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Cognition, adoption intensity, and environmental efficiency of the planting and breeding circular model: Evidence from Northeast China

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Abstract: Based on 1 051 survey observations from 83 villages in Northeast China and the conceptual framework of 'model cognition – whether to adopt – adoption intensity – adoption benefits', this study empirically analyses how farmers' cognition of the circular model of planting and breeding (CMPB) affects adoption decisions and adoption intensity, as well as the impact of adopting the CMPB on environmental efficiency. The results indicate that perceived economic benefits and perceived ease of use significantly increase farmers' adoption intensity. Moreover, adopting the CMPB has a significant positive effect on environmental efficiency; higher adoption intensity is associated with greater improvements in environmental efficiency. Additionally, internal circulation achieves higher environmental efficiency than external circulation. Therefore, the smallholder-based CMPB deserves greater attention. On this basis, the study suggests that farmers' adoption of the CMPB is driven by its perceived ease of use and economic benefits. At the same time, promoting and applying the CMPB in rural areas aligns with the macro-level policy objective of green agricultural development.

Keywords: combination of planting and breeding; economic benefits; environmental benefits; perceived ease of use

The transition of agricultural production from traditional extensive models to green and efficient systems represents a critical development pathway for addressing structural contradictions in agricultural supply, improving the allocation efficiency of agricultural resources, and enhancing the comparative advantages of the agricultural sector (Abbasi and Zhang 2024). Since the early 1980s, in response to increasingly severe constraints on rural resources and the environment, scholars have continuously advanced theoretical and practical research on integrating traditional agricultural advantages with modern science and technology, thereby giving rise to the development theory of circular agriculture. The circular model of planting and breeding (CMPB) is a direct result of this development process, which achieves an organic integration of planting and breeding technologies, establishing a material recycling mechanism across agricultural production sectors. Hence, it represents a green agricultural production model that integrates rural development, farmers' economic well-being, and environmental sustainability (Hassan et al. 2023). A substantial body of research has demonstrated that the CMPB provides

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significant environmental and economic benefits, effectively promoting the synergy between environmental protection and economic development (Moreira et al. 2023).

As the CMPB makes intensive use of land and improves crop yields, broadly speaking, its application in rural areas can broadly be regarded as the development of 'land-saving' agricultural techniques. Farmers' adoption of new technologies is a dynamic, multi-stage process involving stages such as cognition, adoption intensity, and adoption outcomes. Individual cognition constitutes the endogenous source of behavioural intentions and actions (Lyu et al. 2024). In the transformation of agricultural production models, the preferences and cognition perceptions of production and management actors develop symbiotically with the production model itself. However, in the long-term development of circular agriculture in China, top-down policy changes or formal regulations, such as agricultural technology promotion programmes aimed at guiding farmers toward greener production behaviour, have often ignored farmers' preferences and cognitive frameworks regarding circular agriculture. More importantly, as an integrated production model, the CMPB involves greater uncertainty in farmers' adoption decisions than other agricultural technologies. Furthermore, when farmers face uncertainty in their decision-making, individual cognition emerges as one of the critical factors influencing their choices. Therefore, to better understand farmers' decisions concerning the adoption of agricultural production models, it is crucial to investigate the role of cognition from the farmers' perspective.

Farmers' technology adoption behaviour is inherently multi-stage, and this dynamic process can be precisely modelled and analysed using panel data. However, due to the difficulty of obtaining panel data in this field, existing research on technology adoption is largely dominated by static analysis approaches. In static analyses of technology adoption, when a technology is indivisible, farmers' technology adoption behaviour can only be represented by a binary variable indicating 'adoption' or 'non-adoption'. In general, farmers opt to diversify their production activities to mitigate risks and maximise the value of land use. In the context of the CMPB, which entails substantial technological and market risks, farmers' adoption decisions encompass not only a binary choice between adoption and non-adoption but also variations in adoption intensity. Based on their endogenous knowledge of the CMPB, farmers evaluate the associated benefits and risks before making adoption decisions at two levels: whether to adopt and adoption intensity. Although the CMPB is inherently indivisible, adoption intensity can be quantified by the proportion of farmland allocated to this model or the proportion of organic fertiliser applied within agricultural practices (Mwaura et al. 2021). Therefore, when examining how farmers' perceptions influence their adoption decisions regarding the CMPB, it is necessary to distinguish two stages of decision-making: whether to adopt and adoption intensity.

Circular agriculture has garnered significant attention in both theoretical research and policy practice (Moreira et al. 2023). However, the majority of studies still focus on supporting technologies and qualitative analyses, with less research conducted from an economic perspective. Nevertheless, a substantial body of literature on farmers' technology adoption behaviour provides an important reference for analysing farmers' adoption decisions regarding the CMPB, which represents a comprehensive agricultural technology. Existing research on technology adoption mainly focus on the following aspects. The first aspect is the incentives and motivations that drive farmers' technology adoption decisions. Kong (2003) proposed that farmers' decision logic in regard to adopting new technologies involves comparing the net benefits of old and new technologies on the basis of previous research. Specifically, farmers adopt a new technology only if the expected benefits of the new technology exceed the net benefits of the existing technology. The second aspect concerns factors influencing farmers' willingness and behaviour in technology adoption, which can be categorised into macro-level policy levels and micro-level farmer characteristics. The literature focuses mainly on macro-level policy variables, such as government subsidy policies (Awotide et al. 2016), technological innovation environments (Olum et al. 2020), public agricultural extension services (Aydoğdu 2017), and market conditions (Xu et al. 2024). At the micro level, studies mainly focus on heterogeneity in farmers' resource endowments.

To some extent, existing studies have explained the internal mechanisms of technology adoption decisions and the factors influencing them. However, economic rationality serves as the primary starting point for farmers' production decisions (Githinji et al. 2023). Farmers' multi-stage technology adoption decision-making process should include their assessment of post-adoption impacts. However, most existing studies on technology adoption have not examined the outcome variables associated with adoption behaviour. Since the CMPB is a green development model capable of generating between environmental and economic benefits, the incentives for technology adoption and the environmental and these benefits are closely interconnected in farmers'

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adoption decisions (Zadgaonkar et al. 2022). In addition, in existing research, environmental efficiency takes into account not only the economic efficiency of agricultural production activities but also their resource and environmental constraints by integrating environmental variables into the framework for measuring agricultural production efficiency, thus aiming to achieve the win-win goal of agricultural production growth and environmental management. Hence, this framework is currently widely used in research conducting analyses of the synergistic environmental and economic benefits (Xu et al. 2024).

While the literature provides a wealth of relevant insights into technology adoption, certain shortcomings remain in the following areas. First, current theoretical research on the CMPB focuses mainly on technical and qualitative analysis, and lacks an economic explanation of the underlying logic behind farmers' adoption behaviour from an economic perspective, particularly the role of bounded rationality, cognitive bias, and heuristic decision-making. Second, as a systematic and integrated technology, the CMPB requires re-examining farmers' adoption decisions from the cognitive perspective, including how loss aversion, present bias, and limited information processing affect both this model and the adoption intensity. Third, most existing studies have not sufficiently examined the outcome variables of technology adoption behaviour, particularly the synergistic environmental and economic benefits resulting from adoption. Taken together, these gaps indicate that existing studies have not yet formed a coherent analytical chain linking farmers' cognition, multi-stage adoption decisions, and post-adoption environmental outcomes.

Thus, based on 1 051 points of survey data from 83 villages in Northeast China and the 'model cognition – whether to adopt – adoption intensity – adoption benefits' conceptual framework, this study empirically analyses the effect of the CMPB cognition on adoption decisions and adoption intensity. We also explore the impact of adopting the CMPB on environmental efficiency.

MATERIAL AND METHODS

Theoretical analysis

The mechanism of the impact of adopting the CMPB on environmental efficiency from an input–output perspective. First, the mechanism involves reducing pollutant and greenhouse gas emissions (undesired outputs) and mitigating non-point source pollution. From a behavioural economics perspective, farmers' bounded rationality and present bias may reinforce environmentally suboptimal practices in conventional production systems. The CMPB promotes an internal energy cycle in which planting provides feed and breeding provides fertiliser. This reciprocal structure aligns with farmers' preference for mutually beneficial exchanges, lowering psychological resistance to changing traditional practices. By improving manure utilisation, reducing chemical fertiliser use, and increasing soil organic carbon, CMPB helps mitigate environmental degradation and enhance environmental efficiency (Swastika et al. 2024).

Second, the mechanism involves reducing transaction costs, mitigating market risks, and increasing economic benefits (desired outputs). Using crop residues to feed livestock and returning manure to farmland reduces perceived effort and production costs. Product diversification through integrated crop and livestock production weakens loss aversion, reduces the risk associated with single-crop planting, and stabilises agricultural income (Sikiru et al. 2024).

Third, the mechanism involves improving resource allocation efficiency and optimising the structure of planting and breeding. Determining an appropriate production scale, structure, and spatial layout ensures manure can be fully recycled as organic fertiliser. Given bounded rationality, CMPB acts as a 'nudge' by providing clearer information and incentives, helping farmers adopt sustainable nutrient cycling instead of short-term cost-driven decisions. This supports an efficient material and energy cycle and improves resource allocation efficiency (Nehra and Jain 2023).

Mechanisms for improving environmental efficiency by optimising desired and undesired outputs. Building on the input–output mechanisms discussed above, Figure 1 shows that adopting the CMPB helps reduce pollutant and greenhouse gas emissions while increasing economic benefits, thus improving environmental efficiency. However, farmers must also decide the intensity with which they adopt the CMPB. Assuming that harmless resource inputs in planting and breeding process are denoted by a and harmful resource inputs by b. The undesired output can then be expressed as $y = f(a,b)$. For a given level of desired output, environmental efficiency can be improved by reducing either harmful or harmless resource inputs (Figure 2). The arrows in the figure indicate the direction of the unit change. Suppose the initial agricultural production is A, where the undesired output is $y_1 = f(a_1, b_1)$ when planting and breeding are separated. Given that the CMPB is a comprehensive production model and farmers face uncertainty in adoption decisions, adoption intensity may vary across farmers. When the adoption

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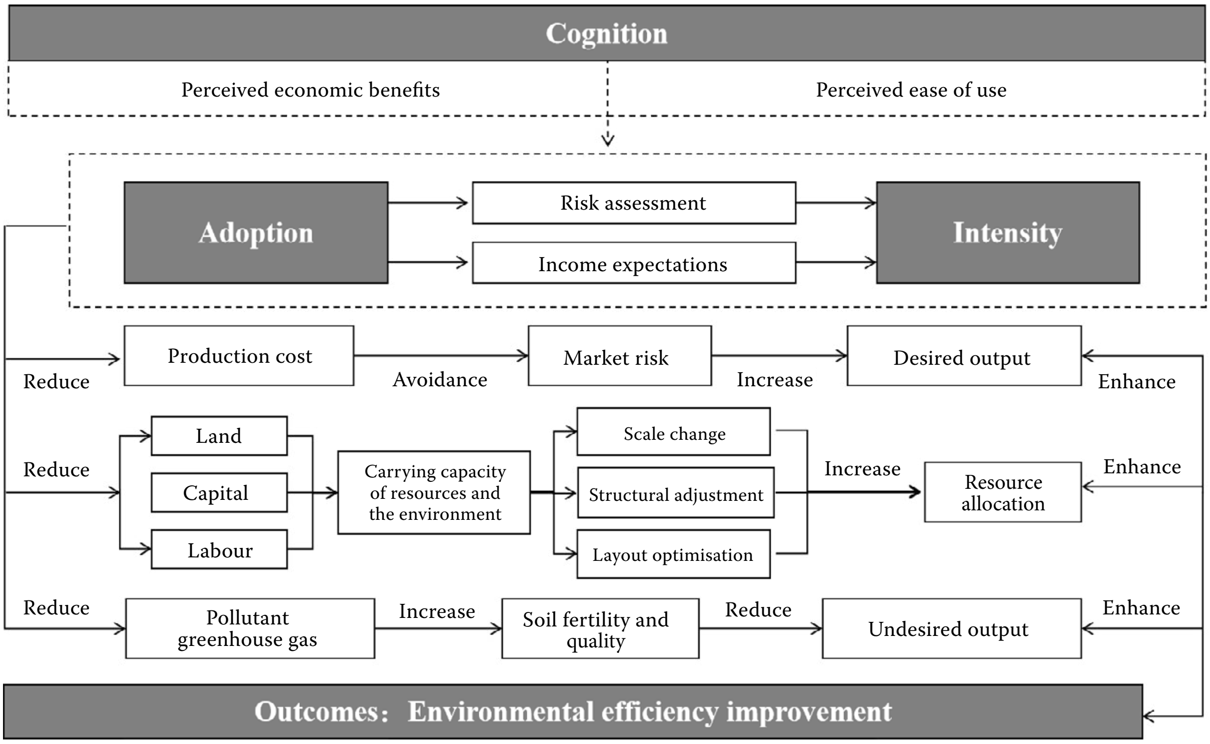

Figure 1. The mechanism of the impact of the CMPB (circular model of planting and breeding) on environmental efficiency from an input–output perspective

Source: Authors' own elaboration

intensity of the CMPB is relatively low, agricultural production efficiency is increased, and agricultural production is shifted to point *B*. With the desired output set, the input of harmful resource elements remains unchanged, but the input of harmless resource elements is reduced to a_2. As a result, the total input elements are reduced to $a_2 + b_1$, and the undesired output becomes $y_2 = f(a_2, b_1)$. Although total inputs decrease, undesired outputs

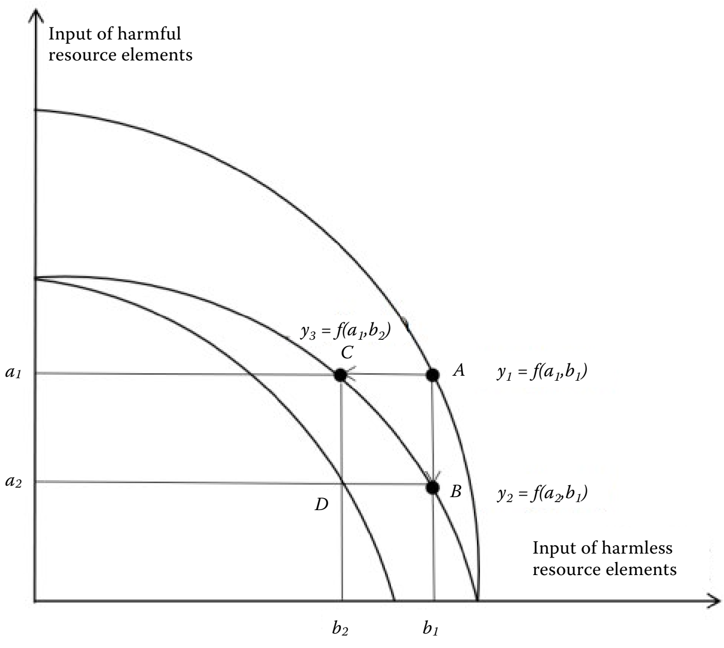

Figure 2. The laws of improving environmental efficiency by optimising desired and undesired outputs

Source: Authors' own elaboration

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do not increase, thereby improving environmental efficiency. With increasing adoption intensity, the inputs of harmful resource elements are reduced, and agricultural production shifts to point *C*. With the desired output held constant, the inputs of harmless resource elements remain unchanged, but the inputs of harmful elements are reduced to b_2, and the total and undesired outputs are reduced, leading to an improvement in environmental efficiency. When the adoption intensity of the CMPB is relatively high, both the inputs of harmless and harmful resource elements are reduced, and the two forces work together to move environmental efficiency from the initial point *A* to point *D* and to achieve a leap in environmental efficiency from a lower level to a higher level. Low levels of adoption intensity can only moderately improve environmental efficiency, whereas high levels of adoption intensity can substantially improve environmental efficiency.

Patterns of environmental-economic synergy enhancement under different types of integrated farming and breeding systems. Because environmental efficiency gains depends not only on whether the CMPB is adopted but also on how material circulation is organised, this study focuses on two types of crop-livestock recycling systems: the on-farm integrated recycling model (individual farms) and the contractual recycling model linking large-scale livestock farms with planting farmers In the integrated crop-livestock recycling model within farmland, agricultural operators can improve manure utilisation efficiency through coordinated allocation of land, capital, and labour. However, when production scale is limited, constraints in management capacity and economies of scale may restrict the full realisation of environmental-economic synergy. As production scale expands, factor allocation in planting and breeding can be optimised, and joint production helps reduce operational costs, thereby enhancing environmental-economic synergy beyond what can be achieved through specialisation in non-recycling systems. In contrast, the crop-livestock recycling model based on contractual relationships enables improvements in infrastructure, industry clustering, and access to policy, credit, and bulk procurement advantages, which can lower management costs. Nevertheless, small-scale operators often face weaker bargaining power and higher transaction costs in such arrangements while third-party services tend to be concentrated on large-scale operators, potentially limiting the benefits of external circulation for smallholders.

Model construction

Tobit model. To investigate the impact of adopting the CMPB on environmental efficiency, this study uses a Tobit regression model as the baseline framework. This model is suitable for the dependent variable, environmental efficiency, which is left-censored at 0 and right-censored at 1. The baseline regression model is specified as follows:

$$Y = \alpha_0 + \alpha_1 X_i + \alpha_i \sum control_i + \varepsilon_i \tag{1}$$

Where: Y – the environmental efficiency score, calculated using stochastic frontier analysis (SFA), which ranges between 0 and 1; X_i – whether to adopt the CMPB; α_i – the regression coefficients of the variables; $\Sigma control_i$ – the control variables; ε_i – the random disturbance term.

Heckman two-stage model. On the basis of the preceding theoretical analysis framework, the adoption decision concerning the CMPB is divided into two stages. The first stage involves farmers' decision on whether to adopt it, whereas the second stage concerns the adoption intensity, which is defined as the proportion of organic fertiliser applied. Ignoring the differences between the adoption decision and adoption intensity may lead to estimation bias. The most common method is the Heckman two-stage model. Specifically, this study employs a binary probit model to analyse whether farmers adopt the CMPB. The decision model for the first stage can be expressed as follows:

$$A_i^* = Z_i \mu + \nu_i \tag{2}$$

$$A_i = \begin{cases} 1, \; Z_i \mu + \nu_i > 0 \\ 0, \; Z_i \mu + \nu_i \le 0 \end{cases} \tag{3}$$

where: A_i^* – a latent variable representing the difference in environmental efficiency between adopting and not adopting the CMPB, explained by a set of factors Z_i; μ – the coefficients to be estimated; ν_i – the random disturbance term.

In Equation (3), when $A_i^* > 0$, farmers adopt the CMPB, i.e. $A_i^* = 1$ is observed; otherwise, farmers choose not to adopt, i.e. $A_i^* = 0$ is observed.

Considering that OLS estimation may suffer from sample selection bias, inverse Mills ratio λ calculated from Equation (2) is included as a correction parameter, alongside other explanatory variables, in the second-stage regression. The expression for the second-stage regression is as follows:

$$y_i = X_i \tau + \lambda \theta + \eta_i \tag{4}$$

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where: y_i – the dependent variable in the second-stage regression, i.e. the adoption intensity of the CMPB; θ and τ – the coefficients to be estimated.

If θ passes the significance test, it indicates the presence of selection bias. Additionally, the Heckman two-stage model requires that X_i is a strict subset of Z_i, meaning that there must be at least one variable that affects whether farmers adopt the CMPB but that has no partial effect on adoption intensity.

Propensity score matching. The adoption of CMPB depends on farmers' characteristics and their cost-benefit assessments. While influencing the adoption of CMPB, there are some unobservable factors that may affect environmental efficiency, leading to biased estimation results when using the Tobit model for regression. To address the potential selection bias caused by unobserved factors that may simultaneously affect the adoption of CMPB and environmental efficiency, this study employs propensity score matching (PSM) as a robustness test (Rosenbaum and Rubin 1983). The purpose of PSM is to match farmers who adopted the CMPB (treatment group) with those who did not (control group) based on observable characteristics, thereby constructing a balanced counterfactual framework. This process consists of two steps. First, we use the logit model to estimate the propensity score:

$$P\left(Adopt_i = \frac{1}{X_i}\right) = \tau\left(\vartheta_0 + \vartheta \sum control_i + \omega_i\right) \tag{5}$$

where: P – the probability of adopting CMPB; τ – the logistic cumulative distribution function; $\Sigma control_i$ – control variables; ω_i – the error term.

Secondly, we use methods such as 1 : 1 nearest-neighbour matching, 1 : 2 nearest-neighbour matching, 1 : 5 nearest-neighbour matching, Calliper matching and Kernel matching to match samples. Balance tests are conducted to ensure that there are no systematic differences after matching, including overall reduction in pseudo-R^2 and covariate standardised bias below 20%.

After matching, Average Treatment Effect on the Treated (*ATT*) can accurately measure the net effect of farmers' adoption of CMPB on environmental efficiency. Formally, *ATT* represents the expected impact of the adoption of CMPB on environmental efficiency:

$$ATT = E\left[Y(1) - Y(0),\, D = 1\right] \tag{6}$$

where: $Y(1)$ – the result after treatment (adoption, $D = 1$) (environmental efficiency); $Y(0)$ – the counterfactual result without treatment.

Since the $Y(0)$ of the adopter is unobservable, PSM approximates using the matched non-adopters:

$$ATT \approx \left(\frac{1}{N_t}\right) \sum \left[Y_i(1) - Y_j(0)\right] \tag{7}$$

where: N_t – the number of treatment units; i represents the treated farmers; j – the matched control group.

This provides a non-parametric estimation of causal effects, complementing the Tobit and Heckman two-stage models.

Variables

Explained variable: Environmental efficiency. Environmental efficiency is modelled by using agricultural income (desired outputs) as the output variable and land area, labour, capital input, energy consumption, and greenhouse gas emissions (undesired outputs) as input variables (Table 1), with a translog production frontier model constructed via stochastic frontier analysis (SFA):

$$\begin{aligned} \ln(income_i) = \delta_0 + \sum_{k=1}^{5} \delta_k \ln(X_{ki}) + \\ + \frac{1}{2} \sum_{k=1}^{5} \sum_{m=1}^{5} \delta_{km} \ln(X_{ki}) \ln(X_{mi}) + v_i - u_i \end{aligned} \tag{8}$$

where: $\ln(income_i)$ – the logarithm of agricultural income for the i^{th} observation; X_{ki} – the logarithm of the k^{th} input variable (including land area, labour, capital, energy consumption, and greenhouse gas emissions); v_i – the random error term; u_i – the technical efficiency loss term, indicating the extent of deviation from the production frontier.

Environmental efficiency (*EE*) is defined as the ratio of actual output to the potential maximum output:

$$EE_i = E\left[exp(-u_i) | (v_i - u_i)\right] \tag{9}$$

where: EE_i – the environmental efficiency of the i^{th} observation, ranging from 0 to 1, with 1 indicating full efficiency.

In the planting and breeding production process, greenhouse gas emissions, primarily carbon dioxide, nitrous oxide, and methane, are evaluated using life cycle assessment (LCA) (Xing et al. 2022), the specific procedure for which is outlined as follows:

In planting systems, the quantification of agricultural greenhouse gas emissions can be categorised into four types: fertiliser application, energy consumption, crop cultivation, and straw management. The crops

https://doi.org/10.17221/270/2025-AGRICECON

Table 1. Environmental efficiency indicator system

Type	Primary indicator	Secondary indicator
Input	land input	agricultural land area
	labour input	family labour force
		hired labour force
	capital input	seeds
		nitrogen fertiliser
		phosphorus fertiliser
		potassium fertiliser
		compound fertiliser
		organic fertiliser
		agricultural film
		pesticides
		small farming tool purchase cost
		machinery depreciation cost
		land lease fee
		silage feed additives
		livestock and poultry offspring
		purchased feed
		medical drugs and epidemic prevention expenses
		aquaculture water fee
Output	undesired output	total greenhouse gas emissions
	energy consumption	diesel
		production electricity
	desired output	economic benefits

Source: Authors' own elaboration

surveyed in this study include rice, wheat, maize, and soybeans, with the specific calculation process detailed in Table 2.

In breeding systems, the quantification of agricultural greenhouse gas emissions is categorised into three distinct processes: (ruminant) enteric fermentation, energy consumption, and manure management. This study selected representative livestock from Northeast China, including pigs, beef cattle, dairy cows, poultry, goats, and sheep, with the specific calculation process detailed in Table 3.

Our study employs the ReCiPe midpoint method to calculate the results of the life cycle impact assessment model for the aforementioned cropping and livestock systems. According to Equation (10), the life cycle inventory is converted into a common unit, and the converted results are aggregated.

$$M_{p,r} = \sum_{i} E_{i,p,r} \times C_i \qquad (10)$$

Core explanatory variable: The CMPB. The explanatory variable is measured by the item concerning '*whether the farmer adopts the CMPB*' in the survey questionnaire. This is a binary dummy variable, where a value of 1 is assigned if the farmer adopts the CMPB and a value of 0 is assigned otherwise.

The adoption intensity is measured by the proportion of the market value of organic fertiliser applied to the total market value of all fertilisers used, as adopted from the study by Zhao et al. (2025). This continuous variable is further categorised into three types: low, medium, and high, corresponding to value ranges of 0–0.2, 0.2–0.5, and 0.5–1, respectively.

Control variables. With reference to existing research, the following control variables are included in the analysis:

The adoption of agricultural technology can be viewed as an investment in fixed assets during the pre-production phase of agricultural production. The effects of adopting technology are determined not by the

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Table 2. Quantification of GHG emissions in the planting system

Processes and greenhouse gases	Calculation equation	Equation definition
Fertiliser application (N_2O)	$E_{Fertiliser\ application\ N_2O,r} = \frac{44}{28} \times \left[\left(\frac{D_{1r} + D_{2r}}{3} \right) \times R_{2r} + \left(\frac{D_{1r} + D_{2r}}{3} \right) \times B \times R_3^{v} + \left(\frac{D_{1r} + D_{2r}}{3} \right) \times R_{4r} \times R_3^{l\&r} \right]$	$E_{Fertilizer\ application\ N_2O,r}$ – the N_2O emissions from the fertiliser application process of farmer r; D_1 and D_2 – nitrogen fertiliser and compound fertiliser inputs, respectively, and are estimated from the regional fertiliser input per hectare of crop n and the sown area of crop n; R_2 – the direct emission coefficient of N_2O fertiliser application by each farmer; B – the proportion of NH_3 and NO_x volatilised in compound fertilisers; R_3^{v} and $R_3^{l\&r}$ – the indirect emission coefficients of N_2O caused by nitrogen deposition and nitrogen leaching and runoff, respectively; R_4 – the ratio of nitrogen leaching to runoff
Energy consumption (CO_2, N_2O, CH_4)	$E_{Energy\ consumption i,r} = D_{3r} \times R_{5i} + \sum_n E_n \times R_6$	$E_{Energy\ consumption i,r}$ – the emission of greenhouse gases i from the energy consumption process of farmer r; D_{3r} – the diesel input for agricultural machinery by farmer r; R_{5i} – the emission factor of greenhouse gas i in the production and use of fossil fuels; R_6 – the emission factor of greenhouse gas CO_2 in China's regional power grid; E_n – the electricity consumption of farmers
Crop farming (CH_4)	$E_{Crop\ planting CH_4,r} = D_{4Rice,r} \times R_{7r}$	$E_{Crop\ planting CH_4,r}$ – the CH_4 emissions from the crop cultivation process of each farmer; D_4 – the sown area of rice of each farmer; R_7 – the CH_4 emission factor for paddy fields
Straw management (N_2O, CH_4)	$E_{Straw\ reuse N_2O,r} = \sum_n \left[\begin{pmatrix} D_{5n,r} \times H_{Manure,r} + \\ D_{6n,r} \times G_{n,r} \times (1 - C_n) \end{pmatrix} \times A_n \times R_2 \right]$ $E_{Open\ burning CH_4,r} = \sum_n D_{5n,r} \times H_{Disuse,r} \times R_8$ $E_{5n,r} = D_{6n,r} \times G_{n,r} \times C_n$	$E_{Straw\ reuse N_2O,r}$ – the N_2O emissions generated by the straw reuse process of farmers; $D_{5n,r}$ – the amount of straw that can be collected by crop n, which is obtained by multiplying the grain yield $D_{6n,r}$ of crop n, the grass-to-grain ratio G_n of crop n, and the straw collection coefficient C_n of crop n; $H_{Manure,r}$ – the proportion of straw reused as fertiliser; $H_{Disuse,r}$ – the proportion of straw wasted by open burning; A_n – the nitrogen content of crop n straw; $E_{Open\ burning CH_4,r}$ – the CH_4 emissions from open burning by farmer r; R_8 – the CH_4 emission factor for open burning of straw

Source: Authors' own elaboration

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Table 3. Quantification of GHG emissions in the breeding system

Processes and greenhouse gases	Calculation formula	Formula definition
Enteric fermentation (CH_4)	$E_{Enteric\ fermentationCH_4,r} = D_{7n,r} \times R_{9n}$	$E_{Enteric\ fermentationCH_4,r}$ – the CH_4 emission of enteric fermentation from livestock in region *r*; $D_{7n,r}$ – the number of heads of livestock n of farmer *r*; R_{9n} – the CH_4 emission factor of *n* enteric fermentation in livestock
Energy consumption (CO_2, N_2O, CH_4)	$E_{Energy\ consumption\ i,r} = D_{8Electricity,r} \times R_{6i,r} + D_{8Diesel,r} \times R_{5Diesel,r}$ $D_{8n,r} = \sum_n \left(D_{7n,r} \times O_{Electricity,r} + D_{7n,r} \times O_{Coal,n} \right)$	$E_{Energy\ consumption\ i,r}$ – the emissions of greenhouse gases *i* for energy consumption by farmer *r;* $D_{8n,r}$ – the energy consumption of the production farm of region *r* livestock *n*, which is obtained by multiplying the number of heads of livestock *n* in farmer *r* ($D_{7n,r}$) and the energy consumption coefficient of the livestock production farm O_n
Stool management (N_2O, CH_4)	$E_{Stool\ managementi,r} = D_{7,n} \times R_{10,n,i}$	$E_{Stool\ managementi,r}$ – the emission of greenhouse gases *i* from the management of livestock manure by farmer *r*; $R_{10,n,i}$ – the emission factor for greenhouse gas *i* produced by the management of livestock manure in category *n*

Source: Authors' own elaboration

specific actions of farmers during the production process but by the inherent characteristics of the technology. At this stage, perceived economic benefits are the main factor considered by farmers. The difference is that the CMPB is a systematic, integrated technology with a high technical threshold; thus, the effect of its adoption largely depends on technical operations in the production process. In other words, farmers perceived ease of use of the CMPB is an important factor influencing their adoption decision (Davis, 1989). In this context, *perceived economic benefits* are assessed on a three-point scale (low = 1, medium = 2, high = 3), capturing farmers' perceptions of the economic advantages of their practices. *Perceived ease of use* is similarly measured (difficult = 1, medium = 2, easy = 3), reflecting the perceived simplicity of adopting agricultural techniques. Gender is a binary variable (male = 1, female = 0). Education is categorised into three levels (primary school = 1, junior high school = 2, high school or above = 3). *Village cadre status* is binary (yes = 1, no = 0), indicating leadership roles within the community. *Household labour* is measured as the number of household members engaged in agricultural labour. *The number of outworkers* represents the number of household members employed outside agriculture. *Skills training* is a binary variable (yes = 1, no = 0), indicating participation in agricultural production or management training. *The number of operating land parcels*

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quantifies the total land parcels managed by the household. *Participating in cooperatives* is binary (yes = 1, no = 0), reflecting membership in agricultural cooperatives. *Risk preference* is measured on a three-point scale (low = 1, medium = 2, high = 3), indicating farmers' risk tolerance. *Land transfer* is a binary variable (yes = 1, no = 0), capturing whether the household has engaged in farmland transfer. *Land transfer into household* and *land transfer out of household* are also binary (yes = 1, no = 0), indicating whether the household has acquired or transferred out land, respectively. *Household registration type* is categorised into two types: agricultural household registration is coded as 1, and non-agricultural household registration is coded as 2. *Environmental awareness* is measured on a five-point scale (1 to 5, with higher values indicating stronger agreement with the concept that 'lucid waters and lush mountains are invaluable assets').

Data sources

To investigate farmers' green agricultural production behaviour at the micro level, primary data were collected through a household survey in Liaoning Province, Northeast China, a major grain-producing region facing significant agricultural pollution challenges. From April to August 2024, the research team randomly selected farmers from 83 villages across 34 towns in 15 counties. The survey region focuses on two core agricultural zones of Liaoning Province: (*i*) the central grain-producing area (including Haicheng City, Liaozhong District, Xinmin City etc.), characterised by concentrated contiguous farmland, large-scale planting, and strong foundations for crop-livestock recycling – where Shenbei New District, Tai'an County, and Changtu County are provincial pilot counties for green crop-livestock recycling; (*ii*) the eastern ecologically sensitive area (including Fengcheng City and Kuandian County), which is dominated by hilly and mountainous terrain and where crop-livestock recycling practices began relatively early. The sample area covers a variety of 'plain-hill-mountain' landforms, including large farms and smallholders, as well as households engaged in integrated crop-livestock farming and those not engaged in such practices. This diversified sampling framework helps ensure representativeness and mitigates concerns regarding sample selection bias despite not covering all areas of Northeast China.

The survey, which focused on farmers' activities in 2023, was conducted through face-to-face interviews encompassing 48 questionnaire items across four main categories: household demographic characteristics, inputs in crop and livestock production, outputs from crop and livestock activities, and policy-related variables. After excluding samples with substantial missing data or unreliable responses, a total of 1 051 valid questionnaires were retained for analysis. All econometric analyses, including the Tobit regression, Heckman two-stage model, Propensity Score Matching (PSM), and Stochastic Frontier Analysis (SFA) for environmental efficiency, were conducted using Stata version 18.0 (StataCorp LLC, USA). The descriptive statistics of the data are shown in Table 4.

RESULTS

Analysis of the cognition of and adoption decisions concerning the CMPB

This study first explored the impact of the CMPB cognition on adoption decisions and adoption intensity. The results are presented in Table 5, which shows that λ in the Heckman two-stage model is significant at the 5% level. This result indicates that the problem of sample selection bias, implying a correlation between farmers' adoption decisions and adoption intensity and confirming the necessity of applying the Heckman two-stage model. Additionally, the Wald test is significant at the 1% level, indicating that the overall regression coefficients are significant.

According to Table 5, the perceived economic benefits pass the significance test at the 1% and 5% levels, indicating that the perceived economic benefits positively affected both the decision to adopt and the adoption intensity of the CMPB. That is, when farmers believe that the CMPB will produce greater economic benefits, their adoption intensity will also be greater. This finding aligns with the production reality in Northeast China, where high input costs for feed, fertilisers, and labour make farmers particularly sensitive to technologies that can reduce costs or increase revenue. Under such conditions, farmers tend to prioritise economic returns, and technologies like the CMPB – capable of improving resource efficiency and lowering production expenditures – naturally receive stronger behavioural responses.

Perceived ease of use is also significantly positive at the 1% and 10% levels, suggesting that adoption intensity increases only when farmers perceive the CMPB to be easier to grasp or simpler to implement. In Northeast China, where many small and medium-sized farmers have limited access to technical training and face constraints in labour allocation, technologies perceived as complex or time-consuming are

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Table 4. Data descriptive statistics (n = 1 051)

Variable category	Variables	Mean	Standard deviation	Min	Max
Explained variable	*environmental efficiency*	0.989 3	0.042 6	0.650 1	1
Core explanatory variable	*adoption intensity of the CMPB*	0.333 3	0.326 9	0	1
	adopting the CMPB	0.384 3	0.486 6	0	1
Attitudinal variables	*perceived economic benefits*	2.615 6	0.704 2	1	3
	perceived ease of use	2.249 2	0.793 2	1	3
	risk preference	1.783 0	0.876 4	1	3
	environmental awareness	4.959 0	0.288 2	1	5
Demographic variables	*gender*	0.713 6	0.452 2	0	1
	education	1.887 7	0.663 8	1	3
	village cadre status	0.152 2	0.359 4	0	1
	household labour	2.624 1	1.100 0	0	8
	number of outworkers	0.539 4	0.780 1	0	4
	household registration type	1.038 0	0.191 4	1	2
	skills training	0.530 9	0.499 2	0	1
	number of operating land parcels	7.775 4	11.287 4	0	110
	participating in cooperatives	0.267 3	0.442 7	0	1
Institutional variables	*land transfer*	0.507 1	0.500 1	0	1
	land transfer into household	0.445 2	0.497 2	0	1
	land transfer out of household	0.080 8	0.272 7	0	1
Endogenous variable	*neighbouring CMPB adoption*	0.652 7	0.476 3	0	1

CMPB – circular model of planting and breeding
Source: Authors' own elaboration

less likely to be adopted intensively. Overall, farmers' decisions to adopt the CMPB are based on economic rationality.

The impact of adopting the CMPB on environmental efficiency

Multicollinearity diagnostics. To rule out serious multicollinearity among explanatory variables, we report the variance inflation factors (*VIF*) in Table 6. All *VIF* values are below 1.28 (mean *VIF* = 1.16), far below the conventional threshold of 10 (or the more stringent threshold of 5), indicating that multicollinearity does not pose a threat to the stability of our estimates.

Baseline regression results. The results of the impact of CMPB adoption on environmental efficiency are shown in Table 7. The core explanatory variable, that is, adopting the CMPB, is significant at the 1% level under different model settings, showing strong stability. This result means that adopting the CMPB significantly improves environmental efficiency. This conclusion validates the theoretical hypothesis presented earlier in this study. Adopting the CMPB has a clear positive impact on environmental efficiency, and this effect is consistent with the mechanisms expected from the model. Specifically, the CMPB enhances the internal cycling of livestock manure and crop residues, reduces the reliance on chemical fertilisers, and mitigates pollutant and greenhouse gas emissions – an effect particularly important in Northeast China, where large-scale grain production generates substantial agricultural waste.

Endogeneity discussions. The relationships between *the CMPB* and *environmental efficiency* and between *adoption intensity* and *environmental efficiency* may face endogeneity problems, mainly due to reverse causality or omitted variable bias, which leads to biased estimates in the baseline regression. To address this problem, we use an instrumental variable (IV) approach with the Tobit model (IV-Tobit) to account for the censored nature of environmental efficiency, which ranges between 0 and 1.

The instrumental variable, *number of surrounding adoptions of the CMPB*, is chosen based on its exogeneity and relevance. With respect to exogeneity, this variable captures the local prevalence and adoption intensity of the CMPB, which is unlikely to directly affect

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Table 5. The results of the cognition of and adoption decisions concerning the CMPB

	(1) First stage of the Heckman model adoption decisions (n = 1 051)	(2) Second stage of the Heckman model adoption intensity (n = 404)
Perceived economic benefits	0.191 2*** (3.173 4)	0.249 7** (2.167 0)
Perceived ease of use	0.321 5*** (5.960 5)	0.365 2* (1.905 9)
Gender	0.151 6* (1.666 4)	0.192 6** (2.091 8)
Education	−0.027 8 (−0.408 5)	−0.024 4 (−0.766 6)
Village cadre status	0.034 7 (0.285 9)	0.086 7* (1.662 8)
Household labour	0.122 9*** (3.026 6)	0.129 0* (1.779 9)
Number of outworkers	−0.061 0 (−1.049 5)	−0.060 7 (−1.397 8)
Skills training	0.178 6** (2.001 0)	0.252 3** (2.281 1)
Number of operating land parcels	−0.008 5* (−1.918 9)	−0.019 5*** (−3.355 2)
Participating in cooperatives	−0.322 3*** (−3.291 3)	−0.445 4** (−2.235 4)
Risk preference	0.120 6** (2.474 2)	0.170 1** (2.267 9)
Land transfer	−0.445 2* (−1.653 4)	−0.770 6*** (−2.794 3)
Land transfer into household	0.539 4** (2.060 0)	0.802 1** (2.429 4)
Land transfer out of household	0.056 8 (0.234 9)	0.173 9** (2.040 0)
Household registration type	−0.900 5*** (−3.111 3)	−1.208 3** (−1.992 3)
Environmental awareness	0.004 5 (0.024 4)	0.090 8** (2.512 0)
λ	1.943 2** (2.210 5)	
_cons	−1.171 8 (−1.090 7)	−2.689 3** (−1.975 4)
Wald value	114.57***	

*, ** and ***significance at 10%, 5% and 1% levels, respectively; CMPB – circular model of planting and breeding
Source: Authors' own elaboration

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Table 6. Variance inflation factors (*VIF*)

	(1) *VIF*	(2) 1/*VIF*
Adopting the CMPB	1.10	0.91
Perceived economic benefits	1.11	0.89
Perceived ease of use	1.06	0.94
Gender	1.01	0.99
Education	1.20	0.84
Village cadre status	1.18	0.85
Household labour	1.28	0.78
Number of outworkers	1.24	0.80
Skills training	1.18	0.84
Number of operating land parcels	1.12	0.90
Participating in cooperatives	1.15	0.87
Risk preference	1.10	0.91
Land transfer	1.17	0.85
Household registration type	1.22	0.82
Environmental awareness	1.23	0.81
Mean VIF	1.16	

Source: Authors' own elaboration

an individual farmer's environmental efficiency and therefore satisfies the exclusion restriction. For relevance, the adoption behaviour of neighbouring farmers is expected to influence an individual farmer's decision to adopt the circular model and the intensity of adoption through peer effects and knowledge diffusion, ensuring a strong correlation with the endogenous variable (Meng et al. 2023).

To test for weak instruments, we conduct a two-stage least squares (2SLS) regression, as the IV-Tobit model does not allow for first-stage weak instrument tests. The *F* statistic from the first stage of the 2SLS regression is 17.328 1 (Panel A) and 13.048 6 (Panel B), exceeding the threshold of 10 and confirming that the instrument is sufficiently strong. The IV-Tobit model is implemented in two stages. In the first stage [Equation (11)], adopting the CMPB is regressed on the instrumental variable and control variables and the adoption intensity is used for the instrumental variable and control variable. The instrumental variable has a positive and significant coefficient at the 1% level, confirming its validity. In the second stage [Equation (12)], environmental efficiency is regressed on the predicted adoption decision, as well as the adoption intensity predicted from the first stage, along with the control variables. The results align with the baseline regression, with significantly positive coefficients at the 1%

Table 7. Baseline regression results

	(1) Model 1	(2) Model 2
Adopting the CMPB	0.017 3*** (6.514 9)	0.013 9*** (5.515 1)
Control variables	no	yes
_cons	0.982 7*** (597.661 5)	0.800 6*** (31.117 6)
n	1 051	1 051

***significance at 1% level; CMPB – circular model of planting and breeding

Source: Authors' own elaboration

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Table 8. Endogeneity test results

Panel A: Adopting the CMPB IV-Tobit		
Variables	Stage1 (Y: Adopting the CMPB)	Stage2 (Y: Environmental efficiency)
Number of surrounding adoptions of the CMPB	0.1284*** (4.1969)	
Adopting the CMPB		1.0616*** (8.5026)
Control variables	yes	yes
_cons	0.080 8 (0.327 5)	0.639 7*** (4.637 3)
n	1 051	1 051
Panel B: Adoption intensity IV-Tobit		
Variables	Stage1 (Y: Adoption intensity)	Stage2 (Y: Environmental efficiency)
Number of surrounding adoptions of the CMPB	0.078 7*** (3.641 9)	
Adoption Intensity		0.612 7*** (3.280 6)
Control variables	yes	yes
_cons	0.580 4** (2.425 1)	0.376 7* (1.865 3)
n	1 051	1 051

*, ** and ***significance at 10%, 5% and 1% levels, respectively; CMPB – circular model of planting and breeding
Source: Authors' own elaboration

level in Table 8, indicating that the CMPB and the adoption intensity improve environmental efficiency. These findings suggest robustness to endogeneity concerns.

$$\hat{X} = \beta_0 + \beta_1 IV + \beta_i \sum control_i + \varepsilon_i \quad (11)$$

$$Y = \gamma_0 + \gamma_1 \hat{X} + \gamma_i \sum control_i + \varepsilon_i \quad (12)$$

Robustness tests.

PSM analysis. To correct for potential selection bias, we apply propensity score matching (PSM) as detailed in Table 9. Based on the logit model and various matching methods (1 : 1, 1 : 2, 1 : 5 nearest-neighbour matching, as well as caliper and kernel matching), we control for observable characteristics. Balance tests confirm the matching quality: post-matching, the pseudo-R^2 decreases substantially, and covariate standardised biases are below 20% (Table 9), indicating no systematic differences between treatment and control groups. As shown in Table 9, regardless of the matching method, there is no systematic difference between the treatment and control samples after matching, indicating that the choice of matching variables and matching methods in this study is reasonable.

Table 10 reports the estimation results obtained from the five matching methods. Consistent with the baseline regression results, CMPB adoption has a significant positive effect on environmental efficiency, resulting in an increase of 1.428%. This result further suggests that the CMPB can achieve an environmental and economic synergy.

Other robustness tests. To further confirm the reliability of the baseline results, we conduct seven additional robustness tests along two dimensions. Firstly, the continuous adoption intensity variable (proportion of organic fertiliser) was used to replace the binary CMPB adoption dummy value, to fully utilise the varying degrees of integration within the planting and breeding industry and reduce measurement error of the binary index. Second, we progressively control for unobserved heterogeneity by successively adding prefectural, county-level, and village-level fixed effects. These controls capture location-specific natural conditions, policy implementation intensity, infrastructure,

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Table 9. Balance test for sample matching results

Matching Methods	Pseudo R^2	LR chi^2	$P > chi^2$	Deviation/%
Before matching	0.080	112.28	0.000	14.4
1 : 1 Proximity matching	0.020	22.17	0.103	7.3
1 : 2 Proximity matching	0.007	7.41	0.964	3.4
1 : 5 Proximity matching	0.002	2.46	1.000	2.1
Calliper matching	0.018	19.47	0.193	6.7
Kernel matching	0.001	1.07	1.000	1.3

Source: Authors' own elaboration

and village-level collective norms that are difficult to measure directly. In Table 11 (1) The CMPB adoption dummy variable is replaced with the adoption intensity variable; In Table 11 (2–4) Add prefecture-, county-, and village-level fixed effects to the baseline model; In Table 11 (5–7) After replacing the core explanatory variable with adoption intensity, prefecture-, county- and village-level fixed effects are introduced successively. The results are shown in Table 11, confirming the high robustness of our core findings.

Heterogeneity analysis.

Heterogeneity of the business entity type. This study divides farmers into two categories, new-type agricultural business entities and ordinary farmers, according to the type of business entity. These two types of farmers are very different in terms of their capital, technical equipment, capacity, policy, etc. Consequently, their adoption costs, expected benefits and risk judgements also differ. The main criterion for identifying new-type agricultural business entities is whether the household operates as a large professional household or a family farm. Households that operate as either large professional households or family farms are classified as new-type agricultural business entities in this study. Table 12 reports the business entity type heterogeneity results. Adopting the CMPB has a significant positive effect on both the new-type agricultural business entities and ordinary farmers, but the effect is more pronounced for ordinary farmers, which deviates from the expected results. This result may be because, compared with ordinary farmers', new-type agricultural business entities have a higher level of production, technology, and business management. Additionally, at this time, even if new technologies are adopted, the marginal returns to additional technological inputs are lower, and therefore, the impact on environmental efficiency is less than that for ordinary farmers'.

Heterogeneity of the part-time employment level. In the literature, farmers with a share of non-agricultural income of more than 50% are usually classified into the high part-time employment group, and those with a share of less than 50% are classified into the low part-time employment group. This study follows this approach in classifying the farmer sample. Table 13 reports the part-time employment level heterogeneity results. Adopting the CMPB has a significant positive effect on the low part-time employment group, but the effect on the high part-time employment group is not significant. This result is mainly because the

Table 10. Average treatment effect (ATT) results

Methods	ATT	Standard error	T Value	△（%）
1 : 1 Proximity matching	0.014 1	0.004 0	3.57***	1.43
1 : 2 Proximity matching	0.011 3	0.004 7	2.41**	1.15
1 : 5 Proximity matching	0.009 0	0.003 3	2.73***	0.91
Calliper matching	0.017 9	0.005 6	3.19***	1.81
Kernel matching	0.019 1	0.004 5	4.22***	1.94
Mean	0.014 28	–	–	1.448

*, ** and ***significance at 10%, 5% and 1% levels, respectively
Source: Authors' own elaboration

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Table 11. Robustness test results

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Adoption intensity	0.008 4** (2.251 8)				0.006 4* (1.696 7)	0.006 7* (1.741 0)	0.008 2** (2.083 0)
Adopting the CMPB		0.012 7*** (4.947 4)	0.012 7*** (4.864 3)	0.014 0*** (5.036 5)			
Control variables	yes	yes	yes	yes	yes	yes	yes
_cons	0.797 0*** (30.504 8)	0.800 6*** (31.213 5)	0.830 5*** (30.052 3)	0.799 5*** (27.699 9)	0.798 4*** (30.702 5)	0.827 6*** (29.653 6)	0.798 8*** (27.394 5)
City dummy variables	no	yes	no	no	yes	no	no
County dummy variables	no	no	yes	no	no	yes	no
Village dummy variables	no	no	no	yes	no	no	yes
n	1 051	1 051	1 051	1 051	1 051	1 051	1 051

*, ** and ***significance at 10%, 5% and 1% levels, respectively; CMPB – circular model of planting and breeding
Source: Authors' own elaboration

household income of the high part-time group comes mainly from non-agricultural employment; accordingly, those in this group invest less in agricultural production and management and are less interested in and willing to adopt new technologies.

Heterogeneity of the circulation type. The CMPB can achieve an energy cycle between farming and breeding, and this energy cycle can be achieved within either farmers or farms; it can also be achieved through contractual relationships between large-scale farms or breeding enterprises and farmers. This study classifies the sample farmers into internal, external and no circulation groups. Among them, the integrated farming and planting model within farmland is considered an internal cycle, while the farming cycle achieved through contractual relationships between large-scale livestock farms and planting households is considered an external cycle. Table 14 shows the circulation type heterogeneity results. Adopting the CMPB has a significant positive effect on both the internal circulation and external circulation groups but has a greater effect on the internal circulation group than on the external circulation group. This result is mainly because the external circulation is mostly formed between the farm or farming enterprise and the farmer through a linkage of interests, which is relatively loose. However, internal

Table 12. Business entity type heterogeneity results

	(1) New-type agricultural business entities	(2) Ordinary farmers
Adopting the CMPB	0.011 7*** (3.760 5)	0.016 5*** (4.132 8)
Control variables	yes	yes
_cons	0.703 8*** (10.077 9)	0.827 9*** (24.696 1)
n	453	598

***significance at 1% level; CMPB – circular model of planting and breeding
Source: Authors' own elaboration

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Table 13. Part-time employment level heterogeneity results

	(1)	(2)
	High part-time employment group	Low part-time employment group
Adopting the CMPB	0.014 5 (1.530 8)	0.015 2*** (5.654 6)
Control variables	yes	yes
_cons	0.901 1*** (5.753 1)	0.804 1*** (30.274 9)
n	215	836

***significance at 1% level; CMPB – circular model of planting and breeding

Source: Authors' own elaboration

circulation can be rationally planned according to the scale of farmers to determine the optimal scale and structure of planting and breeding.

Heterogeneity of adoption intensity. Finally, we focus on the impact of different adoption intensities on environmental efficiency. Table 15 reports the adoption intensity heterogeneity results. Adopting the CMPB has a positive impact on environmental efficiency at all adoption intensities, but contrary to expectations, the impact is most pronounced for high-intensity adoption, followed by low-intensity adoption and finally medium-intensity adoption. This non-linear pattern can be explained by the specific production conditions and technical constraints faced by smallholder farmers in Northeast China. At the low-intensity stage, farmers usually apply only easily accessible manure to nearby plots, which immediately reduces chemical fertiliser use and yields rapid efficiency gains with minimal additional cost or technical difficulty. In contrast, at the medium-intensity stage, most smallholders face a technical bottleneck: limited manure drying and composting capacity, high transport costs, and fragmented land make it difficult to ensure stable manure quality and effective large-scale application, resulting in diminishing marginal returns. Only at the high-intensity stage do farmers adopt technologies such as solid-liquid separation, aerobic composting, or precision application equipment, thereby achieving a second leap in environmental efficiency. This explains the significantly higher gains observed in the high-intensity group.

DISCUSSION

Synergistic environmental and economic development can be achieved by reintegrating farming activities within the agricultural system, reconstructing the combination of planting and breeding, and digesting livestock manure through the internal cycle of the planting and breeding system (Zhao et al. 2025). Our micro-level findings further indicate that such internal cycle generates measurable improvements in environmental efficiency, primarily by substituting chemical fertiliser with organic manure. This aligns with the broader consensus in recent literature. For instance,

Table 14. Circulation type heterogeneity results

	(1)	(2)	(3)
	External circulation	Internal circulation	No circulation
Adopting the CMPB	0.011 5** (2.352 3)	0.014 1*** (4.837 2)	0.018 8 (0.884 3)
Control variables	yes	yes	yes
_cons	0.751 0*** (12.536 8)	0.817 0*** (28.992 3)	0.966 7*** (22.120 6)
n	243	691	117

** and ***significance at 5% and 1% levels, respectively; CMPB – circular model of planting and breeding

Source: Authors' own elaboration

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Table 15. Adoption intensity heterogeneity results

	(1) High intensity	(2) Medium intensity	(3) Low intensity
Adopting the CMPB	0.022 9*** (3.868 9)	0.008 5** (2.479 3)	0.014 2*** (2.774 0)
Control variables	yes	yes	yes
_cons	0.862 6*** (18.629 3)	0.620 2*** (13.583 2)	0.852 7*** (19.263 2)
n	270	261	520

** and ***significance at 5% and 1% levels, respectively; CMPB – circular model of planting and breeding
Source: Authors' own elaboration

Moojen et al. (2024) emphasised that rebuilding crop-livestock integration is critical for the circular economy transition, while Moreira et al. (2023) provided empirical evidence from tropical environments that circular agriculture significantly reduces nitrogen fertiliser use without compromising yields. Our study corroborates these macro-level and regional studies from a micro-farmer perspective, confirming that the internal cycle mode achieves superior environmental-economic synergy compared to external cycle.

Looking at the current situation in China, smallholder farmers will continue to form the foundation of Chinese agriculture in the long term, making smallholder-based CMPB adoption particularly important. Our results show that CMPB adoption significantly improves environmental efficiency a conclusion supported by Xing et al. (2022). However, small-scale farmers rely on natural compost with limited technical support, resulting in poor quality and low fertiliser efficiency. This kind of challenge is not unique to Northeast China. Swastika et al. (2024) also pointed out that due to the intensity of labour and the lack of technical standardisation, post-green revolution practices in Indonesia are facing limitations. Therefore, merely relying on the will to act is not enough. Peng et al. (2025) hold that land transfer and scale expansion are the keys to the adoption of green technologies. Consistent with this, we suggest that institutional support should focus on fostering new business entities and socialised services. These mechanisms can bridge the gap between scattered small-scale farmers and modern, efficient circular technologies.

The core of the CMPB is to determine the structure and scale of planting and breeding in relation to the carrying capacity of resources and the environment. Our results show that the environmental efficiency gains stem mainly from manure recycling and reduced chemical fertiliser inputs, mechanisms that also determine the absorptive limits of arable land at the regional scale. As the scale of the breeding industry continues to expand, the quantity, volume and concentration of livestock manure are increasing, increasing the cost and difficulty of manure treatment, transfer and disposal. Similarly, Zhao et al. (2025) predict that by 2050, the livestock industry in most areas of Northeast China will exceed it carrying capacity. Combining these viewpoints with our research findings, we believe that enhancing environmental efficiency is not merely a technical issue of adoption, but rather a spatial planning problem. Based on the absorption capacity of farmland, determine the upper limit of breeding, rationally plan the regional layout, and ensure that the CMPB practice at the micro level operates within the sustainable macro ecological boundary.

CONCLUSION

This study follows the conceptual framework of 'model cognition – whether to adopt – adoption intensity – adoption benefits'. Based on this framework, we construct an integrated analytical chain that links farmers' cognitive perceptions, sequential adoption decisions, and measurable environmental outcomes, using 1 051 points of survey data from micro research in 83 villages, 34 towns and 15 counties in China, the effect of the cognition of the CMPB on adoption decisions and adoption intensity is empirically analysed using the Heckman two-stage model, and the impact of adopting the CMPB on environmental efficiency is further analysed in conjunction with the Tobit regression model.

In conclusion, perceived economic benefits are the fundamental driver of adoption behaviour and the increase in adoption intensity among farmers, while perceived ease of use is an important factor influencing the occurrence of adoption behaviour and the increase in adoption intensity in the CMPB. Adopting the CMPB

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has a significant positive effect on environmental efficiency, resulting in an increase of 1.448%. A comparison with the benchmark of similar studies on circular agriculture in China reveals that the efficiency of agricultural circular economy has increased by approximately 2.5% within four years (from 0.882 in 2017 to 0.904 in 2020) (Guo et al. 2023). Our finding of 1.362% represents a moderate but statistically significant enhancement, especially for small-scale farmers, where incremental income accumulates over time and with increasing scale. Crucially, this can be translated into meaningful environmental benefits. Although it is not transformative in itself, a 1.362% increase in environmental efficiency per hectare, when widely adopted, can make a significant contribution to China's green agriculture goals and be in line with the national goal of achieving carbon neutrality by 2060. Moreover, a higher adoption intensity (Table 15) amplifies this impact, indicating that policy support may have a greater effect. Additionally internal circulation achieves higher environmental efficiency than does external circulation. Thus, the smallholder-based CMPB deserves more attention.

Therefore, this study has several policies implications, including implementing spatial control of 'land-based farming', setting the upper limit of breeding according to the absorption capacity of farmland, and rationally planning the regional structure and spatial layout of planting and breeding. The government should strengthen extension services and information dissemination to raise farmers' awareness and enhance their motivation. In addition, it should provide resources such as introductions to new technologies, application cases and training videos and increase the efficiency and coverage of technology promotion. The government should vigorously cultivate specialised social service bodies and actively guide the participation of leading enterprises, cooperatives, social service organisations and other new types of main bodies to form a benefit-sharing mechanism for multi-party supply.

Although the research findings are already quite robust, there may still be aspects that require further study due to data availability. On one hand, there is a limitation in terms of data longitudinally. Since this study uses survey data from 2023 as cross-sectional data, it may not capture dynamic changes. Future research will continue to survey data from 2024 and beyond, using longitudinal panel data to address this issue. On the other hand, there is a limitation in terms of data coverage. While the sample can effectively reflect the situation in the black soil region of Northeast China, it is still uncertain whether it applies to southern regions of China with different agricultural structures. We plan to expand our scope in subsequent surveys.

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