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EDITED BY
Jiachao Peng,
Wuhan Institute of Technology, China

REVIEWED BY
Zhuang Zhang,
South China Agricultural University, China
Yang Liu,
Inner Mongolia University of Finance and Economics, China

*CORRESPONDENCE
WeiTheng Lau,
xelx6415@outlook.com

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Can green finance reduce agricultural carbon emissions? evidence from China's green finance reform and innovation pilot zones

Ting Li, WeiTheng Lau* and Mohamed Hisham Dato Haji Yahya

School of Business and Economics, Universiti Putra Malaysia, Serdang, Selangor Darul Ehsan, Malaysia

Background: Agriculture contributes approximately 17% of China's greenhouse gas emissions. In 2017, China established Green Finance Reform and Innovation Pilot Zones (GFRIPZ) to promote green development, yet its effectiveness in reducing agricultural carbon emissions remains unclear.
Objectives: This study examines whether GFRIPZ reduces agricultural carbon emissions, identifies transmission mechanisms, and explores regional heterogeneity in policy effectiveness.
Methods: Using GFRIPZ establishment as a quasi-natural experiment, we employ a Double/Debiased Machine Learning (DML) framework with provincial panel data from 30 Chinese provinces (2011–2024, N = 420). Three algorithms (Lasso-CV, Elastic Net-CV, Random Forest) ensure robustness. Parallel trend tests, placebo tests (500 iterations), and mediation analysis validate identification and mechanisms.
Results: GFRIPZ reduces agricultural carbon emissions by approximately 41.2 × 10^4 tons annually (10.9% reduction, $p < 0.01$). Three transmission mechanisms are identified: input structure optimization (19.8%), green technology innovation (15.6%), and industrial structure adjustment (11.8%), collectively explaining 47.2% of total effect. Heterogeneity analysis reveals stronger effects in eastern regions ($\beta = -54.0$, $p < 0.01$) than central/western regions ($\beta = -31.4$, $p < 0.10$), and in economically developed provinces.
Conclusion: GFRIPZ effectively reduces agricultural carbon emissions, with input structure optimization as the primary channel. Policy recommendations include expanding pilot coverage, prioritizing fertilizer reduction investments, and strengthening financial infrastructure in less developed regions.

KEYWORDS
agricultural carbon emissions, double machine learning, green finance, policy evaluation, quasi-natural experiment

1 Introduction

Global challenges posed by climate change represent an important issue for human society in the 21st century. According to the IPCC (2021), exceeding the 1.5 °C global warming threshold will increase the occurrence of extreme weather events that threaten food security and the stability of ecosystems. Based on the Paris Agreement's NDC framework, the global pace of reducing carbon emissions has accelerated. China pledged to peak carbon dioxide emissions before 2030 and strive to become carbon neutral before 2060 (Liu et al., 2022). It formulated the strictest demand for the reduction of carbon dioxide emissions from all sectors. Among the sources of emissions, the challenge of agricultural decarbonization remains inadequately addressed. Agricultural carbon dioxide emissions range from 13% to 17% of the total emissions in China, covering various types of gases such as nitrous oxide from fertilizer use, methane from rice-growing and livestock rearing, and carbon dioxide from burning farm-made agricultural diesel oil. Unlike industrial point-source emissions that can be regulated through facility-level standards, agricultural emissions are characterized by diffuse sources, biological processes, and strong dependence on natural conditions, posing unique policy challenges. Yet despite the existence of already established policies in sectors like industry and energy, low-carbon agricultural transformation remains inadequately addressed and requires innovative policy instruments.

Green finance provides an institutional channel to deal with these problems. Green finance is a crucial policy tool to channel funds from non-green pursuits toward green growth. Green transformation is achieved through instruments such as green credit, green bonds, and green insurance. To discuss a model of green finance development with Chinese characteristics, in June 2017, the State Council Executive Meeting determined to set up Green Finance Reform and Innovation Pilot Zones (GFRIPZ) in five provinces (regions), which are Zhejiang, Guangdong, Jiangxi, Guizhou, and Xinjiang provinces (regions), marking the shift from green finance thought advocacy to institutionalized implementation (Zhang and Li, 2022). Each pilot zone has made use of its resource advantages and industrial features to implement financial innovation in agriculture, which provides a quasi-natural experiment to test policy effects on agricultural carbon emissions from green finance policies. Ever since 2017, there has been an increase in relevant research within academia to test policy effects in these pilot zones with specifically multiple aspects in mind such as energy consumption performance, green innovation performance, and input-output performance on industry structural optimization (Lv and Guo, 2025), which has been found to show obvious shortages in present studies in terms of research range and mechanism identification to generate a thorough understanding on green finance impact to agricultural carbon emissions.

A literature review introduces the following limitations of the former literature: In the literature, the main findings are on industrial green innovation, urban carbon emission intensity, and regional energy structure, without considering samples of agricultural sector policies in evaluations to a considerable extent (Mo et al., 2023). In the literature on green finance and carbon emissions, evaluations of industrial or overall regional emissions are mainly concerned (Ran and Zhang, 2023; Su et al., 2024), with agricultural carbon emissions receiving limited scholarly attention (Yu et al., 2025). Although recent studies have begun exploring this intersection—for example, Deng and Zhang (2024) examined green finance effects on agricultural carbon emissions through green technology innovation, and Liu et al. (2025a) identified technological innovation and energy structure optimization as mediating channels for green finance's carbon reduction effects—systematic evaluation of GFRIPZ effects specifically on agricultural emissions remains absent. Methodologically, evaluations are mainly done using the Classical Difference-in-Differences approach to evaluate the effects of policies. However, the approach used makes very strict functional form assumptions. In situations with nonlinear relationships among variables representing controls and the outcome of interest, Classical Difference-In-Differences methods are biased; hence, with large-dimensional controls, it becomes challenging to solve issues of omitted variables with traditional approaches to evaluations. Double/Debiased Machine Learning approaches are relatively new methodologies proposed to address the limitations of former literature approaches to evaluations (Chernozhukov et al., 2018; Li et al., 2025). Recent applications have demonstrated DML's superiority over traditional DID in green policy evaluation, with Yuan and Liu (2024) finding that DML yields more precise estimates by flexibly capturing nonlinear control-outcome relationships. In terms of mechanisms for evaluations, former literature mainly stays at the aggregate level for evaluations, with mechanisms not yet decoded.

To address these gaps, this study uses the establishment of pilot zones in 2017 as a quasi-natural experiment to estimate the causal effect of GFRIPZ policy on agricultural carbon emissions. The contributions are threefold: (1) extending GFRIPZ policy evaluation to the agricultural sector, complementing studies on agricultural subsidy (Zhang X. et al., 2025) and informatization policies (Zhang Y. et al., 2025); (2) employing a DML framework that relaxes the linearity assumption, with results showing the traditional DID estimate is approximately 12.8% lower than the DML estimate (see Section 4.2); and (3) simultaneously quantifying three transmission mechanisms and their relative contributions.

The remainder of this paper is organized as follows. Section 2 presents the policy background, theoretical analysis, and research hypotheses. Section 3 describes the research design. Section 4 reports baseline results and robustness tests. Section 5 provides mechanism testing and heterogeneity analysis. Section 6 concludes with policy recommendations and limitations.

2 Policy background and theoretical analysis

2.1 Policy background

In June 2017, the State Council Executive Meeting decided on the establishment of the first round of Green Finance Reform and Innovation Pilot Zones within the eight prefecture-level areas of five regions: Zhejiang, Guangdong, Jiangxi, Guizhou, and Xinjiang regions, namely, Huzhou, Quzhou, Guangzhou, Ganjiang New Area, Gui'an New Area, Hami, Changji, and Karamay (Zhao et al., 2023). The scope of pilot zones has expanded. In November 2019, it included Lanzhou New Area in the second batch, and in August 2022, it covered Chongqing in its third batch.

For each pilot area, differentiated positioning is developed according to resource advantages. The emphasis of Zhejiang is on green finance integration with green intelligent manufacturing; Guangdong seeks cross-border green finance collaboration within the framework of Guangdong-Hong Kong-Macao Greater Bay Area; Jiangxi concentrates on green finance services for building an ecological civilization; investigations on green finance schemes for rural revival are being explored in Guizhou; and in Xinjiang, green finance services targeting clean energy and unique agricultural development are being promoted. In agriculture, based on differentiated positioning, innovations of diversified green financial instruments have been encouraged. Specialized products have been developed in participating financial institutions within pilot zones, including green credit, green insurance, green funds, and carbon finance (Zhao et al., 2023; Yang et al., 2024). Green credit directs finance to low-carbon agriculture projects using differentiated interest rates and reduces financing risks (He et al., 2019). Green funds offer long-term equity investment for agricultural green transformation. Carbon finance instruments transform ecological value in agriculture into financeable assets. These innovations serve as channels whereby green finance policies can impact agricultural carbon emissions.

Although direct policy scope is limited to specific municipalities, spillover effects may extend province-wide through multiple channels. The branches of province-level financial institutions usually set unified green credit standards, province-level policies are often province-wide, and the high mobility rate of agricultural factors allows green production methods to spill over to the surrounding areas. Starting from these spill-over channels, using the province as the research unit seems reasonable.

Regarding agriculture-specific relevance, GFRIPZ provisions can be classified into three categories: (1) policies directly targeting agricultural production, such as Guizhou's green credit for ecological agriculture and Jiangxi's carbon sink trading involving forestry and agriculture; (2) agricultural pollution reduction measures, including preferential financing for fertilizer substitution and green insurance for non-point source pollution control; and (3) indirect spillover effects from province-wide green credit standards that influence lending to agricultural enterprises beyond designated pilot municipalities.

2.2 Theoretical analysis and research hypotheses

Carbon emissions in agriculture are essentially from energy and material used in production activities. In particular, six source categories formulate the total emissions of agricultural carbon: nitrous oxide emissions from the conversion of nitrogen in fertilizers, carbon emissions from pesticide production and usage, greenhouse gases from agricultural film production and residual degradation, carbon dioxide emissions from burning agricultural diesel oil, indirect emissions from using electricity in agricultural irrigation, and organic carbon emissions from soil tillage activities (Liang et al., 2021). Thanks to continuing advancements in calculations of carbon emissions, significant achievements have been made in calculating provincial and county-level emissions of agriculture (Li et al., 2024; Song et al., 2023).

Theoretically, GFRIPZ policy can affect agricultural carbon emissions in multiple ways. At the level of resource allocation, the policies of pilot zones promote the favorable allocation of financial resources to low-carbon agriculture projects by formulating green project certification criteria and green credit guidelines, so as to ensure an optimized structure of financial resource allocation. According to previous research, green financial innovation has been proven to facilitate reduced pollution emissions through optimized resource allocation (Cui et al., 2023). At the level of financing constraint, green financial product innovation lowers costs and financial thresholds, which may ease financial constraints for agricultural enterprises adopting green technologies. At the level of signal transmission, the setup of pilot zones sends out strong government support for green development, which can guide agricultural enterprises to change their production behavior and generate low-carbon expectations. According to the above-mentioned analysis, we put forward the following hypothesis:

H1: The establishment of GFRIPZ significantly reduces agricultural carbon emissions in the provinces where they are located.

Beyond the direct effects discussed above, GFRIPZ may also reduce agricultural carbon emissions through indirect transmission mechanisms. Innovations in green technology represent an important mediating institution. Financial support for green technology R&D reduces financing costs, encouraging research organizations and enterprises to increase investment in emission-reduction technologies. Low-carbon technologies such as soil testing and formula fertilization, precision agriculture, and green plant protection enhance production efficiency and lower unit carbon emission intensity. Based on existing research findings, green innovation was demonstrated to reduce carbon emissions (Shan and Shao, 2024). Environmental policies and low-carbon policies could encourage green technology innovation (Du et al., 2021), which could lower agro-carbon emissions (Li et al., 2023). Increased agricultural green total-factor productivity implies that an equivalent level of output could be obtained with lower high-carbon factors, which would lower emissions from the source (Liu et al., 2020). This leads to our first mechanism hypothesis:

H2a: The GFRIPZ policy reduces agricultural carbon emissions by promoting green technology innovation.

Input structure optimization is another important transmission channel. Green credit policies, by means of differential financing thresholds and rates of interest, increase the financing costs of high-carbon input producers, which in turn inhibits overproduction of fertilizers and pesticides from the supply side. Green insurance innovation offsets risks in adopting green inputs like organic fertilizers and biologic pesticides from the demand side. Green subsidy policies, by means of price incentive channels, encourage agricultural operators to decrease the use of chemical inputs while adopting low-carbon inputs instead. These policies can be mutually enhancing to advance low-carbon input structure adjustment. Based on previous research studies, it is known that agricultural input structure optimization is related to decreases in the intensity of carbon emissions (Yu et al., 2020), which validates the path through which policies can decrease the reduction of carbon emissions by means of optimal factor allocation (Du et al., 2023). Accordingly, we hypothesize:

H2b: The GFRIPZ policy reduces agricultural carbon emissions by optimizing agricultural input structures.

Industrial structure adjustment is the third transmission channel. Green finance steers the agricultural industry structure adjustment toward low-carbon development with differentiated credit policies. Specifically, in terms of crop growing, green finance gives priority to economic crops with high carbon sequestration capability, such as forestry crops and tea gardens, while constraining the development of high-carbon crops. At the

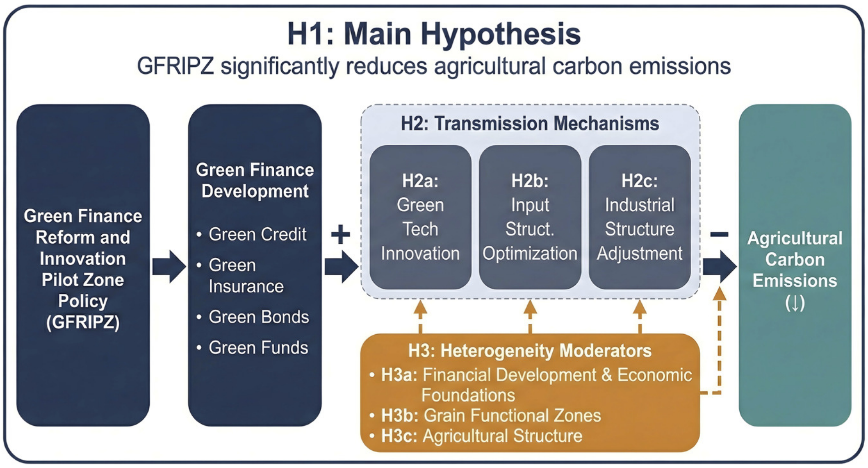

FIGURE 1
Theoretical framework: Gfripz policy transmission mechanisms and heterogeneity moderators for agricultural carbon emission reduction.

crop and livestock structure level, green finance steers the breeding industry toward large-scale standardized development with lower breeding industry carbon emission intensity. Current research shows that industry structure adjustment can be an important transmission channel for green finance. Evidence from the region shows that industry structure adjustment in agriculture plays an important role in reducing carbon emissions (Huang et al., 2025). Agricultural carbon emission intensity shows significant space-temporal differences, with industry structure differences playing an important role (Zhu and Shao, 2025). Jointly reduced carbon emissions from the agricultural industry also require industry optimization (Hou et al., 2024). Following this reasoning:

H2c: The GFRIPZ policy reduces agricultural carbon emissions by adjusting agricultural industrial structure.

As shown in Figure 1, to achieve agricultural carbon emissions reduction, the GFRIPZ policy pursues direct effects via instruments of green credit, green insurance, and green bonds, followed by transmission channels including green technology innovation (H2a), input structure optimization (H2b), and industrial structure change (H2c).

Beyond average effects, policy impacts may exhibit regional heterogeneity. Financial development and economic foundations moderate policy effectiveness through two channels: developed financial markets provide more diverse green financial instruments enabling efficient policy transmission, and stronger institutional capacity ensures better implementation of green credit standards (He et al., 2019). Regarding agricultural heterogeneity, major grain-producing areas face food security constraints that may limit input adjustment flexibility, while provinces dominated by crop cultivation versus animal husbandry face different emission structures requiring distinct interventions. Based on these considerations:

H3a: GFRIPZ effects on agricultural carbon emissions are stronger in regions with higher financial development and economic foundations.

H3b: GFRIPZ effects differ across grain functional zones, with non-major grain-producing areas exhibiting stronger effects due to greater input adjustment flexibility.

H3c: GFRIPZ effects may vary across provinces with different agricultural structures (crop-dominated vs. livestock-dominated).

3 Research design

3.1 Model construction

While the theoretical framework provides clear hypotheses, empirical implementation faces methodological challenges. The conventional Difference-in-Differences (DID) method has been widely applied in policy research, yet it assumes linear relationships between controls and outcomes. When true relationships exhibit nonlinearity, such assumptions induce specification bias. Regularization techniques offer partial solutions for high-dimensional controls, but at the cost of introducing regularization bias that compromises estimation precision. To address these limitations, this study employs Double/Debiased Machine Learning (DML), which applies machine learning algorithms to flexibly model nonlinear relationships while using Neyman orthogonalization to eliminate regularization bias (Athey and Imbens, 2019).

In this problem, a Partial Linear Model (PLM) can be considered an appropriate choice. It allows primary variables to enter into a model in a parametric manner, and it uses nonparametric methods to deal with control variables. In particular, equations of mathematical expectation related to estimation can be expressed in a study as follows:

$$ACE_{it} = \theta_0 Policy_{it} + g(X_{it}) + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

$$Policy_{it} = m(X_{it}) + \eta_i + \gamma_t + v_{it} \tag{2}$$

$$\tilde{Y}_{it} = \theta_0 \tilde{D}_{it} + \varepsilon_{it} \tag{3}$$

Equation 1 represents the outcome equation, where ACE_{it} denotes agricultural carbon emissions in province i during year t, $Policy_{it}$ is the policy treatment variable, θ_0 is the average treatment effect to be estimated, $g(X_{it})$ is an unknown nonparametric function of control variables X_{it}, μ_i and λ_t capture individual heterogeneity and time trends respectively, and ε_{it} is the random error term. Equation 2 represents the treatment equation, where $m(\cdot)$ characterizes the nonparametric effect of control variables on treatment status. Equation 3 represents the orthogonalized estimation equation, where $\tilde{Y}_{it} = ACE_{it} - \hat{g}(X_{it})$ denotes the residualized outcome variable after partialling out control variable effects, and $\tilde{D}_{it} = Policy_{it} - \hat{m}(X_{it})$ denotes the residualized treatment variable. This orthogonalization ensures that the estimator θ_0 is immune to regularization bias and achieves $\sqrt{n}$-consistency.

A two-step estimation procedure is followed. In the first step, machine learning algorithms are employed to estimate $g(\cdot)$ and $m(\cdot)$, obtaining predicted values conditional on controls. In the second step, treatment effect θ_0 is estimated based on residualized variables using Equation 3. Lasso-CV is employed as the benchmark algorithm, achieving variable selection and coefficient shrinkage through L1 regularization for high-dimensional sparse data (Belloni et al., 2014). Robustness checks are conducted using Elastic Net-CV and Random Forest algorithms. Elastic Net-CV combines L1 and L2 regularization advantages; Random Forest captures complex nonlinear relationships through ensemble learning (Wager and Athey, 2018). To prevent overfitting, K = 5-fold cross-validation is employed for sample splitting. The sample is partitioned into five subsets, with four used for training and one for residual calculation in each iteration. Results from all folds are then aggregated to estimate treatment effects.

3.2 Variable selection

The dependent variable is agricultural carbon emissions (ACE). Following the IPCC coefficient method, ACE is calculated by aggregating six categories of carbon sources: fertilizers, pesticides, agricultural plastic films, agricultural diesel, irrigation, and tillage. The emission coefficients are: 0.8956 kg CE/kg for fertilizers, 4.9341 kg CE/kg for pesticides, 5.1800 kg CE/kg for agricultural plastic films, 0.5927 kg CE/kg for diesel, 25.00 kg CE/hm^2 for irrigation, and 312.60 kg CE/km^2 for tillage.

The core explanatory variable is the policy treatment variable $Policy_{it} = Treat_i \times Post_t$, where $Treat_i$ is a treatment group dummy variable assigned a value of 1 for provinces containing pilot zones (Zhejiang, Guangdong, Jiangxi, Guizhou, and Xinjiang) and 0 otherwise; $Post_t$ is a policy timing dummy variable assigned a value of 1 for 2017 and subsequent years and 0 for prior years. As discussed in Section 2.1, provincial-level treatment assignment is justified by intra-provincial policy spillover mechanisms through financial institution networks and agricultural factor mobility.

Control variable selection follows a systematic framework encompassing economic, agricultural, and institutional dimensions. For economic development, GDP (lnGDP) and its squared term test the Environmental Kuznets Curve hypothesis, which posits an inverted-U relationship between economic development and environmental degradation. Urbanization rate captures dual effects on agricultural emissions: potential reductions through farmland consolidation and agricultural labor transfer, versus potential increases from peri-urban agricultural intensification. For agricultural production, agricultural GDP share controls for sectoral economic importance, as provinces with higher agricultural dependence may exhibit systematically different emission patterns and policy responsiveness. Machinery power density proxies for mechanization level, which directly affects energy-related emissions from agricultural operations. Rural human capital (average education years) captures green technology absorption capacity, as higher education levels are associated with greater adoption of precision agriculture and low-carbon practices. For the policy environment, agricultural fiscal expenditure share reflects government support intensity that may directly influence production practices. Environmental regulation stringency, measured by pollution control expenditure, controls for concurrent environmental policies that could confound GFRIPZ effect identification.

For the mechanism variables, we align concepts underlying the hypotheses. Green technology innovation (H2a) is operationalized through the number of agricultural green patents applied for, a validated proxy for green R&D activity (Li et al., 2025). Input structure optimization (H2b) is operationalized through fertilizer application intensity (kg/hm^2), a key indicator of agricultural emission sources (Li et al., 2024; Song et al., 2023). Industrial structure adjustment (H2c) is operationalized through the ratio of crop cultivation output to animal husbandry output, reflecting structural shifts toward lower-emission activities (Liu et al., 2020).

3.3 Data sources

The empirical analysis relies on a sample of 30 Chinese provinces (excluding Tibet because of large gaps in the data) from 2011 through 2024, providing 420 province-years of data (30 provinces x 14 years). The treatment group includes Zhejiang, Guangdong, Jiangxi, Guizhou, and Xinjiang provinces, and the control group includes the other 25 provinces, with a treatment-control ratio of roughly 1:5, which provides ample power for identification. The empirical analysis relies on the following sources of data: (i) the basic data required for the computation of agricultural carbon emissions,—namely, the amounts of fertilizer, pesticide, agricultural plastic films, and diesel fuel consumption, irrigated area, and sown area—are collected from various editions of the "China Rural Statistical Yearbook" (2012-2025); (ii) macroeconomic variables including GDP, urbanization rate, and expenditure of fiscal funds are retrieved from the "China Statistical Yearbook"; (iii) the power and output of agricultural machinery separated by agricultural sub-sectors are derived from the "China Rural Statistical Yearbook"; (iv) the set of human capital variables is collected from the "China Population and Employment Statistics Yearbook"; (v) the environmental regulation variables are retrieved from the "China Environmental Statistics Yearbook"; and (vi) the number of agricultural green patents is derived from the patent search database of the National Intellectual Property Administration of the People's Republic of China by using the corresponding IPC Green Patent. Descriptive statistics for all variables are presented in Table 1.

TABLE 1 Descriptive statistics.

Variable	N	Mean	S.D.	Min	Max
Agricultural carbon emissions (10^4 tons)	420	379.811	244.285	23.870	1,003.190
Ln (GDP)	420	10.364	0.535	9.205	11.576
Agricultural output share	420	0.097	0.039	0.031	0.180
Urbanization rate	420	0.650	0.104	0.435	0.893
Fiscal agricultural expenditure share	420	0.104	0.014	0.080	0.130
Mechanization level (kW/hm^2)	420	8.622	1.490	5.689	11.856
Human capital (years)	420	8.973	0.548	7.840	10.135
Environmental regulation	420	0.018	0.004	0.010	0.025
Agricultural green patents	420	215.162	90.234	63.000	472.000
Fertilizer application intensity (kg/hm^2)	420	297.567	50.125	189.697	404.354
Crop/livestock output ratio	420	1.587	0.345	1.003	2.215

Agricultural carbon emissions are calculated using the IPCC, coefficient method based on six carbon sources: fertilizers, pesticides, agricultural plastic films, diesel, irrigation, and tillage.

TABLE 2 DML baseline regression results.

Variable	(1) Lasso-CV	(2) Elastic Net-CV	(3) Random forest
Policy	−41.239*** (8.663)	−38.964*** (8.873)	−42.331*** (9.052)
Control variables	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	420	420	420
Out-of-sample R^2	0.853	0.845	0.918

Cluster-robust standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. N = 420 (30 provinces × 14 years). Out-of-sample R^2 for first-stage nuisance estimation: Lasso-CV (0.853), Elastic Net-CV (0.845), Random Forest (0.918). Province FE, and Year FE, are included in all specifications.

As shown in Table 1, the average value of agricultural carbon emissions is 379.811 (×10^4 tons), with a minimum of 23.870 (×10^4 tons in Qinghai province) and a maximum of 1,003.190 (×10^4 tons in Henan province). The standard deviation of 244.285 (×10^4 tons) indicates large differences among provinces in agricultural carbon emissions. It should be noted that this pattern is closely related to the scope of agricultural production in each province, with large grain-producers such as Henan, Shandong, and Heilongjiang being at the top of this list. As regards control variables, the average value of the urbanization index is 65.0%, ranging from 43.5% to a maximum of 89.3%, thereby showing quick urbanization in China over the time span of this study; the average value of the human capital index is 8.973 years, showing an average educational attainment of rural workers tending towards junior high school; the average value of environmental regulation index is 1.8%, showing a moderate variety of inter-provincial disparity. As regards mechanism variables, it should be noted that average number of agricultural green patents is 215.162, with a maximum of 472.000, thereby showing vigorous innovation in the area of green agriculture patents in certain provinces; average application of fertilizer is 297.567 kg/hm^2, thereby showing large inter-provincial disparity; the average ratio of crop production to livestock production value is 1.587, thereby showing crop production value exceeding livestock production value in the sampled provinces.

4 Empirical results

4.1 Baseline regression results

Using the DML framework in Equations 1–3, three algorithms—Lasso-CV, Elastic Net-CV, and Random Forest—were employed to estimate GFRIPZ policy effects. The baseline regression results are reported in Table 2. These algorithms represent linear regularization and nonlinear approaches, with consistent results providing cross-validation for policy effect identification.

As presented in Table 2, the Policy coefficient is statistically significant at the 1% level across all three algorithms, with consistent estimates: the Lasso-CV algorithm yields a coefficient of −41.239 (standard error 8.663), the Elastic Net-CV algorithm yields −38.964 (standard error 8.873), and the Random Forest algorithm yields −42.331 (standard error 9.052). The coefficient range across algorithms is only 3.367 (coefficient of variation <9%),

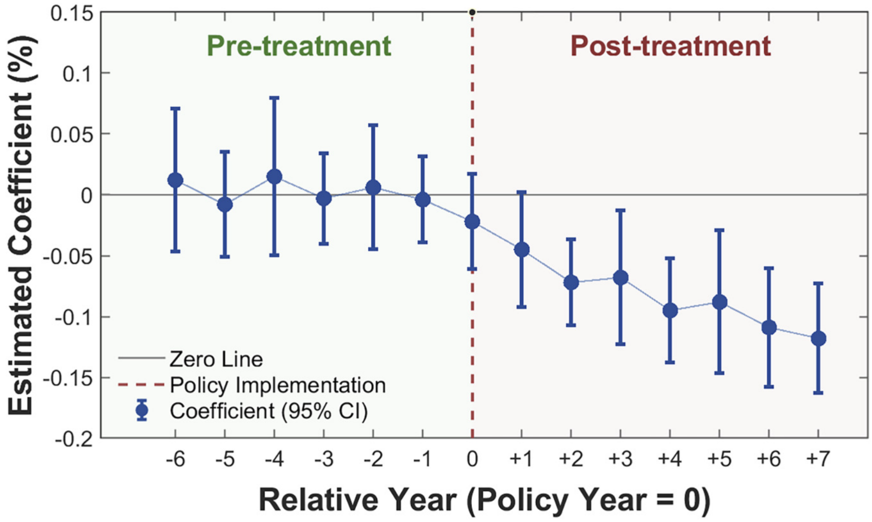

FIGURE 2
Event study estimates for parallel trend test.

indicating strong robustness to algorithm selection and ruling out dependence on specific algorithmic assumptions. The model controls for province and year fixed effects. Province fixed effects absorb time-invariant characteristics including geography, endowments, and institutions; year fixed effects control for common trends including macroeconomic cycles and nationwide policy changes, ensuring unbiased estimation.

The Policy coefficient can be interpreted in absolute and relative terms. In absolute terms, GFRIPZ policy is associated with a reduction in annual agricultural carbon emissions in pilot provinces by approximately 41.2×10^4 tons. In relative terms, against mean emissions of 379.811×10^4 tons (Table 1), this represents approximately 10.9% reduction in agricultural carbon emissions. This magnitude is consistent with findings in related studies. Deng and Zhang (2024) reported that green finance reduces agricultural carbon emissions through green technology channels using provincial data through 2021, while Yu et al. (2025) documented significant green finance effects on agricultural emissions using a traditional DID framework. For broader comparison, Ran and Zhang (2023) found green finance reduced overall regional carbon emissions by 6.2%–12.8%, and Liu et al. (2025a) reported that green finance significantly reduces carbon emission intensity through technological innovation and energy structure optimization. Our agricultural-sector estimate of 10.9% falls within these ranges, suggesting that agricultural emissions may be particularly responsive to financial incentive restructuring due to the feasibility of input substitution. Lv and Guo (2025) found GFRIPZ reduced energy consumption using a similar quasi-natural experimental design, and Tang and Zhou (2025) employed DML to evaluate GFRIPZ effects on urban carbon efficiency, confirming the methodological advantages of the DML approach adopted in this study. Notably, agricultural carbon emission reduction effects may exhibit temporal lag. Policy effects require gradual transmission through financial allocation adjustments, production method changes, and technological upgrades. The observed 10.9% reduction may represent a phased manifestation of long-term effects. These findings are consistent with Hypothesis H1, suggesting that GFRIPZ establishment is associated with significant reductions in agricultural carbon emissions in pilot provinces.

4.2 Robustness tests

Causal interpretation of baseline results depends on identification assumption satisfaction and estimation robustness. This section examines these through parallel trend tests, placebo tests, robustness tests, and method comparisons.

DID internal validity requires parallel pre-treatment trends between treatment and control groups. If violated, observed effects may reflect pre-existing differences rather than genuine policy impact. An event study is employed to test the parallel trend assumption. Each year before and after policy implementation is specified as an independent time dummy interacted with the treatment dummy to estimate period-specific effects. The results are presented in Figure 2. The horizontal axis represents event time relative to 2017; the vertical axis displays estimated effects with 95% confidence intervals. Before policy implementation (2011–2016), coefficients fluctuate around zero with confidence intervals covering zero. The trend difference between groups is merely 0.22%, not significantly different from zero, indicating consistent pre-treatment trajectories and validating the parallel trend assumption. After implementation (2017 onwards), coefficients become significantly negative with increasing absolute values, demonstrating progressively strengthening effects. This pattern aligns with expectations of lagged policy effect release—initially, effects manifest through signaling and resource allocation adjustments. As green credit expands, technologies mature, and production methods transform, carbon emission reduction effects accumulate and amplify.

Figure 2. Event study estimates for parallel trend test. Coefficients represent proportional effects relative to mean

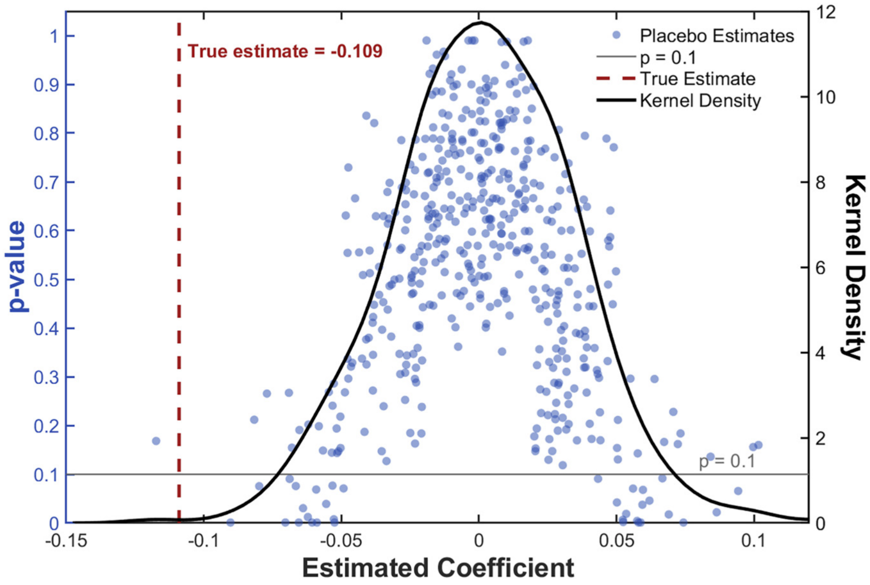

FIGURE 3
Placebo test distribution (500 iterations).

TABLE 3 Robustness tests.

Test	Policy coefficient	S.E.	N	R^2
Excluding municipalities	−43.119***	(9.375)	364	0.857
Shortened window (2014–2021)	−38.459***	(9.738)	240	0.841
Alternative DV: Carbon intensity	−0.088***	(0.025)	420	0.869
Alternative DV: Per capita emissions	−0.050**	(0.021)	420	0.848
Controlling for low-carbon city pilots	−40.225***	(8.960)	420	0.855
Controlling for ecological civilization zones	−39.914***	(9.100)	420	0.858
Traditional DID comparison	−35.965**	(10.812)	420	0.834

All robustness tests support the baseline regression conclusions. The traditional DID, coefficient is approximately 12.8% smaller than the DML, estimate. Sample sizes: baseline N = 420; excluding municipalities N = 364. Province FE, and Year FE, are included in all specifications.

agricultural carbon emissions. The vertical dashed line marks policy implementation (2017). Error bars indicate 95% confidence intervals. Pre-treatment coefficients fluctuate around zero, supporting the parallel trend assumption.

The placebo test excludes interference from random factors or unobservable confounders. If baseline effects are genuinely attributable to GFRIPZ policy, they should disappear under random treatment assignment. Five provinces were randomly selected as pseudo-treatment, and DML estimation was performed with other specifications unchanged. This procedure was iterated 500 times to obtain the pseudo-effect distribution (Figure 3). The solid line depicts the kernel density of pseudo-effects from the 500 simulations; the dashed line indicates the true estimate (−41.239). Pseudo-effects are approximately normally distributed around zero, indicating effects disappear under random assignment, consistent with placebo test expectations. The true estimate lies in the left tail beyond the 5% critical value ($p < 0.05$), demonstrating statistically significant divergence from the pseudo-effect distribution. This result suggests that baseline findings are unlikely to be driven by random factors or omitted variables, supporting the statistical reliability of estimated GFRIPZ effects.

Figure 3. Placebo test distribution (500 iterations). The solid curve shows kernel density of placebo estimates under random treatment assignment. The vertical dashed line indicates the true standardized estimate (−0.109). The true estimate falls below the 5th percentile ($p < 0.05$), rejecting the null hypothesis of random effects.

In addition to these tests, robustness tests were conducted across sample, variable, confounding policy, and method dimensions (Table 3). Sample adjustment tests examine whether results are influenced by specific samples. Excluding Beijing, Tianjin, Shanghai, and Chongqing, the coefficient is −43.119 (SE 9.375), significant at 1%, with slightly larger absolute value, indicating municipality inclusion did not overestimate effects. Shortening the window to 2014–2021 yields a coefficient of −38.459 (SE 9.738), significant at 1%, confirming insensitivity to time window selection.

Variable substitution tests examine robustness under alternative emission measures. Using carbon emission intensity (emissions/value added) as dependent variable, the coefficient is −0.088 (SE 0.025), significant at 1%, indicating GFRIPZ is associated with reductions in both absolute emissions and carbon emission intensity. Using per capita emissions (emissions/rural population), the coefficient is −0.050 (SE 0.021), significant at 5%, further supporting robust policy effects. Confounding policy controls isolate GFRIPZ effects from concurrent environmental policies. Low-carbon city pilots and ecological civilization demonstration zones may also affect agricultural emissions; failure to control for these could overestimate GFRIPZ effects. Controlling for low-carbon city pilots yields −40.225 (SE 8.960); controlling for ecological civilization zones yields −39.914 (SE 9.100). Both remain significant at 1% with coefficient changes within 5.0%, indicating GFRIPZ effects appear to operate independently of other environmental policies.

Estimation discrepancies between traditional DID and DML provide evidence for method selection and reveal specification bias impacts (Goodman-Bacon, 2021; Lechner, 2023). Traditional DID yields −35.965 (SE 10.812), significant at 5%, approximately 12.8% lower than the DML estimate (−41.239) with diminished significance. This discrepancy stems from fundamental differences in how the methods handle controls. Traditional DID presupposes linear control-outcome relationships; when true relationships are nonlinear, linear models may misattribute residual nonlinear effects to error terms, inducing downward bias. DML employs machine learning to flexibly approximate unknown functional forms, effectively isolating control influences and obtaining more precise estimates. The 12.8% underestimation by traditional methods suggests that significant nonlinear control-outcome relationships may exist in agricultural carbon emission research, making DML methodologically advantageous. In summary, robustness tests consistently support baseline conclusions. Regardless of sample, variable, confounding policy, or method choices, Hypothesis H1—that GFRIPZ is associated with reduced agricultural carbon emissions—demonstrates strong reliability.

5 Further analysis

5.1 Mechanism testing

Baseline regression results suggest GFRIPZ inhibitory effects on agricultural carbon emissions; however, transmission pathways require further identification. While Baron and Kenny's (1986) causal steps approach has been widely adopted for mediation analysis, Zhao et al. (2010) demonstrated its limitation of low statistical power. This study therefore employs a two-step mediation model with Sobel tests, which is compatible with the DML framework, to test three pathways: green technology innovation, input structure optimization, and industrial structure adjustment. The first step examines GFRIPZ impact on mechanism variables; the second tests mechanism variable impacts on emissions while controlling for policy. The Sobel test is employed to assess mediation significance, with 95% confidence intervals constructed via Bootstrap (1,000 replications). Results are presented in Table 4.

As presented in Table 4, all three pathways passed the Sobel test, providing empirical support for Hypotheses H2a, H2b, and H2c. For green technology innovation (H2a), the first-step Policy coefficient is 28.777 (SE 7.750), significant at 1%, suggesting a statistically significant positive association between GFRIPZ and green patent applications. The second-step green patent coefficient is −0.084, significant at 1%, indicating that green innovation is associated with reduced agricultural carbon emissions. The Sobel Z-statistic is 2.68 ($p < 0.01$), with mediation accounting for 15.6% of total effect. These results suggest that GFRIPZ may reduce green technology R&D financing costs, thereby potentially incentivizing emission-reduction technology investment and facilitating low-carbon technology application including precision agriculture and green plant protection.

Turning to input structure optimization (H2b), the first-step coefficient is −15.424 (SE 4.515), significant at 1%, indicating that GFRIPZ is associated with reduced fertilizer application intensity. The second-step fertilizer intensity coefficient is 0.139, significant at 1%, indicating a positive relationship between fertilizer application intensity and agricultural carbon emissions. The Sobel Z-statistic is 2.40 ($p < 0.05$), with mediation accounting for 19.8%—the largest among the three pathways. These findings suggest how green finance may optimize input structures: differentiated credit suppresses high-carbon input supply, green insurance mitigates organic alternative risks, and subsidies guide chemical input reduction.

With respect to industrial structure adjustment (H2c), the first-step coefficient is 0.201 (SE 0.082), significant at 5%, indicating that GFRIPZ is associated with an increased crop-to-livestock output ratio. The second-step coefficient for this ratio is −22.456, significant at 5%, indicating that crop-oriented structure shifts are associated with carbon emission reduction. The Sobel Z-statistic is 1.86 ($p < 0.1$), with mediation accounting for 11.8%.

The three pathways collectively explain 47.2% of total effect: input optimization (19.8%), technology innovation (15.6%), and structure adjustment (11.8%). These mechanism findings align with and extend existing literature. The dominance of input structure optimization (19.8%) is consistent with Du et al. (2023), who found that agricultural input adjustment is a primary channel for policy-induced emission reductions. The green technology innovation pathway (15.6%) corroborates Deng and Zhang (2024), who documented significant mediating effects of green technology innovation between green finance and agricultural carbon emissions, and Shan and Shao (2024), who reported that green patents reduce carbon emissions. The industrial structure adjustment pathway (11.8%) aligns with Huang et al. (2025), who found that structural shifts account for significant regional emission variations. Notably, our simultaneous quantification of three pathways (collectively 47.2%) extends prior single-mechanism analyses (Xu et al., 2024), highlighting the value of multi-pathway decomposition. The finding that input structure optimization constitutes the largest pathway carries significant policy implications: compared to long-cycle technological and industrial changes, input measures such as fertilizer reduction have shorter implementation cycles and may represent a core policy lever for agricultural carbon emission reduction.

TABLE 4 Mechanism tests.

Transmission pathway	First step	S.E.	Second step	Sobel Z	Mediation effect	Bootstrap 95% CI	N
Green technology innovation (H2a)	28.777 ***	(7.750)	−0.084 ***	2.68 ***	15.6%	[0.091, 0.235]	420
Input structure optimization (H2b)	−15.424 ***	(4.515)	0.139 ***	2.40 **	19.8%	[0.115, 0.264]	420
Industrial structure adjustment (H2c)	0.201 **	(0.082)	−22.456 **	1.86 *	11.8%	[0.026, 0.202]	420

N = 420. The three pathways collectively explain 47.2% of the total effect. Input structure optimization (fertilizer reduction) is the largest pathway (19.8%). Sobel test z-statistics: H2a ($z = 2.68$, $p < 0.01$), H2b ($z = 2.40$, $p < 0.05$), H2c ($z = 1.86$, $p < 0.10$). Bootstrap 95% confidence intervals (1,000 replications): H2a [0.091, 0.235], H2b [0.115, 0.264], H2c [0.026, 0.202]. None of the bootstrap CIs, includes zero. Province FE, and Year FE, are included.

TABLE 5 Heterogeneity analysis.

Dimension	Group 1 (N)	Coefficient	Group 2 (N)	Coefficient	Chow F	p-value
Regional	Eastern (168)	−53.956*** (9.294)	Central-western (252)	−31.372* (12.565)	4.512	0.004 ***
Grain functional zone	Major grain area (182)	−36.103** (10.355)	Non-major grain area (238)	−48.756*** (9.172)	1.923	0.126
Agricultural structure	Crop-dominated (182)	−42.458*** (9.028)	Livestock-dominated (238)	−38.825** (10.390)	0.587	0.557
Economic development	Above median (210)	−51.020*** (9.009)	Below median (210)	−33.545* (13.292)	4.105	0.008 ***

Policy effects are stronger in eastern regions and provinces with higher economic development, supporting H3a. Sample sizes: Eastern (N = 168) vs. Central/Western (N = 252); Major grain-producing (N = 182) vs. Non-major (N = 238); Crop-dominated (N = 182) vs. Livestock-dominated (N = 238); Above-median GDP (N = 210) vs. Below-median GDP (N = 210). Chow test results: Region ($F = 4.512$, $p = 0.004$***), Economic development ($F = 4.105$, $p = 0.008$***), Grain zones ($F = 1.923$, $p = 0.126$), Agricultural structure ($F = 0.587$, $p = 0.557$). Province FE, and Year FE, are included.

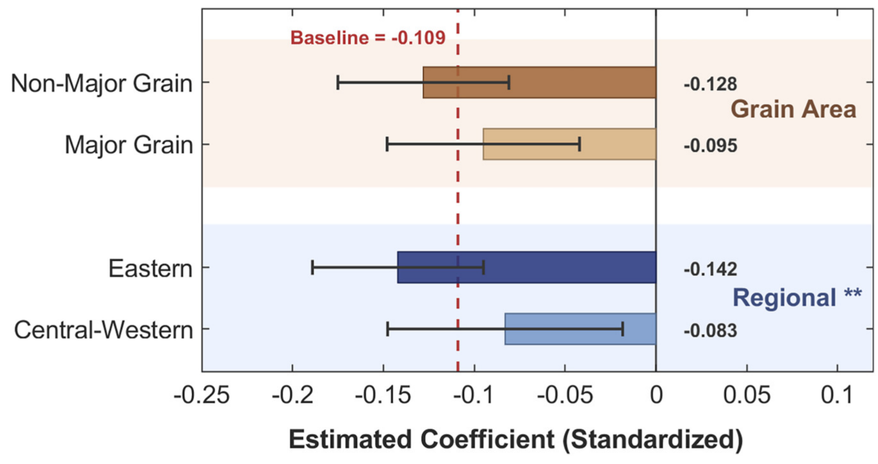

FIGURE 4
Heterogeneity analysis by region and grain functional zone.

5.2 Heterogeneity analysis

As discussed in Section 2.2, policy effects may exhibit heterogeneity due to differences in institutional capacity and structural conditions. To examine these patterns and identify GFRIPZ boundary conditions, grouped regressions were conducted across four dimensions: region, grain functional zones, agricultural structure, and economic development. Results are presented in Table 5, with cross-group comparisons illustrated in Figure 4.

Figure 4. Heterogeneity analysis by region and grain functional zone. Coefficients are standardized (proportional to sample mean). Error bars represent 95% confidence intervals. The vertical dashed line shows the baseline estimate (−0.109). Asterisks indicate statistical significance of inter-group differences: **p < 0.05, *p < 0.10.

As presented in Table 5 and Figure 4, GFRIPZ effects exhibit significant heterogeneity across dimensions. Regarding regional heterogeneity, the Policy coefficient for the eastern region is −53.956 (standard error 9.294), significant at the 1% level; the coefficient for central and western regions is −31.372 (standard error 12.565), significant only at the 10% level, and the inter-group difference passes the 5% significance test. Stronger policy effects in eastern regions may be attributed to several factors: higher financial market development, greater green product variety and coverage, stronger institutional risk management and project identification capabilities, and more accessible financing channels, potentially resulting in higher transmission efficiency. Additionally, eastern agricultural modernization leadership suggests that operators may demonstrate stronger green technology acceptance and adoption, enabling more effective policy realization.

Economic development heterogeneity exhibits a similar pattern: the Policy coefficient for provinces with per capita GDP above the median is −51.020 (standard error 9.009), significant at the 1% level; the coefficient for provinces below the median is −33.545 (standard error 13.292), significant only at the 10% level, and the inter-group difference passes the 5% significance test. This finding is consistent with a positive moderating role of financial development and economic foundation on policy effectiveness, indicating that GFRIPZ may achieve better outcomes in regions with developed financial infrastructure and higher marketization.

Regarding grain functional zone heterogeneity, the Policy coefficient for major grain-producing areas is −36.103 (standard error 10.355), significant at the 5% level; the coefficient for non-major grain-producing areas is −48.756 (standard error 9.172), significant at the 1% level, although the inter-group difference does not reach conventional significance levels ($F = 1.923$, $p = 0.126$). Stronger effects in non-major grain areas may be attributed to several factors: major grain areas have larger production scales and higher baseline input usage, potentially resulting in higher marginal carbon reduction costs; food security constraints suggest that major grain areas may face greater yield risk concerns when adjusting input structures; non-major grain areas possess more flexible structures with higher cash crop proportions and greater green premium sensitivity, potentially reducing resistance to green finance-guided production transformation.

Regarding agricultural structure heterogeneity, the Policy coefficient for provinces dominated by crop cultivation is −42.458 (standard error 9.028), significant at the 1% level; the coefficient for provinces dominated by animal husbandry is −38.825 (standard error 10.390), significant at the 5% level, and the inter-group difference is not statistically significant. The absence of significant differences between these provincial types suggests that GFRIPZ is associated with emission reductions in both crop and livestock sectors without systematic bias from structure differences.

These heterogeneity patterns are consistent with existing evidence. The stronger effects in eastern and economically developed regions corroborate He et al. (2019), who demonstrated that green credit effectiveness depends on financial market maturity, and Liu et al. (2025b), who found more pronounced green finance effects in regions with higher financial development. The weaker effects in major grain-producing areas echo Li et al. (2023), who reported that food security constraints limit emission reduction flexibility in grain-intensive regions. In summary, heterogeneity analysis reveals GFRIPZ effect boundary conditions: financial development and economic foundation appear to be key moderating factors. Eastern and developed regions should leverage first-mover advantages to deepen innovation, while central/western and less developed regions should prioritize infrastructure improvement and coverage expansion to narrow regional disparities.

6 Conclusion and policy recommendations

This paper leverages the establishment of GFRIPZ in 2017 as a quasi-natural experiment and establishes a DML framework to investigate causal effects on agricultural carbon emissions. The results show that GFRIPZ is associated with a reduction in agricultural carbon emissions in pilot provinces of about 10.9%. The effect is shown to be robust to parallel trend tests, placebo tests, alternative samples, alternative specifications of variables, and interaction tests with confounding policies. Three mediating mechanisms—input optimization (19.8%), technological innovation (15.6%), and structural adjustment (11.8%)—together explain 47.2% of the total effect, with input-side adjustments found to be the dominant mechanism. Heterogeneity analysis reveals that policy effects are significantly stronger in eastern regions and economically developed provinces, supporting H3a. Non-major grain-producing areas exhibit stronger effects than major grain-producing areas, consistent with H3b, likely reflecting greater input adjustment flexibility in the absence of food security constraints. The difference between crop-dominated and livestock-dominated provinces is not statistically significant, and H3c is not supported, suggesting that GFRIPZ operates effectively across both agricultural structures. Chow tests confirm significant inter-group differences for regional ($F = 4.512$, $p = 0.004$) and economic development ($F = 4.105$, $p = 0.008$) dimensions, while differences across grain functional zones ($F = 1.923$, $p = 0.126$) and agricultural structure ($F = 0.587$, $p = 0.557$) are not statistically significant. Compared to traditional DID estimation, DML effects are 12.8% larger in magnitude, highlighting the benefit of machine learning in addressing specification concerns.

These findings yield four policy implications. First, pilot zone coverage should expand to additional provinces, particularly in central and western regions where agricultural emissions remain substantial but policy effects are weaker. Second, given that input structure optimization is the largest transmission pathway (19.8%), green credit products should offer preferential rates for organic fertilizer substitution and precision fertilization technology. Third, the regional heterogeneity calls for differentiated design: eastern provinces should deepen green financial product innovation, while central and western provinces require foundational investments in rural financial service networks. Fourth, tailored products should address grain-producing versus non-grain-producing areas differently.

This study has several limitations that suggest directions for future research. First, provincial-level data may mask intra-provincial heterogeneity in policy implementation and agricultural practices; future research could employ prefecture- or county-level data for finer-grained analysis. Second, the sample period covers only eight post-treatment years (2017–2024), which may not fully capture long-term policy effects, including potential diminishing returns or accelerating impacts as green financial markets mature. Third, the three identified mechanisms collectively explain 47.2% of the total effect, suggesting that additional channels—such as agricultural land transfer, rural financial literacy improvement, or green supply chain development—remain to be explored. Fourth, the expansion of pilot zones to Lanzhou (2019) and Chongqing (2022) introduces treatment timing variation that this study does not exploit; future work could apply staggered DID or heterogeneous treatment effect designs to account for multi-cohort treatment structures.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: The datasets are publicly available from: (1) China Rural Statistical Yearbook (2012-2025): https://www.stats.gov.cn/; (2) China Statistical Yearbook: https://www.stats.gov.cn/; (3) China Population and Employment Statistics Yearbook: https://www.stats.gov.cn/; (4) China Environmental Statistics Yearbook: https://www.stats.gov.cn/; (5) National Intellectual Property Administration patent database: https://pss-system.cponline.cnipa.gov.cn/.

Author contributions

TL: Software, Writing – review and editing, Data curation, Conceptualization, Writing – original draft, Methodology, Visualization. WL: Supervision, Methodology, Conceptualization, Writing – review and editing, Project administration, Resources. MY: Methodology, Supervision, Conceptualization, Writing – review and editing.

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