J. Econ. 136 (3), 1665–1717. https://doi.org/10.1093/qje/qjab010.
Horbach, J., Rammer, C., 2025. Climate change affectedness and innovation in firms. Res. Pol. 54 (1), 16. https://doi.org/10.1016/j.respol.2024.105122.
Huang, H.X., 2023. The future of carbon-neutrality science and technology from an industrial transition perspective: an interview with hou-liang dai. Natl. Sci. Rev. 10 (9), 3. https://doi.org/10.1093/nsr/nwac295.
Jerath, K., Ren, Q.T., 2021. Consumer rational (in)Attention to favorable and unfavorable product information, and firm infor mation design. J. Mark. Res. 58 (2), 343–362. https://doi.org/10.1177/0022243720977830.
Jeschke, P., 2016. Progress of modern agricultural chemistry and future prospects. Pest Manag. Sci. 72 (3), 433–455. https://doi.org/10.1002/ps.4190.
Ji, M., Li, J.R., Zhang, M.D., 2024. What drives the agricultural carbon emissions for low-carbon transition? Evidence from China. Environ. Impact Assess. Rev. 105, 11. https://doi.org/10.1016/j.eiar.2024.107440.
Jiang, T., 2022. Mediating and moderating effects in empirical studies of causal inference. China Industrial Economics 5, 100–120. https://doi.org/10.19581/j.cnki.ciejournal.2022.05.005.
Joëlle Noailly, L. N., Matthias van den Heuvel, Ireneu Pla. Heard the news? Environmental policy and clean investments. J. Publ. Econ., 238. https://doi.org/10.1016/j.jpubeco.2024.105190.
Kahneman, D., 1973. Attention and Effort. Prentice-Hall, Englewood Cliffs, NJ.
Lankoski, J., Thiem, A., 2020. Linkages between agricultural policies, productivity and environmental sustainability. Ecol. Econ. 178, 9. https://doi.org/10.1016/j.ecolecon.2020.106809.
Li, B., Zhang, J.B., Li, H.P., 2011. Temporal and spatial characteristics of agricultural carbon emissions in China and decom position of influencing factors. China Population, Resources and Environment 8, 80–86. https://doi.org/10.3969/j.issn.1002-2104.2011.08.013.
Li, F.D., Yang, P., Zhang, K.J., Yin, Y.S., Zhang, Y.N., Yin, C.B., 2022. The influence of smartphone use on conservation agricultural practice: evidence from the extension of rice-green manure rotation system in China. Sci. Total Environ. 813, 13. https://doi.org/10.1016/j.scitotenv.2021.152555.
Li, J.K., Gao, M., Luo, E.R., Wang, J.Y., Zhang, X.B., 2023. Does rural energy poverty alleviation really reduce agricultural carbon emissions? The case of China. Energy Econ. 119, 12. https://doi.org/10.1016/j.eneco.2023.106576.
Liu, L.W., Chen, C.X., Zhao, Y.F., Zhao, E.D., 2015. China's carbon-emissions trading: overview, challenges and future. Renew. Sustain. Energy Rev. 49, 254–266. https://doi.org/10.1016/j.rser.2015.04.076.
Ma, G.Q., Tan, Y.W., 2021. A study on the impact of environmental regulation on agricultural green total factor productivity—analysis based on the panel threshold model. Journal of Agricultural Technology Economics 5, 77–92. https://doi.org/10.13246/j.cnki.jae.2021.05.006.
Macher, J.T., Rutzer, C., Weder, R., 2024. Is there a secular decline in disruptive patents? Correcting for measurement bias. Res. Pol. 53 (5), 104992. https://doi.org/10.1016/j.respol.2024.104992.

Mancuso, T., De Cianni, R., Di Vita, G.A., Spada, E., Brun, F., Spadaro, D.C., Zanchini, R., 2024. Understanding Italian consum ers' perceptions of tomato agricultural innovation: exploring the nexus between sustainability, health and consumer beliefs. J. Clean. Prod. 435, 11. https://doi.org/10.1016/j.jclepro.2023.140528.

Niu, Z.H., Chen, C., Gao, Y., Wang, Y.Q., Chen, Y.S., Zhao, K.J., 2022. Peer effects, attention allocation and farmers' adoption of cleaner production technology: taking green control techniques as an example. J. Clean. Prod. 339, 10. https://doi.org/10.1016/j.jclepro.2022.130700.

Peng, X., Ci, J., Liu, D., 2022. Research on the formation process of organizational resilience in crisis context: from the perspective of attention allocation. Science of Science and Management of S.& T 43 (6), 145–160.

Quang, N.M., de Wit, J., 2020. Transformative learning and grassroots climate adaptation: case studies in Vietnam's mekong Delta. Nature Conservation-Bulgaria (39), 19–43. https://doi.org/10.3897/natureconservation.39.29551.

Ren, Y., Fu, J., 2019. Research on the effect of carbon emissions trading on emission reduction and green development. China Population Resources and Environment 29 (5), 11–20.

Russell, J. Funk, Owen-Smith, Jason, 2016. A dynamic network measure of technological change. Manag. Sci. 63 (3), 791–817. https://doi.org/10.1287/mnsc.2015.2366.

Saurabh Singhal, F.T., 2024. Commodity price volatility and the psychological well-being of farmers. Am. J. Agric. Econ. ajae.12468. https://doi.org/10.1111/ajae.12468.

Schäufele, I., Hamm, U., 2017. Consumers' perceptions, preferences and willingness-to-pay for wine with sustainability character istics: a review. J. Clean. Prod. 147, 379–394. https://doi.org/10.1016/j.jclepro.2017.01.118.

Sharma, G.D., Shah, M.I., Shahzad, U., Jain, M., Chopra, R., 2021. Exploring the nexus between agriculture and greenhouse gas emissions in BIMSTEC region: the role of renewable energy and human capital as moderators. J. Environ. Manag. 297, 13. https://doi.org/10.1016/j.jenvman.2021.113316.

Sol Hart, P., E. C. N. T. A. M, 2015. Public attention to science and political news and support for climate change mitigation. Nat. Clim. Change 5 (6), 541–545.

Song, Y.G., Zhang, B.C., Wang, J.H., Kwek, K., 2022. The impact of climate change on China's agricultural green total factor. Technol. Forecast. Soc. Change 185, 18. https://doi.org/10.1016/j.techfore.2022.122054.

Tone, K., 2001. A slacks-based measure of efficiency in data envelopment analysis. Eur. J. Oper. Res. 130 (3), 498–509. https://doi.org/10.1016/S0377-2217(99)00407-5.

Tone, K., 2002. A slacks-based measure of super-efficiency in data envelopment analysis. Eur. J. Oper. Res. 143 (1), 32–41. https://doi.org/10.1016/s0377-2217(01)00324-1.

Turhan, E., 2016. Value-based adaptation to climate change and divergent developmentalisms in Turkish agriculture. Ecol. Econ. 121, 140–148. https://doi.org/10.1016/j.ecolecon.2015.11.021.

Virginia, H., Dale, K.L.K., Kaffka, Stephen R., (Hans) Langeve, J.W.A., Ecology, Landscape, 2013. A landscape perspective on sustainability of agricultural systems. Landsc. Ecol. 28 (6), 1111–1123. https://doi.org/10.1007/s10980-012-9814-4.

Wang, D., Zhang, P., Chen, S., Zhang, N., 2024. Adaptation to temperature extremes in Chinese agriculture, 1981 to 2010. J. Dev. Econ. 166, 18. https://doi.org/10.1016/j.jdeveco.2023.103196.

Wang, Q.Q., Liu, Y.W., Zhu, G.F., Lu, S.Y., Chen, L.H., Jiao, Y.Y., Wang, Y.H., 2025. Regional differences in the effects of atmospheric moisture residence time on precipitation isotopes over eurasia. Atmos. Res. 314, 10. https://doi.org/10.1016/j.atmosres.2024.107813.

Wei, W., Cui, Q., Sheng, Y., 2022. Dual carbon goals and the impact on future agricultural development in China: a general equilibrium analysis. China Agric. Econ. Rev. 14 (4), 664–685. https://doi.org/10.1108/caer-02-2022-0020.

Xiang, W., Bin, H., Jie, X., 2020. Understanding heterogeneous consumer preferences in Chinese milk markets: a latent class approach. J. Agric. Econ. 71 (1), 184–198. https://doi.org/10.1111/1477-9552.12327.

Xu, Z., 2025. Harmony between nature and humanity: a systematic environmental governance approach to address climate change. Energy & Environmental Sustainability 1 (1), 100002. https://doi.org/10.1016/j.eesus.2025.01.001.

Yang, T.F., Huang, X.T., Wang, Y., Li, H.J., Guo, L.L., 2022. Dynamic linkages among climate change, mechanization and agricultural carbon emissions in rural China. Int. J. Environ. Res. Publ. Health 19 (21), 24. https://doi.org/10.3390/ijerph192114508.

Yu, D.S., Liu, L.X., Gao, S.H., Yuan, S.Y., Shen, Q.L., Chen, H.P., 2022. Impact of carbon trading on agricultural green total factor productivity in China. J. Clean. Prod. 367, 10. https://doi.org/10.1016/j.jclepro.2022.132789.

Zhang, Y.C., Wu, X.S., 2025. Global space-time patterns of sub-daily extreme precipitation and its relationship with temperature and wind speed. Environ. Res. Lett. 20 (8), 10. https://doi.org/10.1088/1748-9326/ade607.

Zhou, Q., Qu, S., Hou, W.R., 2023. Do tourism clusters contribute to low-carbon destinations? The spillover effect of tourism agglomerations on urban residential CO2 emissions. J. Environ. Manag. 330, 12. https://doi.org/10.1016/j.jenvman.2022.117160.

Zhou, Q., Ye, X.Y., Gianoli, A., Hou, W.R., 2024. Exploring the dual impact: dissecting the impact of tourism agglomeration on low-carbon agriculture. J. Environ. Manag. 361, 25. https://doi.org/10.1016/j.jenvman.2024.121204.