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Eco-efficiency and its determinants of major grain-producing areas in China

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Accurately measuring the eco-efficiency of grain production and exploring pathways for its improvements are essential for promoting green agricultural transformation and achieving China's "dual carbon" goals. This study assesses the eco-efficiency of grain production in China by incorporating carbon emissions and agricultural non-point source pollution as non-desired outputs, utilizing the SBM-Undesirable model and micro-level survey data from 1,208 farm households in major grain-producing regions. The results suggest that the average eco-efficiency score across these regions is 0.627, marginally above the acceptable threshold and 0.219 points higher than traditional production efficiency, providing empirical support for the Porter hypothesis. Mechanism analysis identifies that eco-efficiency is positively associated with household head's age, family income, grain-sown area, land quality, and membership in agricultural organizations. In contrast, it is negatively associated with family size, land fragmentation, cropping index, agricultural subsidies, agricultural production outsourcing, and investment in fixed productive assets. Regional heterogeneity analysis confirms the robustness of these findings, showing only minor variations across provinces. Overall, the study offers critical insights into the determinants of eco-efficiency in grain production and proposes actionable strategies to enhance sustainability across China's agricultural sector.

KEYWORDS

food security, farmer behavior, SBM-Undesirable model, carbon emissions, agricultural non-point source pollution

Highlights

- This study measured the eco-efficiency of major grain-producing areas in China.
- The study analyzed the determinants of eco-efficiency.
- Agricultural non-point source pollution and carbon emissions are considered non-desired outputs.
- This study focuses on the micro-foundations of enhancing eco-efficiency.
- Determinants of eco-efficiency are largely stable and slightly different in different provinces.
- Strong support is provided to ensure food security.

1 Introduction

Food security has long been a strategic priority for China, a country with a large population and relatively underdeveloped agricultural conditions. As the Chinese proverb warns, “Without agriculture, there will be instability; without food, there will be chaos”. The issue extends beyond national boundaries, with profound implications for global security and social stability (Zhang Q. et al., 2021). However, China’s extensive agricultural production model—characterized by high input, high output, and high waste—has led to serious ecological consequences, including land degradation and environmental pollution (Li et al., 2022). Consequently, grain production in China now faces dual constraints of environmental sustainability and resource scarcity, making the challenge of ensuring food security increasingly acute (Mumtaz et al., 2021). Against this backdrop, traditional economic theory attributes economic growth primarily to two drivers: increased inputs—such as labor, land and capital—and improvements in production efficiency that enable higher output to be produced from the same level of inputs. However, such framework often neglects the environmental and resource constraints that inherently accompany economic growth (Xie and Teo, 2022). As economic and societal development continues to advance, the conflict between economic growth and environmental sustainability has become more pronounced (Adejumo, 2020; Jie et al., 2023). In response, scholars have called for the integration of ecological considerations into agricultural development frameworks (Adisa et al., 2024). In particular, the concept of eco-efficiency in grain production—defined as the coordination among resource conservation, environmental protection, and economic performance—has emerged as a focal point in recent research (Czyewski et al., 2021; Wang et al., 2022).

Agricultural eco-efficiency is a key measure of sustainable agricultural development. It guides the balance between ecological conservation and economic growth and underpins modern ecological agriculture (Wu et al., 2023). Developed countries, including the United States, the United Kingdom, and Japan, have already integrated eco-efficiency into their agricultural practices (Fuhrmann-Aoyagi et al., 2024; Grassauer et al., 2021; Puertas et al., 2022; Suh, 2018). By contrast, its implementation in China remains relatively limited and uneven across regions. Studies indicate that China’s agricultural green total factor productivity (AGTFP) is constrained by economic-policy suppression and human capital-economic suppression (Lu et al., 2025), as well as environmental and resource-related factors such as extreme weather events (Song et al., 2022), greenhouse gas emissions including methane and nitrous oxide (Wang et al., 2025), and the natural endowment of arable land (Liu et al., 2020). These factors further exacerbate regional disparities in agricultural eco-efficiency.

In terms of spatial distribution, Wang et al. (2025) find that higher nitrous oxide (N₂O) emissions in southeastern China lead to a clear spatial pattern of agricultural eco-efficiency, with higher efficiency in the northwest and lower efficiency in the southeast. This shows significant regional differences. Specifically, in major grain-producing areas, major grain-purchasing areas, and balanced grain production and consumption areas, agricultural eco-efficiency is underestimated by 7.83%, 8.23%, and 16.75%, respectively, revealing spatial biases in assessment. Liao et al. (2021) identify energy input,

water resource input, and carbon emissions as the core drivers of these spatial differences. Additionally, water resource input, pesticide input, and labor input are key factors affecting eco-efficiency across eastern, central, and western regions. Recognizing this gap, recent studies have focused on measuring agricultural eco-efficiency and examining its evolution and driving forces. These assessments typically consider three components: inputs, desirable outputs, and undesirable outputs. While inputs and desired outputs are relatively well-defined, incorporating undesirable outputs—such as agricultural non-point source pollution (e.g., nitrogen and phosphorus runoff, pesticide use, COD) and carbon emissions—presents methodological challenges (Zhuang et al., 2021).

With mounting pressure on land and environmental resources, China’s grain supply-demand balance has become increasingly fragile (Zhan, 2022). Relying on material inputs to boost yield is no longer a sustainable strategy (Zhou et al., 2020). Furthermore, global uncertainties—such as long-term structural shifts and the COVID-19 pandemic—have underscored the risks associated with reliance on international food markets (FAO, 2020). In response to worsening environmental degradation, China has implemented stringent land protection measures, commonly known as “long teeth” regulations (Liao et al., 2021). While these policies aim to preserve ecological integrity, they have also led to higher production costs and reduced agricultural competitiveness (Zhong, 2016). In the short term, a tension appears to exist between achieving food security and promoting the growth of a green agricultural economy (Li et al., 2011). However, in the long run, enhancing eco-efficiency is increasing recognized as a strategic pathway toward sustainable agriculture (Malan et al., 2022).

Given this context, accurately assessing agricultural eco-efficiency has become essential for informing policy decisions and balancing productivity with sustainability goals. In recent years, the Data Envelopment Analysis (DEA) model has been widely employed, particularly the Slacks-Based Measure (SBM) model introduced by Tone (2004), which effectively accounts for input and output slacks. The SBM-Undesirable model, as a cutting-edge improvement framework for data envelopment analysis (DEA), effectively addresses the limitations of traditional models through three core theoretical assumptions. First, the non-radial treatment assumption breaks through the constraints of traditional DEA radial optimization, allowing input and output variables to be adjusted in a non-proportional manner, which is more in line with the gradual and differentiated reality of factor adjustments in agricultural production; Secondly, the assumption of endogenous slack variables directly incorporates slack issues such as excess inputs and insufficient outputs into the objective function, accurately identifying the specific sources of inefficient resource allocation (Zhan et al., 2023); Finally, the assumption of weak disposability of non-expected outputs combines environmental negative outputs such as soil compaction and carbon emissions with expected outputs in a joint model. The construction of an environmental technology set embodies the fundamental ecological-economic trade-off, where pollution reduction necessitates partial sacrifice of economic output (Huang and Yao, 2022). In the context of research on green transformation in agriculture, the advantages of applying this model are reflected in its triple compatibility: It can analyze the non-linear relationship between factors such as land and

labor and output, quantify ecological compensation standards through environmental shadow prices, and calculate specific optimization paths based on slack variables. This integrated analytical framework of “diagnosis-pricing-optimization” not only distinguishes between technological inefficiency and managerial inefficiency but also provides a differentiated policy basis for technological innovation and institutional adjustment, thereby systematically promoting the coordinated development of agricultural productivity improvement and environmental sustainability (Ma and Mu, 2024). As a result, the SBM-Undesirable model has become the mainstream method for assessing agricultural ecological efficiency (Akbar et al., 2021; Wang and Liu, 2024). Empirical evidence suggests that excluding environmental costs can lead to substantial overestimation of production efficiency (Pang et al., 2016). Although China’s agricultural eco-efficiency has shown a gradual upward trend, considerable regional disparities persist (Wu et al., 2023; Wang and Liu, 2024). Specifically, major grain-producing areas tend to exhibit higher eco-efficiency compared to other regions, though intra-regional variation remains notable (Wang S. et al., 2020). Moreover, the literature is divided on the direction of these trends—while some studies report improvements, others identify stagnation or decline (Xu et al., 2021; Aslam et al., 2021).

Regarding the determinants of eco-efficiency, existing research has examined macro-level factors including R&D investment, technological progress, and resource allocation efficiency (Li et al., 2024; Wang et al., 2020); meso-level influences including industrial structure, urbanization, policy environment, and agricultural mechanization (Lu et al., 2020; Chen et al., 2022); and micro-level factors including human capital, agricultural production behavior, and social capital (Nurul, 2019; Minviel et al., 2022; Wang H. et al., 2024). Nevertheless, two critical gaps remain. First, few studies integrate both carbon emissions and non-point pollution within a unified analytical framework. Second, most existing work often overlooks the micro-foundations of eco-efficiency, particularly the role of farmers’ perceptions.

To address these gaps, this study draws on survey data from 1,208 farm households in China’s major grain-producing areas to quantify both types of environmental pollutants. These undesirable outputs are incorporated into the SBM-Undesirable model to evaluate eco-efficiency and examine its key determinants. The findings aim to offer policy-relevant insights for promoting the sustainable development of China’s grain sector.

2 Materials and methods

2.1 Overview of the research area

During the reform of China’s grain distribution system, the government designated three major functional zones—major grain-producing areas, major grain-purchasing areas, and balanced grain production and consumption areas—based on provincial differences in grain production and consumption patterns, historical grain cultivation traditions, and regional variations in resource endowments across 31 provinces.

Since the founding of the People’s Republic of China, the spatial distribution of grain production has undergone significant

changes. Initially, 12 of the 14 southern provinces were net grain exporters, with annual transfers exceeding 20 million tons. Even by the time of the reform and opening up, 7 southern provinces continued to export surplus grain. However, since then, the southern region has accelerated its industrialization and urbanization. Traditional grain-producing provinces, including Guangdong, Fujian, Zhejiang, and Jiangsu, began to prioritize economic development over agriculture. As a result, leading to a shift in grain cultivation patterns characterized by a “decline in the south and stability in the north”.

Grain production is a sector that relies heavily on land scale. Although southern China enjoys high land productivity, its *per capita* arable land is limited. Against this backdrop, many southern farmers transitioned into non-agricultural sectors or began cultivating high-value economic crops, leading to a continuous decline in grain-planting areas. At the same time, with improvements of agricultural technologies and mechanization, the comprehensive agricultural production capacity in northern China increased significantly. Consequently, the center of gravity for national grain growth has gradually shifted from south to north.

In the 21st century, China implemented a reform of its grain circulation system. Based on the overall characteristics of grain production and consumption across provinces, as well as differences in resource endowments and historical grain production traditions, the central government officially categorized the 31 provinces (including autonomous regions and municipalities) into the three aforementioned functional zones. This classification aimed to better coordinate national grain supply by aligning production, distribution, and consumption patterns with regional characteristics.

Among these regions, the major grain-producing areas are characterized by favorable natural conditions—including geography, soil quality and climate—that are well-suited for grain cultivation. These areas have high grain yields and a large proportion of land devoted to grain crops. In addition to achieving self-sufficiency, they are also capable of supplying substantial amount of commercial grain to other regions. Provinces in this category include Heilongjiang, Jilin, Liaoning, Inner Mongolia, Hebei, Henan, Shandong, Jiangsu, Anhui, Jiangxi, Hubei, Hunan and Sichuan. The major grain-purchasing areas, by contrast, are economically more developed but face land constraints and high population density, resulting in a significant gap between grain supply and demand. These areas include Beijing, Tianjin, Shanghai, Zhejiang, Fujian, Guangdong and Hainan. Balanced grain production and consumption areas contribute relatively less to national grain output but are generally able to achieve self-sufficiency. This group includes Shanxi, Ningxia, Qinghai, Gansu, Tibet, Yunnan, Guizhou, Chongqing, Guangxi, Shaanxi and Xinjiang. The government has designated the major grain-producing areas as a cornerstone of national food security. These areas not only reflect China’s overall grain production capacity but also serve as representative zones for assessing agricultural eco-efficiency and exploring its key determinants.

The major grain-producing areas constitute a vital foundation for ensuring China’s food security. The eco-efficiency of grain production in these areas plays a pivotal role in shaping both national food security and the prospects for green agricultural development. The data for this study were collected from a micro-level farm household survey conducted in October 2021 across three major grain-producing provinces of

Heilongjiang, Henan, and Hunan. A multi-stage sampling method was employed, with the procedure outlined as follows:

In the first stage, three provinces were selected from among the 13 designated major grain-producing provinces in China¹. The selection was based on a typical sampling method², considering characteristics of geographic location, level of economic development, crop type, and maturity system. As a result, Heilongjiang, Henan and Hunan were chosen to represent three distinct geographic zones: the middle reaches of the Yellow River Basin and the middle reaches of the Yangtze River. These provinces also encompass China's three major crop types—maize, wheat and rice—as well as three cropping systems: single-season, double-season and triple-season cultivation.

In the second stage, based on the clustering characteristics of six indicators, namely, resident population, GDP *per capita*, cultivated land area, the share of cultivated land area in municipal land area, the share of agricultural resident population in municipal resident population, and the share of agricultural output value in municipal GDP, and in combination with the sown area and yield level of major crops, three sample municipalities were taken in each sample province respectively using typical sampling method³.

In the third stage, based on geographic location and production of major grain crops, a typical sampling method⁴ was used to select

two national-level grain-producing counties (districts) that are not geographically adjacent to each sample city.

In the fourth stage, two sample townships (townships) were selected in each sample county (district) using a typical sampling method⁵ according to the economic development status.

In the fifth stage, a random sampling method was used to select two sample villages in each sample township (town).

In the sixth stage, using the random sampling method⁶, 16 to 18 sample farm households were selected in each sample village respectively.

The study employed a structured survey approach comprising two types of questionnaires. The village questionnaire systematically collected data on the village's basic socio-economic characteristics, topography and geomorphology, crop cultivation structure, the extent of agricultural production outsourcing, the main providers of outsourcing services, pricing across different production stages, and the proportion of outsourcing purchases. The farm household questionnaire comprises five core modules: (1) Individual and household characteristics, including age, education level, health status, and farming or off-farm employment experience. (2) Land resource endowment and land transfer status, such as farmland management practices, land transfers, soil quality, and cultivation types. (3) Grain production inputs and outsourcing behavior, covering production methods, input costs, outsourcing activities, and yields across different production stages. (4) Awareness and decision-making related to green technology, including farmers' knowledge of, willingness to adopt, and actual use of green inputs and production technologies, as well as their awareness of, willingness to purchase, and types of agricultural production outsourcing services and (5) Asset allocation and risk management, including livestock and poultry breeding,⁷ participation in agricultural organizations, ownership of

1 The division of China's major grain-producing areas originated with the 2001 reform of the grain circulation system. On the basis of the overall characteristics of grain production and consumption in each province, and taking into account such factors as differences in resource endowments and historical traditions of grain production, the State divides China's 31 provinces (autonomous regions and municipalities) into three functional areas: the major grain-producing area, the area of balanced production and marketing, and the main marketing area. There are 13 provinces in the major grain production area, including Heilongjiang, Jilin, Liaoning, Inner Mongolia, Hebei, Henan, Shandong, Jiangsu, Anhui, Jiangxi, Hubei, Hunan and Sichuan; 11 provinces in the production and marketing balance area, including Shanxi, Ningxia, Qinghai, Gansu, Tibet, Yunnan, Guizhou, Chongqing, Guangxi, Shaanxi and Xinjiang; and 7 provinces in the main marketing area, including Beijing, Tianjin, Shanghai, Zhejiang, Fujian, Guangdong and Hainan. There are 7 provinces in the main sales area, including Beijing, Tianjin, Shanghai, Zhejiang, Fujian, Guangdong and Hainan.

2 At this stage, typical sampling was used, and the selection of sample provinces was based on the researchers' judgment and specific objectives. This may not fully represent all internal differences among the 13 major producing provinces, and there is a risk of incomplete sampling frame coverage or subjective selection bias, which limits the strict generalisability of the results to all major producing provinces.

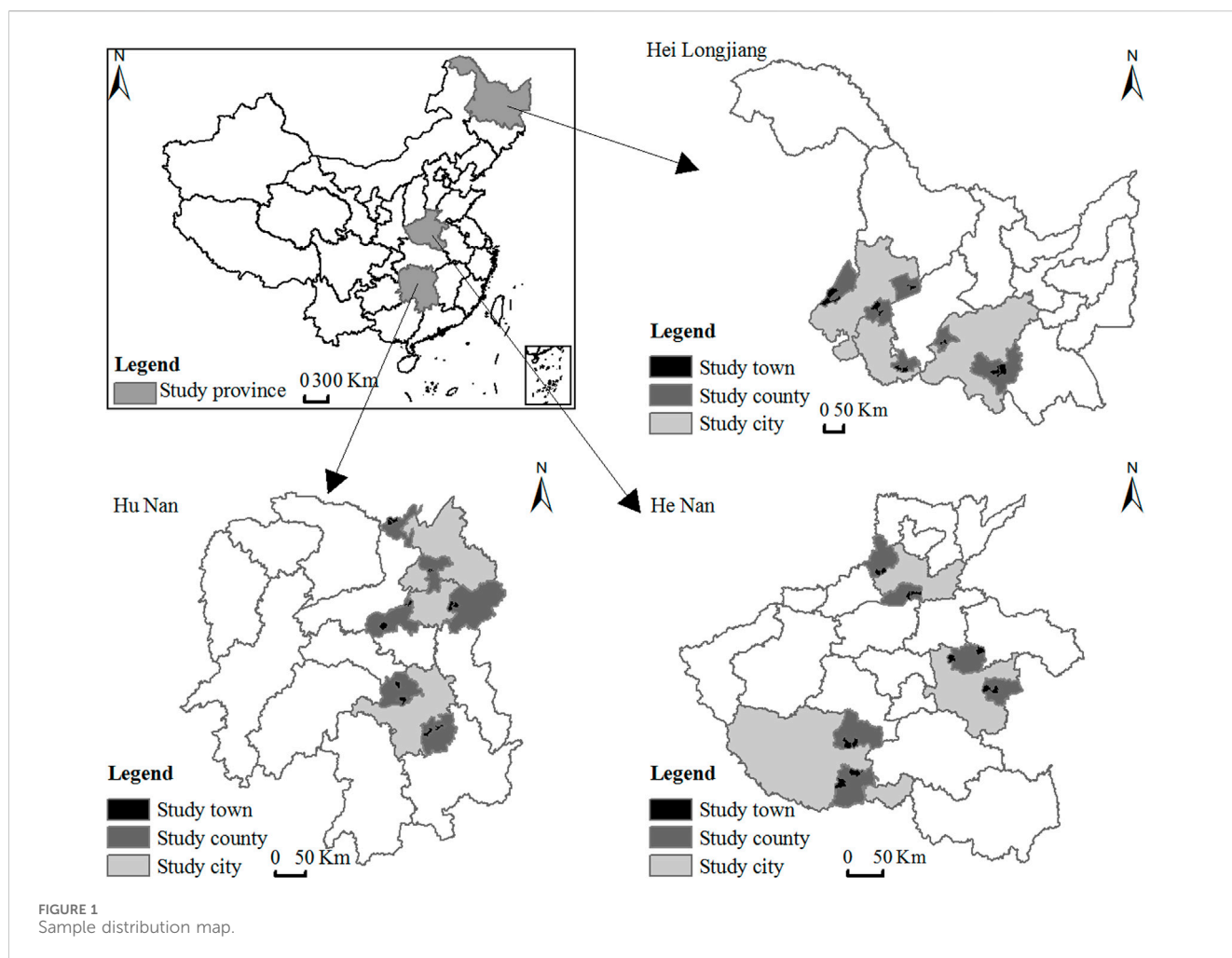
3 The subjectivity of typical sampling at this stage may lead to bias in the representativeness of the selected cities, failing to cover all types of areas within the province.

4 This stage focuses on national-level grain-producing counties, which may overlook non-national-level but important grain-producing counties or counties of different types, resulting in an overrepresentation of "typical" large counties and an underrepresentation of other types of counties.

5 Typical sampling based on economic conditions may make the sample townships representative in terms of economic development, but it may overlook the diversity of other important characteristics (such as terrain and subtle differences in crop structure).

6 The last two stages used random sampling to improve representativeness within villages and households, but their representativeness was strictly limited to the sample townships and sample villages selected in the previous stages. In multistage sampling, potential biases in the upper stages (especially the typical sampling stage) can be transmitted and affect the representativeness of the final sample. Terminal random sampling cannot correct for systematic biases introduced by non-probability sampling in the upper stages.

7 It should be emphasized that, the multi-stage sampling framework (province→municipality→county→township) employed purposive selection of typical grain-producing regions as defined by provincial agricultural authorities. The representativeness of the final sample mainly reflects the "typical" situation in the "typical" grain-producing cities, counties, and townships in Heilongjiang, Henan, and Hunan provinces as defined by the researchers. Any inferences should be cautiously limited to this scope. There are certain limitations to strictly generalizing the results to non-typical areas within the three provinces or other major grain-producing provinces nationwide.



household machinery, household income and expenditure, agricultural insurance coverage and claims, risk preferences, and social capital. Data were collected through standardized face-to-face interviews, resulting in 1,242 completed questionnaires. After excluding inconsistent responses and samples with missing key variables, 1,208 valid responses were retained, yielding an effective sample rate of 97.26%. Of the valid samples, 416 were from Heilongjiang, 393 were from Henan, and 399 were from Hunan. Figure 1 shows the sample distribution.

The sample areas encompass three distinct geographical regions: the northeast, the middle reaches of the Yangtze River, and the middle reaches of the Yellow River basin. These areas include three major crop types: maize, wheat, and rice, and feature three crop maturity systems: single-season, double-season, and triple-season. This diversity provides strong regional representation. The survey collected data on farm households, agricultural production, regional meteorological conditions, disasters, and the cognitive attitudes of farmers in 2020. The data include gender, age, education level, household labor endowment, cultivation types, plot characteristics, agricultural labor, capital inputs, agricultural outputs, meteorological disaster types, frequency and intensity of disasters, and agricultural knowledge reserves. These data provide a rich empirical foundation for analyzing the eco-efficiency of China's major grain-producing regions.

The basic characteristics of the sample farm households are presented in Table 1. More than 70% of household heads were aged 50 or older, nearly 80% had an education level of junior high school or below, and over 70% had 3 to 6 members. The household types were divided according to the ratio of farm income to the total income⁸. Among the farm households, pure farm households and part-time non-farm households were more prevalent, each accounting for over 30% of the total sample. This is followed by part-time farm households and non-farm households, accounting for 23.59% and 6.87%, respectively. The definition of farm size used in this study follows that of the Food and Agriculture Organization (FAO), which classifies farms of less than 2 ha as small-scale. Consequently, small-scale farms dominated the sample, accounting for 66.31%. Only

⁸ The classification is defined as follows: pure farm households derive more than 95% of their total income from agriculture; part-time farm households derive greater than 50% but less than or equal to 95% from agriculture; part-time non-farm households derive greater than 5% but less than or equal to 50% from agriculture; and non-farm households derive less than or equal to 5% from agriculture.

TABLE 1 Basic characteristics of the sample farmers.

Variables	Categories	N	P (%)	Variables	Categories	N	P (%)
Age (years)	[26,35]	24	1.99	Household type	Pure farm household	425	35.18
	[35,50]	263	21.77		Part-time farm household	285	23.59
	[50,65]	609	50.41		Part-time non-farm household	415	34.35
	[65,88]	312	25.83		Non-farm household	83	6.87
Education (years)	[0,6]	451	37.33	Scale of grain cultivation	Small-scale farms	801	66.31
	[7,9]	515	42.63		Large-scale farms	407	33.69
	[10,12]	205	16.97	Agricultural organization membership	Yes	278	23.01
	[13,16]	37	3.06		No	930	76.99
Family size (persons)	[1,2]	239	19.78	Number of production fixed assets (pcs)	0	243	20.12
	[3,4]	408	33.77		[1,2]	549	45.45
	[5,6]	439	36.34		[3,5]	295	24.42
	[7,11]	122	10.10		[6,93]	121	10.02

23.01% of the sample farmers were members of agricultural organizations, and nearly 90% of farm households owned fewer than six productive fixed assets. At present, the basic characteristics of the sample farm households align with the general conditions of China's major grain-producing areas in China, which makes the sample highly representative.

2.2 Methods

2.2.1 Measurement model of eco-efficiency

Referring to Tone (2001), Chen et al. (2022), and Wu et al. (2023), a non-radial, non-angle SBM-Undesirable eco-efficiency evaluation model was constructed as follows:

Supposing that there are n decision units in the agricultural production system, each with four vectors, that is, input vector, desirable output vector, non-point source pollution vector, and carbon emission vector denoted as $x \in R^m$, $y^a \in R^{S_1}$, $y^b \in R^{S_2}$, $y^c \in R^{S_3}$, respectively. The matrices X , Y^a , Y^b , Y^c are defined as follows.

$$\begin{aligned}
 X &= [x_1, x_2, \dots, x_n] \in R^{m \times n} > 0 \\
 Y^a &= [y_1^a, y_2^a, \dots, y_n^a] \in R^{S_1 \times n} > 0 \\
 Y^b &= [y_1^b, y_2^b, \dots, y_n^b] \in R^{S_2 \times n} > 0 \\
 Y^c &= [y_1^c, y_2^c, \dots, y_n^c] \in R^{S_3 \times n} > 0
 \end{aligned}$$

The finite set of production possibilities P is.

$$P|(x_0, y_0) = \left\{ \left(x, \bar{y}^a, \bar{y}^b, \bar{y}^c \right) \left| \begin{aligned} &\bar{x} \geq \sum_{j=1}^n \lambda_j x_j, \bar{y}^a \leq \sum_{j=1}^n \lambda_j y_j^a, \\ &\bar{y}^b \leq \sum_{j=1}^n \lambda_j y_j^b, \bar{y}^c \leq \sum_{j=1}^n \lambda_j y_j^c, \bar{y}^a \geq 0, \lambda \geq 0 \end{aligned} \right. \right\}$$

P in the above equation excludes the decision unit (x_0, y_0) , which effectively circumvents the possible simultaneous validity of multiple decision units in the SBM model with undesirable outputs.

Considering undesirable outputs (variable returns to scale, VRS), the fractional planning form of the SBM model is:

$$\begin{aligned}
 P^* &= \min \frac{1 - \frac{1}{m} \sum_{k=1}^m \frac{\bar{x}_k}{x_k}}{1 + \frac{1}{s_1 + s_2 + s_3} \left(\sum_{r=1}^{s_1} \bar{y}_r^a / y_0^a + \sum_{i=1}^{s_2} \bar{y}_i^b / y_0^b + \sum_{\mu=1}^{s_3} \bar{y}_\mu^c / y_0^c \right)} \\
 s.t. \bar{x} &\geq \sum_{j=1, \neq 0}^n \lambda_j x_j, \bar{y}^a \leq \sum_{j=1, \neq 0}^n \lambda_j y_j^a, \bar{y}^b \geq \sum_{j=1, \neq 0}^n \lambda_j y_j^b, \bar{y}^c \geq \sum_{j=1, \neq 0}^n \lambda_j y_j^c, \\
 \bar{x} &\geq x_0, \bar{y}^a \leq y_0^a, \bar{y}^b \geq y_0^b, \bar{y}^c \geq y_0^c, \sum_{j=1, \neq 0}^n \lambda_j = 1, \bar{y}^a \geq 0, \\
 \bar{y}^b &\geq 0, \bar{y}^c \geq 0, \lambda \geq 0
 \end{aligned}$$

where P^* is the target efficiency value, x , y^a , y^b , and y^c are the input vector, desirable output vector, non-point source pollution vector, and carbon emission vector, respectively. \bar{x}_k , \bar{y}_r^a , \bar{y}_i^b , and \bar{y}_μ^c are the input slack, desirable output slack, non-point source pollution slack, and carbon emission slack, respectively. λ is the weight vector. The subscript "0" indicates the evaluated decision unit. P is strictly monotonically decreasing to \bar{x}_k , \bar{y}_r^a , \bar{y}_i^b , \bar{y}_μ^c , and satisfies $0 \leq P \leq 1$. If the constraint on the sum of the weight variables $\sum_{j=1, \neq 0}^n \lambda_j = 1$ is removed, it is a directional distance function under constant returns to scale (CRS).

2.2.2 Analytical model of the determinants of eco-efficiency

Eco-efficiency is a variable with non-negative truncation characteristics of 0–1. For the estimation of such constrained dependent variables, the OLS method tends to yield biased estimation outcomes. The Tobit model is used for estimation as follows.

$$AEE_n = \beta_0 + \sum_q \beta_q X_{qn} + \varepsilon_n$$

AEE_n denotes the eco-efficiency of the n farmer, X_{qn} denotes the vector of determinants affecting the eco-efficiency of the n farmer, β_q

denotes the estimated coefficient for determinants, and ε_n is the random error term.

2.3 Variable selection

2.3.1 Measurement variables of eco-efficiency

2.3.1.1 Input variables

Following Lin et al. (2018) and Huan and Hou (2021), input variables in this study comprise three categories: labor input, capital input and land input. Among them, labor input is measured as total workdays (unit: workday) devoted to grain production by farm households in 2020. This aggregates all labor time across grain production stages. Capital input refers to the total monetary investment (unit: 10,000 yuan) farm households allocated to grain production in 2020, primarily comprising the sum of expenses on chemical fertilizers, pesticides, agricultural film, seeds, diesel fuel, electricity, hired labor, purchased machinery services, and depreciation of self-owned agricultural machinery⁹ etc. Land input is represented by the total sown area (unit: hectare) of grain crops cultivated by farm households in 2020, disregarding subsequent increases or decreases in harvested area due to natural or anthropogenic factors.

2.3.1.2 Desirable output variable

To address aggregation biases arising from heterogeneous crop types and varieties, following Zeng, L et al. (2020), desirable output is represented by the gross grain production value (unit: 10,000 yuan) of farm households in 2020.

2.3.1.3 Undesirable output variables

Undesirable outputs, as defined by Di Maria and Sisani (2019) and Zhuang et al. (2021), primarily denote various environmental pollution emissions from agricultural production, manifested in two primary forms: total agricultural non-point source pollution unit: 10,000 m³, dominated by losses of total phosphorus (TP), total nitrogen (TN), and chemical oxygen demand (COD) in water bodies; and total agricultural carbon emissions (unit: tonne), characterized by greenhouse gas (GHG) emissions from agricultural

production. Primary pollutants and sources in grain production systems are illustrated in Figure 2. The specific calculation process and results of undesirable outputs are presented in Part IV.

2.3.2 Determining variables of eco-efficiency

Based on relevant studies (Weerasekara et al., 2022; Ma and Li, 2021; Liu et al., 2018; Czyżewski, B et al., 2021; Tenaye, 2020), it is evident that eco-efficiency is co-determined by many factors, including regional natural environmental endowments, economic development level, farming practices, policy interventions, and farm household characteristics. Therefore, this study systematically examines determinants of eco-efficiency in China's major grain-producing areas from four perspectives: household head attributes, family characteristics, agricultural production features, and regional traits. To identify enhancement pathways and diagnose inefficiency sources at the micro-level, key variables include household head's age, household head's education, household head's health, family income, family size, non-farm employment, social capital, land quality, land fragmentation, grain-sown area, cropping index, agricultural subsidies, agricultural production outsourcing level, productive fixed assets, membership in agricultural organizations, agricultural technical training, meteorological disasters, residence-county distance, and provincial characteristics. Variable definitions and descriptive statistics are presented in Table 2.

3 Eco-efficiency measurement

3.1 Calculation of agricultural non-point source pollution emissions

Agricultural non-point source pollution emissions are calculated using the unit survey evaluation method (Lai et al., 2004). This method decomposes various pollution sources into pollution-producing elementary units (EUs) and quantifies emissions by establishing a relationship between the units, pollution generation, and pollution emissions. The calculation formula for each pollution unit is as follows:

$$E = \sum_i EU_i \rho_i (1 - \eta_i) C_i$$

In this model, E represents agricultural non-point source pollution emissions, and III denotes the indicator statistics of the unit UUU . α is the pollution production intensity coefficient in the unit. β is the utilization efficiency coefficient in the unit. The products of α and β represent the generation of agricultural pollution, which indicates the maximum potential pollution caused by agricultural production in the absence of integrated resource utilization or management factors. γ is the emission coefficient in the unit, which is measured by unit and spatial characteristics. This reflects the combined effects of hydrology, rainfall, regional environment, and management measures on agricultural pollution.

⁹ Calculation of depreciation costs for self-owned agricultural machinery: Depreciation of fixed assets is typically calculated using either the straight-line method or units-of-production method. For agricultural machinery, given the relatively consistent annual workload and operational patterns across years, the straight-line method is conventionally applied. In this study, the depreciation cost is calculated as the product of the original machinery value and the annual depreciation rate. Distinct annual depreciation rates apply to different machinery types, determined by the ratio of (1 minus the estimated net residual value rate) to the depreciation period. Herein, the estimated net residual value rate is typically set at 3%–5% of the original value; this study adopts 4%. Depreciation periods are referenced from the Depreciation Schedule for Agricultural Machinery in State Farms issued by Finance and Ministry of Agriculture, Animal Husbandry and Fisheries of China.

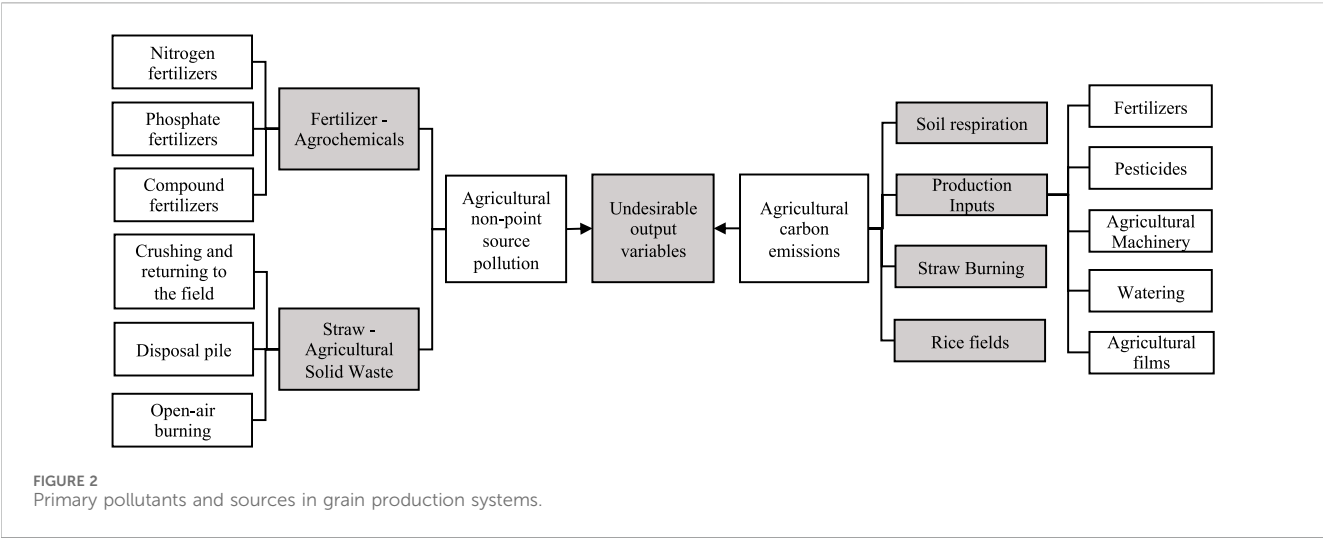


TABLE 2 Variable definitions and descriptive statistics.

Variables	Variable definition and measurement	Mean	Std. Dev.
Age	Age of household head (years)	56.780	10.388
Education	Years of formal education of household head (years)	7.888	3.322
Health status	Health status of household head: 1 = very poor; 2 = poor; 3 = fair; 4 = healthy; 5 = very healthy	4.274	0.984
Family size	Total number of family members (persons)	4.334	1.771
Family income	Annual gross household income in 2020 (yuan), natural log-transformed	11.488	1.105
Non-farm employment	Percentage of non-farm income to total household income in 2020 (%)	39.210	36.876
Social capital	Number of relatives and friends holding public office at county level or above (persons)	1.083	3.998
Grain-sown area	Total grain-sown area in 2020 (ha)	3.320	9.010
Land fragmentation	Number of cultivated land plots (blocks) in 2020	14.057	52.953
Land quality	Self-assessed land fertility: 1 = very poor; 2 = relatively poor; 3 = fair; 4 = relatively good; 5 = very good	3.379	0.767
Cropping index	Ratio of total sown area to cultivated area in 2020 (%)	1.521	0.486
Agricultural subsidies	Agricultural subsidies income received by farmers in 2020 (yuan), ln(amount+1) transformed	7.272	1.674
Outsourcing level	Farmers' expenditure on agricultural production outsourcing services in 2020 (1000 ¥/ha)	2.966	2.121
Productive fixed assets	Value of productive fixed assets of farmers in 2020 (yuan), ln(value+1) transformed	6.332	3.925
Agricultural organization	1 = Participated in cooperatives/family farms/demonstration farms/agribusinesses	0.230	0.421
Agricultural technical training	1 = Received agricultural training in 2018–2020; 0 = None	0.350	0.477
Meteorological disasters	Frequency of weather-related crop losses in 2020 (times)	0.838	1.014
Distance from residence to county	Distance from residence in the village to nearest county seat (meters), ln(distance+1) transformed	9.576	1.069
Province dummy variables (Ref: Henan)			
Heilongjiang	1 = Heilongjiang; 0 = Other	0.344	0.475
Hunan	1 = Hunan; 0 = Other	0.330	0.471

The pollution-producing units in grain production mainly include agrochemicals and farmland solid waste (Table 2). Given that fertilizer loss is the primary cause of non-point source pollution (Xiang et al., 2020; Liu et al., 2021), and straw is another significant contributor (Zou et al., 2020), this study highlights non-point source pollution resulting from fertilizer loss and straw. It calculates the emissions of

TABLE 3 Inventory of agricultural non-point source pollution generating units.

Pollution source	Category	Survey unit	Survey parameter	Unit	Emission inventory
Agrochemicals	Surface runoff and subsurface leaching losses of fertilizers	Compound fertilizer, phosphate fertilizer, and nitrogen fertilizer	Applied amount (pure component basis)	Kg	TN, TP
Agricultural solid waste	Crop residues	Maize stalks, wheat straw and rice stubble	Total yield	Kg	COD, TN, TP

chemical oxygen demand (COD), total phosphorus (TP), and total nitrogen (TN) under different fertilizer loss and straw management practices. Table 3 shows the list of agricultural non-point source pollution-producing units.

The parameters of pollution production intensity, utilization efficiency, and pollution emission coefficients for each pollutant were obtained through an extensive literature review and comparative analysis. The parameters provided in the Manual of Agricultural Source Coefficients in Pollution Source Census were highlighted referring to the work of Liang (2009), Lai et al. (2004), Chen et al. (2006), and Shi and Shang (2021). This approach allowed for considering regional variations in pollution intensity and establishing a comprehensive database of parameters related to pollution intensity coefficients, utilization coefficients, and loss coefficients for agricultural pollution in different pollution-producing units within the sample area.

Subsequently, total agricultural non-point source pollution was quantified as equivalent pollution emissions (in 10^4 m^3) through conversion of TP, TN, and COD concentrations based on Class III water quality standards (GB3838-2002) (Qian, 2001; Chen et al., 2010). Specifically, the equivalent emissions are calculated by dividing measured pollutant concentrations by their respective standard limits: 0.2 mg/L for TP, 1.0 mg/L for TN, and 20 mg/L for COD.

3.2 Calculation of agricultural carbon emissions

Referring to existing studies (Gu et al., 2013; Tian et al., 2012; Shang et al., 2015; Cheng, 2018; Jane, 2007), six agricultural carbon sources were identified from four dimensions¹⁰: soil respiration, production inputs, straw burning, and rice fields, with detailed types, corresponding emission coefficients and reference basis presented in Table 4. The carbon emission levels were estimated using these coefficients (Table 4), which incorporated environmental

characteristics, rainfall patterns, and resource endowments of the study areas. Subsequently, total agricultural carbon emissions were calculated by converting greenhouse gases into carbon equivalents (Ge et al., 2018), expressed in tons.

The carbon emissions from soil respiration, production inputs, and rice fields are quantified using the following equation:

$$E = \sum_{i=1}^n E_i + F = \sum_{i=1}^n T_i \cdot \partial_i + (A \cdot B + C \cdot D)$$

where E_i is the carbon emission from soil respiration, fertilizers, watering, and rice fields, F is the carbon emission from the operation of farm machinery, T_i is the statistical index of soil respiration, fertilizers, watering and rice fields, ∂_i is the coefficient of carbon emission, A represents the grain-sown area, C represents the total power of farm machinery, B and D describe the carbon emission coefficient of the carbon source of agricultural machinery.

Following the methodologies outlined by Cao et al. (2007), Cao et al. (2005), Peng et al. (2016), Wang (2017), and relevant FAO guidelines, the carbon emissions from straw burning are quantified using the following formula:

$$E_{ij} = \sum_{k=1}^K (P_{ik} \times C_k \times R_k \times F_k \times EF_k)$$

where E_{ij} is the greenhouse gas emissions of the category j of the farmer i , P_{ik} is the yield of the crop k of the farmer i , C_k is the straw-to-grain ratio of the crop k in %, R_k is the ratio of open-air burning of the crop k , F_k is the burning efficiency of the crop k , and EF_k is the emission coefficient of open-air burning of the crop k in g/kg .

To determine Maize, wheat, and rice straw-to-grain ratios, the parameters published by the National Development and Reform Commission were mainly used (see Table 5).

For the measurement of straw-burning efficiency, the straw-burning emission coefficient was determined by considering the differences in the emission coefficients for different crops based on the studies of Cao et al. (2005), Zhang (2009), Peng et al. (2016) and Wang (2017). The emission coefficients for straw-burning are shown in Table 6.

In summary, the description and statistics of eco-efficiency input-output variables are shown in Table 7.

3.3 Eco-efficiency measurement results

Since different constraints and orientation choices can lead to different measurement results, MaxDEA Ultra was used as the

¹⁰ Unfortunately, due to data constraints in the survey, this study excludes carbon emissions from pesticide and agricultural plastic film production and usage in the agricultural carbon accounting framework. Moreover, for emissions generated by agricultural machinery operation, only indirect emissions were considered, while direct emissions were excluded from the calculation. However, these exclusions do not materially compromise the integrity of our assessment, as fertilizer application and rice cultivation—the dominant contributors to plantation carbon emissions—are fully incorporated in the accounting framework.

TABLE 4 Carbon emission inventory: sources, coefficients and reference basis.

Carbon source	Emission coefficient	Reference basis
Soil respiration	312.6 kg C/km ²	Li et al. (2011)
Production inputs-fertilizers	0.896 kg C/kg	Oak Ridge National Laboratory, United States
Production inputs-agricultural machinery B	16.47 kg C/hm ²	West and Marland (2002)
Production inputs-agricultural machinery D	0.18 kg C/KW	Gu et al. (2013)
Production inputs-irrigation ¹¹	20.476 kg C/hm ²	Dubey and Lal (2009)
Rice cultivation ¹²	0.46 g CH ₄ /(m ² ·d)	Mingxin et al. (1990), Matthews et al. (1991), Cao et al. (1995)

calculation platform to measure the eco-efficiency of each decision unit by using three constraints of variable returns to scale (VRS), general returns to scale (GRS), and constant returns to scale (CRS), as well as three forms¹³ of input orientation (IO), output orientation (OO), and non-orientation (NO). We set both the total desirable output weight and the total undesirable output weight to 1. The eco-efficiency values were calculated using data from 1,208 field surveys of farm households in China's major grain-producing areas Table 8 presents the mean eco-efficiency values under different constraints and orientation choices. In terms of trends, the mean eco-efficiency values increased from CRS to GRS to VRS under the same orientation across both the total and provincial samples. Conversely, the mean eco-efficiency decreased from output-oriented to input-oriented to non-oriented under the same constraints.

Generally, production technology exhibits three stages of returns to scale: decreasing returns to scale (DRS), constant

TABLE 5 The straw-grain ratios of different crops in sampled regions.

Regions	Maize	Wheat	Rice
Heilongjiang	1.86	0.93	0.97
Henan	1.73	1.34	0.93
Hunan	2.05	1.38	1.28

TABLE 6 Emission coefficients for straw burning.

Crops	Rice	Wheat	Maize
Combustion efficiency	0.93	0.93	0.92
CH ₄	3.20	3.40	4.40
CO ₂	1460	1460	1350

¹¹ Since indirect carbon emissions originate exclusively from fossil fuel consumption in thermal power generation, applying the unadjusted coefficient of 25 kg/hm₂ for agricultural irrigation—as reported by Li et al. (2011)—fails to account for energy mix variations. This coefficient must instead be scaled by the thermal power share (i.e., the proportion of fossil-based electricity in total generation). We therefore applied a thermal power coefficient of 0.891, derived from China Statistical Yearbooks (2004–2008), yielding a refined emission factor of 20.476 kg C/hm₂ for agricultural irrigation.

¹² The IPCC Fourth Assessment Report (2007) established that the greenhouse effect caused by 1 ton of CH₄ is equivalent to that caused by 25 tons of CO₂ (about 6.82 t C). Using this standardized conversion, the methane emission coefficient for rice paddies was converted to 3.137 g C/(m₂·d). Furthermore, accounting for varietal and regional heterogeneity in rice growth cycles, we defined region-specific cultivation periods based on IPCC guidelines and empirical field data from China: 145 days for Heilongjiang (japonica), 87 days for Henan, and 85 days for early-season indica rice in Hunan.

¹³ Input orientation refers to minimizing inputs while holding outputs constant. Output orientation denotes maximizing outputs given fixed input levels. Non-oriented approach measures efficiency through simultaneous input reduction and output expansion, thus termed bidirectional input-output optimization.

returns to scale (CRS), and increasing returns to scale (IRS). If it is difficult to determine which stage the study sample is in, or if the sample spans all stages, the VRS model is recommended for evaluating technical efficiency (Cooper et al., 2006; Färe and Grosskopf, 1983; Grosskopf, 1986). The selection of model orientation relies primarily on the purpose of the analysis. If the goal is simply to obtain the efficiency value for each unit, all three orientations (input, output, and non-oriented) can be considered (Cheng and Qian, 2012). Given that Chinese farmers, particularly those involved in grain production, exhibit strong empirical and fixed behavioral patterns in their agricultural practices (Gao and Shi, 2019), output-oriented measurement is deemed more appropriate. Consequently, eco-efficiency values under the VRS and output-oriented (OO) settings were selected for the subsequent analysis.

The average eco-efficiency in grain-producing areas was 0.627, which is only slightly above the “passing threshold”. The mean eco-efficiency values for Heilongjiang, Henan, and Hunan were 0.701, 0.648, and 0.528 (Figure 3), respectively. It can be seen that the agricultural ecological efficiency value of the major grain-producing areas in China is not high, the ecological efficiency of the three major grain-producing provinces is significantly different, and the agricultural ecological efficiency of Hunan Province is the lowest. The possible reason is that compared with Heilongjiang and Henan Province, which are mainly

TABLE 7 Input-output variables: definitions and summary statistics.

Category	Variables	Definition	Mean	Std. dev.	Min	Max
Input variables	Labor input	Total time devoted by farm households to grain production processes in 2020 (workday)	41.8442	58.2605	0.0000	635.0000
	Capital input	Total monetary investment in grain cultivation by farming households in 2020 (10,000 yuan)	4.6895	19.2276	0.0022	541.7333
	Land input	Total sown area for grain crops of farm households in 2020 (ha)	4.5274	14.4712	0.0133	386.8600
Desirable output variable	Gross grain output value	Total economic value of grain production of farm households in 2020 (10,000 yuan)	7.3377	24.0868	0.0040	664.7900
Undesirable output variables	Agricultural non-point source pollution	Calculated pollutant equivalent index of agricultural non-point source pollution (10,000 m ₃)	8.4407	26.8861	0.0000	596.8094
	Agricultural Carbon Emissions	Total calculated emissions (tonne)	11.7900	51.4957	0.0009	1397.4710

plains, Hunan Province is dominated by hilly and mountainous terrain. This geographical feature leads to higher regulatory costs in the implementation of chemical fertilizer and pesticide reduction and efficiency policies. At the same time, the fragmentation of cultivated land in hilly areas has led to a generally low willingness of small-scale farmers to adopt environmental protection technologies, resulting in certain obstacles in the implementation of the policy. On the other hand, limits the popularization and application of mechanization. Although the region is rich in rainwater resources, it is easy to cause the waste of water resources and the spread of agricultural non-point source pollution due to the lag of farmland irrigation and drainage system construction. This finding aligns with the results of Aslam et al. (2021). This indicates, to some extent, that these areas are still in the rough-running agricultural development model, relying more on the input of resources and damage to the environment. Moreover, resources, environment, and agricultural development are in a relative imbalance. However, compared with the efficiency level before 2015¹⁴ (Meng et al., 2019), the eco-efficiency of grain production has slightly improved.

To further assess eco-efficiency, the values of eco-efficiency were compared with those of traditional production efficiency. The results indicate that the average traditional production efficiency is 0.408, lower than the mean eco-efficiency, with a difference of 0.219. This finding aligns with the conclusions of Lv and Zhu (2019). The possible reason is that over the years, in the process of promoting agricultural development, China has gradually realized the importance of environmental pollution control, and has taken a series of measures to promote the coordinated development of agriculture and the environment, such as “Notice on Printing and

Issuing the Construction Plan of the National Agricultural Sustainable Development Experimental Demonstration Zone”, “Notice on the Pilot Work of Carbon Emission Trading” and other policies”, which have actively mobilized farmers’ enthusiasm for environmental protection production and effectively promoted the transformation of the grain industry to a green and low-carbon direction (Du et al., 2023; Yu et al., 2022). The preliminary research results of this study verify the applicability of the Porter Hypothesis in China’s agricultural development, that is, strict environmental regulation can promote farmers’ investment in green technology and sustainable production through technological innovation (Jing et al., 2024), so as to achieve a win-win situation between economic and environmental benefits.

4 Results and discussion

4.1 Baseline regression results for the determinants of eco-efficiency

To improve the accuracy of estimates, different determinants were progressively incorporated into the Tobit model, with the model estimation results labeled as Regression 1–Regression 4, all presented in Table 9. Regression 1 includes only the personal characteristics of household head, Regression 2 adds farm household characteristics, Regression 3 incorporates agricultural production and operational characteristics, and Regression 4 includes all variables. The chi-square test statistics gradually increase, its goodness-of-fit improves, and the estimated results remain consistent in terms of direction and significance levels. The analysis is based on the results from Regression 4.

Regarding the personal characteristics of household heads, age has a positive impact on eco-efficiency at the 5% significance level, challenging the common perception that aging hinders agricultural development. This study suggests that aging does not pose an immediate threat to food security; rather, the older

¹⁴ The eco-efficiency values were compared with 2015 levels, coinciding with China’s enactment of the *One Control, Two Reductions, and Three Basics* policy for emission reduction and carbon sequestration measures such as land fallowing.

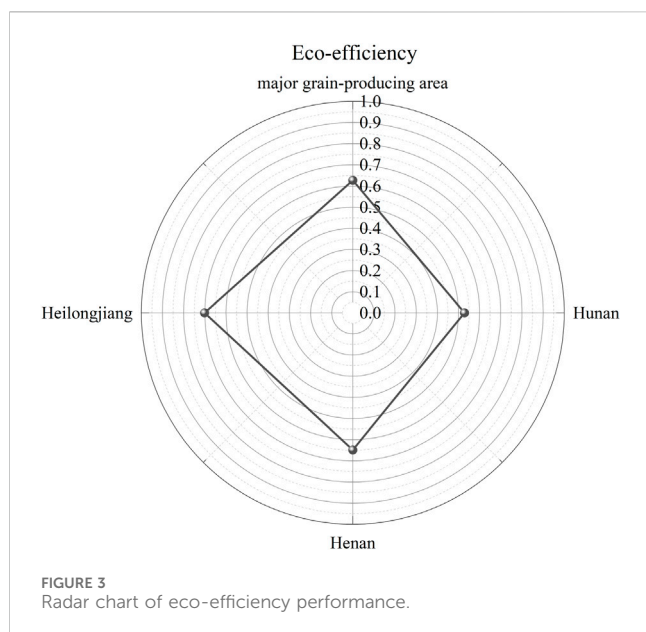
TABLE 8 Mean eco-efficiency under differential constraints and orientation options.

	Mean eco-efficiency											
	Overall sample (N = 1208)			Heilongjiang sub-sample (N = 416)			Henan sub-sample (N = 393)			Hunan sub-sample (N = 399)		
	CRS	GRS	VRS	CRS	GRS	VRS	CRS	GRS	VRS	CRS	GRS	VRS
OO	0.600	0.618	0.627	0.681	0.693	0.701	0.629	0.641	0.648	0.486	0.520	0.528
IO	0.324	0.373	0.388	0.426	0.470	0.486	0.344	0.394	0.410	0.198	0.250	0.264
NO	0.262	0.304	0.319	0.366	0.405	0.420	0.287	0.333	0.349	0.129	0.171	0.184

TABLE 9 Tobit regression results: determinants of eco-efficiency.

Eco-efficiency	Regression 1		Regression 2		Regression 3		Regression 4	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Age	0.000	0.000	0.001**	0.000	0.001**	0.000	0.001**	0.000
Education	0.000	0.001	0.001	0.001	0.002	0.001	0.001	0.001
Health status	−0.010**	0.004	−0.009**	0.004	−0.005	0.003	0.001	0.003
Family size	---	---	−0.011***	0.002	−0.004*	0.002	−0.004*	0.002
Family income	---	---	0.008**	0.004	−0.001	0.004	0.011***	0.004
Non-farm employment	---	---	−0.001***	0.000	−0.000**	0.000	−0.000	0.000
Social capital	---	---	−0.001	0.001	−0.001	0.001	0.000	0.001
Grain-sown area	---	---	---	---	0.006***	0.001	0.006***	0.001
Land fragmentation	---	---	---	---	−0.000***	0.000	−0.000**	0.000
Land quality	---	---	---	---	0.009**	0.004	0.008**	0.004
Cropping index	---	---	---	---	−0.051***	0.007	−0.045***	0.010
Agricultural subsidies	---	---	---	---	−0.006**	0.003	−0.012***	0.002
Outsourcing level	---	---	---	---	−0.017***	0.002	−0.004**	0.002
Productive fixed assets	---	---	---	---	−0.002	0.001	−0.002*	0.001
Agricultural organization	---	---	---	---	0.017**	0.008	0.013*	0.007
Agricultural technical training	---	---	---	---	−0.002	0.007	−0.003	0.006
Meteorological disasters	---	---	---	---	−0.018***	0.003	0.000	0.003
Distance from residence to county	---	---	---	---	---	---	0.001	0.003
Heilongjiang	---	---	---	---	---	---	0.009	0.013
Hunan	---	---	---	---	---	---	−0.144***	0.009
_cons	0.642***	0.034	0.591***	0.051	0.781***	0.053	0.624***	0.056
Observations	1208		1208		1208		1208	
LR chi2	10.47**		97.31***		394.55***		677.00***	

Note: (1) ***, **, * indicate the significant level of 1%, 5%, and 10%, respectively; (2) All models have passed the multicollinearity test.



agricultural labor force may even make a positive contribution. This can be explained by two factors: first, older laborers tend to have higher technical efficiency (Shen et al., 2023; Seok et al., 2018); second, older laborers have fewer non-farm employment opportunities to dedicate more time and energy to agricultural production (Shen et al., 2024). This conclusion is somewhat supported by Li and Sicular (2013), who found that rural aging nationwide did not lead to a decline in grain production, but rather to an increase in the sown area and total grain production.

Concerning farm household characteristics, family size has a negative impact on eco-efficiency at the 10% significance level (Xu et al., 2021). Larger families are more likely to invest labor in agricultural production rather than in machinery, which may hinder the efficiency gains that machinery can provide. In addition, family income positively affects eco-efficiency at the 1% significance level. As family income increases, farmers may become less dependent on agricultural production (Sattar et al., 2024), which reduces their reliance on agrochemicals and enhances eco-efficiency. Additionally, higher income alleviates budget constraints, which may encourage the purchase of eco-friendly production materials and the adoption of new technologies. This is consistent with Li et al. (2024) at the regional level and (Zong et al., 2023) at the national level. Both of them demonstrate a positive association between eco-efficiency and income levels.

Regarding agricultural production characteristics, the grain-sown area positively affects eco-efficiency at the 1% significance level, which suggests that economies of scale are still present in China's major grain-producing areas. Farmers can improve eco-efficiency by reallocating land, which is consistent with national studies (Lu et al., 2024; Zong et al., 2023). In contrast, land fragmentation negatively affects eco-efficiency at the 5% significance level, which aligns with the studies of Blaikie and Sadeque (2000); Hou et al. (2021). Land fragmentation leads to inefficient use of land, improper allocation of agricultural inputs, and increased loss of technical efficiency, which raises economic costs (Tenaye, 2020).

Moreover, it discourages the adoption of new agricultural technologies and the development of farmland infrastructure (Lu et al., 2022).

Land quality positively affects eco-efficiency at the 5% significance level, which indicates that better land quality leads to higher crop yields and reduced demand for production inputs such as fertilizers and irrigation, thereby enhancing eco-efficiency. The cropping index also negatively affects eco-efficiency at the 1% significance level (Hou et al., 2021). Jiang et al. (2024) confirmed that increased cropping index necessitates greater inputs and continuous cropping tends to induce environmental hazards such as soil compaction, salinization, and soil-water erosion, consequently reducing eco-efficiency. Agricultural subsidies negatively affect eco-efficiency at the 1% significance level, which supports the research of (Guo et al., 2021). Subsidies alleviate the budget constraints of farmers, which can lead to the overuse of fertilizers and pesticides (Pan et al., 2022). Additionally, agricultural subsidies may limit output effects due to rising production costs and diminishing returns (Pan, 2016).

The negative influence of agricultural production outsourcing on eco-efficiency at the 5% significance level contrasts with Zhang et al. (2023) and Wang L. et al. (2024), but aligns with Zhang et al. (2015). It is suggested that information asymmetry between farmers and outsourcing providers may explain the reduced eco-efficiency, particularly due to the reduced quality of service from providers and excessive supervision from farmers. The presence of more productive fixed assets negatively affects eco-efficiency at the 10% significance level. Farmers with more productive assets may be inclined to use more agrochemicals to stabilize grain production, which leads to greater environmental pollution and lower eco-efficiency.

Finally, agricultural organization memberships positively influence eco-efficiency at the 10% significance level, likely due to their role in improving farmers' knowledge, attitudes, and practices of green production. These organizations also help reduce transaction costs and negotiate better terms for farmers, which enhances eco-efficiency.

In terms of regional characteristics, Hunan negatively affects eco-efficiency at the 1% significance level, while no significant difference exists between Heilongjiang and Henan. This variation may be related to regional climatic conditions. Located in the mid-reach of the Yellow River Basin, Henan features flat terrain and abundant solar radiation, yet experiences significant diurnal temperature variations and spatially uneven precipitation. The region practices a double-cropping system, with wheat-maize rotation or wheat-rice rotation dominating grain production. Heilongjiang, situated in Northeast China, occupies a high-latitude continental plain characterized by synergistic hydrothermal regimes and phaeozem soils of exceptional fertility. The constrained growing season permits only single annual cropping, rendering it a quintessential low-input high-output agricultural system with minimal environmental externalities. In contrast, Hunan, located in the mid-Yangtze Basin, features hyperthermal conditions and copious precipitation sustained by dense arterial waterways. Dominated by paddy landscapes, it supports double/triple annual cropping rotations. However, its methanogenic rice cultivation constitutes a critical carbon footprint hotspot, epitomizing a high-input high-output paradigm with elevated pollution loading.

TABLE 10 Provincial-level regression analysis: determinants of eco-Efficiency.

Eco-efficiency	Regression 5 Heilongjiang		Regression 6 Henan		Regression 7 Hunan	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Age	0.001	0.001	0.001***	0.000	0.000	0.001
Education	0.000	0.002	0.002*	0.001	0.001	0.002
Health status	0.007	0.007	0.001	0.003	−0.004	0.006
Family size	−0.002	0.005	−0.002	0.002	−0.002	0.003
Family income	0.031***	0.010	0.004	0.005	0.003	0.007
Non-farm employment	−0.000	0.000	−0.000	0.000	0.000	0.000
Social capital	0.000	0.001	0.000	0.002	−0.001	0.001
Grain-sown area	0.004*	0.002	0.016***	0.003	0.005***	0.001
Land fragmentation	0.001	0.001	−0.003*	0.002	−0.000	0.000
Land quality	0.012	0.008	−0.002	0.005	0.011*	0.006
Cropping index	−0.178	0.198	−0.024	0.017	−0.051***	0.010
Agricultural subsidies	−0.018***	0.007	−0.009**	0.004	−0.009***	0.003
Outsourcing level	−0.009*	0.006	−0.016***	0.003	−0.001	0.002
Productive fixed assets	−0.005***	0.002	0.001	0.001	−0.001	0.001
Agricultural organization	0.002	0.016	0.017*	0.010	0.022*	0.011
Agricultural technical training	−0.001	0.013	0.001	0.008	−0.010	0.010
Meteorological disasters	0.007	0.006	−0.005	0.006	−0.005	0.004
Distance from residence to county	0.007	0.004	−0.006	0.007	−0.009**	0.004
_cons	0.532**	0.224	0.737***	0.089	0.694***	0.090
Observations	416		393		399	
LR chi2	58.15***		110.83***		124.54***	

Note: (1) ***, **, * indicate the significant level of 1%, 5%, and 10%, respectively; (2) all models have passed the multicollinearity test.

4.2 Heterogeneity analysis

The measured results of eco-efficiency in the sample areas reveal significant differences among Heilongjiang, Henan, and Hunan, with mean values of 0.701, 0.648, and 0.528, respectively.

This raises the question of whether the determinants of eco-efficiency also vary for farmers in different geographical regions. To this end, a regional sub-estimation was conducted. Table 10 shows the estimation results.

Regressions 5 to 7 display the results for the determinants of eco-efficiency in Heilongjiang, Henan, and Hunan, respectively. Regional differences are evident, though the direction of effect and significance level of each factor closely mirror those in the total sample regression. Specifically, grain-sown area and agricultural subsidies consistently show significant effects across all regions. The grain-sown area positively influences eco-efficiency and agricultural subsidies have a negative impact.

In Henan, the household head’s age and education are positively associated with eco-efficiency, while land fragmentation has a negative effect. In Heilongjiang, family income has a positive effect, while productive fixed assets exert a negative influence. In Hunan, land quality positively affects eco-efficiency, while the

cropping index and distance from residence to county town have negative effects.

Additionally, the negative effect of agricultural production outsourcing is insignificant in Hunan, while the positive effect of agricultural organization memberships is insignificant in Heilongjiang.

4.3 Robustness tests

The previous analysis examined the determinants of eco-efficiency based on eco-efficiency measurements under output orientation. To enhance the robustness of the results, the determinants of eco-efficiency were further analyzed under input orientation and non-orientation. This additional analysis helps mitigate potential biases in the results that may arise from the choice of orientation (Cooper et al., 2007; Tone, 2001). Table 11 shows the regression results. Regression 8 reports the results from the determinants of eco-efficiency under input orientation, while regression 9 presents the results under non-orientation. The direction of influence and significance levels of each variable remain consistent with those in the output

TABLE 11 Determinants of eco-efficiency under input-oriented and non-oriented models.

Eco-efficiency	Regression 8 input orientation		Regression 9 no orientation	
	Coef.	Std. Err.	Coef.	Std. Err.
Age	0.002***	0.000	0.002***	0.001
Education	0.002	0.001	0.002	0.002
Health status	0.006	0.005	0.005	0.005
Family size	−0.007**	0.003	−0.007**	0.003
Family income	0.005	0.006	0.004	0.007
Non-farm employment	0.000	0.000	0.000	0.000
Social capital	0.000	0.001	0.000	0.001
Grain-sown area	0.008***	0.001	0.008***	0.001
Land fragmentation	−0.000*	0.000	−0.000**	0.000
Land quality	0.026***	0.006	0.023***	0.006
Cropping index	−0.063***	0.016	−0.053***	0.017
Agricultural subsidies	−0.023***	0.004	−0.022***	0.004
Outsourcing level	−0.012***	0.003	−0.012***	0.003
Productive fixed assets	−0.007***	0.001	−0.006***	0.001
Agricultural organization	0.005	0.012	0.005	0.013
Agricultural technical training	−0.010	0.010	−0.008	0.011
Meteorological disasters	−0.004	0.005	−0.002	0.005
Distance from residence to county	0.002	0.004	0.003	0.005
Heilongjiang	0.027	0.021	0.032	0.022
Hunan	−0.150***	0.015	−0.166***	0.016
_cons	0.478***	0.090	0.394***	0.094
Observations	1208		1208	
LR chi2	529.36***		518.95***	

Note: (1) ***, **, * indicate the significant level of 1%, 5%, and 10%, respectively; (2) all models have passed the multicollinearity test.

orientation regression, which confirms the robustness and reliability of the findings.

5 Conclusion and recommendations

This study adopts a micro-level perspective to evaluate the eco-efficiency of China’s major grain-producing areas, incorporating both agricultural carbon emissions and non-point source pollution. Using field survey data from 1,208 farm households and employing the SBM-Undesirable model, the study analyzes the determinants of eco-efficiency. The main findings are as follows:

(1) The average eco-efficiency score across China’s major grain-producing areas is 0.627—slightly above the old typically regarded as “passing”. At the provincial level, eco-efficiency values are 0.701 in Heilongjiang, 0.648 in Henan, and 0.528 in Hunan, revealing pronounced regional disparities.

(2) The mean eco-efficiency score (0.627) is 0.219 higher than the traditional production efficiency metric, suggesting that China has begun to decouple agricultural growth from environmental degradation. This finding provides preliminary empirical support for the Porter Hypothesis, which states that well-designed environmental regulation can enhance, rather than hinder, economic efficiency.

(3) Multiple factors significantly influence eco-efficiency in these regions. Positive contributors include household head’s age, family income, grain-sown area, land quality, and membership in agricultural organizations. In contrast, factors such as family size, land fragmentation, cropping index, agricultural subsidies, agricultural production outsourcing, and investment in fixed productive assets tend to suppress eco-efficiency.

(4) The determinants of eco-efficiency exhibit regional heterogeneity. In Henan, promoting vocational education to enhance environmental awareness, encouraging land consolidation to mitigate fragmentation, and strengthening

the extension functions of farmer cooperatives are key policy priorities. Furthermore, to harness the potential of the aging rural labor force, models such as Japan's "senior farmers' gardens" could be adapted to establish silver-haired agricultural service teams. However, the proliferation of pesticide overuse in outsourced production underscores the need for tighter regulation. In Heilongjiang, excessive investment in fixed agricultural assets reflects management inefficiencies within large-scale farming operations, echoing the energy inefficiency concerns associated with over-mechanization in the American Midwest. This calls for improved asset utilization and precision management in mechanized farming systems. For Hunan, the focus should be on enhancing soil quality—potentially through targeted subsidies for eco-efficiency soil improvement practices, as seen in South Korea—and optimizing crop rotation systems, drawing lessons from Thailand's rice–green manure rotation model. Additionally, empowering farmers in remote and ecologically fragile areas through digital agriculture initiatives—modeled after the European Union's smart farming programs—could help alleviate productivity constraints associated with geographic disadvantages.

Compared with the ecological degradation resulting from large-scale monoculture expansion in Brazil, the three provincial cases in China demonstrate the potential for achieving agricultural intensification and ecological sustainability in a synergistic manner. However, compared to France's cluster-based agricultural development, land fragmentation and insufficient regulation of agricultural production outsourcing services remain fundamental challenges in China. Future policies need to build a comprehensive "three-in-one" framework: At the technical level, efforts should focus on promoting precision agriculture to minimize redundant investments, exemplified by initiatives such as the Heilongjiang Agricultural Machinery Sharing Platform. At the institutional level, environmental standards for outsourcing services need to be strengthened, including the formation of a cross-regional regulatory alliance between Henan and Heilongjiang provinces. At the organizational level, the development of age-friendly cooperatives—drawing on Henan's experience—and the provision of digital support for remote suburban areas, as piloted in Hunan, are essential. Collectively, these measures aim to effectively address the "intensification trap" and "marginalization dilemma", providing a uniquely Chinese approach to advancing green transformation in major global grain-producing regions.

Currently, China's major grain-producing regions remain entrenched in an extensive model of agricultural development, characterized by heavy reliance on resource inputs and environmental degradation to sustain production. This has resulted in a persistent imbalance among resource use, environmental sustainability, and agricultural development. Greater attention from government agencies, farmers, and other relevant stakeholders is urgently needed to enhance agricultural eco-efficiency. From a policy perspective, it is critical to integrate environmental concerns into agricultural development strategies. Policymakers should prioritize the promotion of low-carbon

technologies and practices that reduce non-point source pollution, while formulating region-specific strategies tailored to local ecological conditions. Such differentiated approaches can improve the effectiveness of policy interventions and optimize eco-efficiency outcomes across China's diverse grain-producing regions. In addition, intergovernmental cooperation can facilitate the design of unified yet adaptable frameworks for agricultural environmental sustainability. From the farmers' perspective, policy incentives should encourage land consolidation through farmland transfer to expand operational scale and mitigate land fragmentation. In addition, farmers should be encouraged to diversify their operations and reduce their dependence on traditional resource-intensive methods. Expanding access to financial support and targeted credit for sustainable agricultural technologies will further facilitate the transition toward a more eco-efficient model. From the standpoint of other stakeholders in the agricultural sector—including agribusinesses, non-governmental organizations, and research institutions—efforts should focus on advancing technological innovation and accelerating the adoption of sustainable agricultural practices. In addition, stakeholders should also help build a stronger and more integrated system by promoting dialogue and technical assistance to narrow the gap between farmers and policymakers, thereby improving the agricultural eco-efficiency of the entire region.

In summary, this study makes several important contributions. First, a more comprehensive measure of eco-efficiency is provided by incorporating agricultural carbon emissions and non-point source pollution. Second, the adoption of a non-radial, non-angle SBM model allows for more accurate eco-efficiency measurement, which overcomes the limitations of traditional radial models. Third, a clearer evaluation of agricultural development in China's major grain-producing areas is performed by comparing eco-efficiency with traditional production efficiency. Fourth, the determinants of eco-efficiency are identified and discussed from four dimensions (household head characteristics, farm household characteristics, agricultural production and operation characteristics, and regional characteristics), which propose feasible paths for improvement. These findings provide valuable insights for policymakers and farmers to face agricultural and environmental challenges. Fifth, regional differences are further analyzed to increase the applicability of the findings.

6 Research limitations and perspectives

Despite the contribution of this study, several limitations warrant further refinement in subsequent research. First, due to data constraints, the selected output and input indicators are not fully comprehensive. Important environmental factors such as agricultural pollution from pesticide use and plastic film residues were not accounted for, which could be incorporated in future datasets to enhance measurement accuracy. Second, constrained by limited space, this study does not examine the heterogeneity of eco-efficiency across different farm sizes and crop types. Future research could explore these dimensions in greater depth to provide a more nuanced understanding. Third, although the Tobit model is a suitable approach for analyzing

the determinants of eco-efficiency, some explanatory variables (e.g., family income, land fragmentation, agricultural subsidies) may suffer from endogeneity, potentially biasing the estimation results. Due to current data and methodological constraints, this study does not address endogeneity using techniques such as instrumental variables. Future research may mitigate this issue as more suitable data become available. Fourth, this study relies on cross-sectional data, which limits the ability to identify the temporal effects of climate variables on farm-level eco-efficiency. Future studies could integrate high-resolution meteorological time-series data or adopt panel data methods to address this limitation and improve the robustness of temporal inferences. Fifth, this analysis is based on a one-time farm household research data, which limits the availability of longitudinal tracking information and may constrain the examination of dynamic trends or causal relationships. Additionally, the absence of administrative or remotely sensed data for validation may affect the external validity of the results, particularly in macro-level or cross-regional analyses. To address this, future research could incorporate micro-level panel data, such as constructed farm household tracking surveys or official agricultural census data, and enhance causal inference through quasi-natural experiments, panel instrumental variable approaches, or other advanced econometric techniques. Moreover, an integrated analytical framework combining remotely sensed data with official statistics could improve the external validity of the findings and facilitate regional policy comparisons. Sixth, although the subjective indicators of land quality and health status used in this study were designed with standardized scales and supported by interviewer interpretation to minimize respondent bias, these deliberately positioned as farmer perspectives or “subjective assessments”. This approach aims to capture farmers’ behavioral responses to perceived resource conditions rather than treating these variables as objective physical inputs. While this is consistent with prevailing practices in agricultural economics, self-reported variables may still introduce potential biases. In future research, the objectivity and precision of these indicators could be improved through the integration of remote sensing data, soil testing, and agronomic health records.

Data availability statement

The data analyzed in this study is subject to the following licenses/restrictions: The data for this study was obtained from personal research and is confidential, so it cannot be shared. Requests to access these datasets should be directed to Chang Qian, 14924@sicau.edu.cn.

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CQi: Writing – original draft, Project administration, Supervision, Writing – review and editing, Funding acquisition. CXi: Writing – review and editing, Formal Analysis, Visualization. YQ: Writing – review and editing. ZY: Writing – review and editing. HX: Writing – review and editing, Methodology. TX: Methodology, Writing – review and editing. LY: Writing – review and editing, Visualization, Formal Analysis.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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