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Measuring Green Efficiency and Predicting Carbon Emissions in Agriculture After Fertilizer and Pesticide Reduction Actions: A Study from Shandong Province, China

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Abstract: Reducing agricultural carbon emissions while maintaining farm productivity is central to sustainable agricultural development in China. Focusing on Shandong Province, this study estimates agricultural carbon emissions from 2000 to 2021 using the Intergovernmental Panel on Climate Change approach and measures agricultural green total factor productivity with the epsilon-based measure–global Malmquist–Luenberger (EBM–GML) index. An extended STIRPAT model and scenario analysis are then used to examine emission drivers and project the implications of alternative fertilizer-reduction and pesticide-reduction pathways. To complement the aggregate analysis, we use survey data from 174 wheat farms and a slack-based measure of ecological efficiency to assess whether lower chemical input use is compatible with farm performance. Provincial agricultural carbon emissions followed an inverted V-shaped trajectory, rising initially and declining after 2008. Under the simulated reduction scenarios, fertilizer and pesticide use in 2035 are projected to fall by 0.85–1.13 million tons and 0.04–0.05 million tons, respectively, relative to 2020, while agricultural carbon emissions decline by 14.09–20.18 million tons. At the farm level, fertilizer and pesticide use are negatively associated with ecological efficiency. Nonlinear estimates further indicate that fertilizer application beyond approximately 121 jin per mu for yield and 103 jin per mu for net returns is associated with diminishing farm performance. Together, the macro-level and micro-level evidence suggests that more efficient chemical input use can support emission reduction without necessarily compromising productivity. Policies should therefore combine input optimization with green technological innovation and low-carbon farming practices.

Keywords: agricultural carbon emissions, scenario analysis, EBM–GML model, fertilizer, pesticide

1. Introduction

With the increasing severity of global extreme climate changes and environmental pollution, the uncertainty in agricultural production has risen sharply, posing a threat to human survival and the sustainable development of society and the economy [1, 2]. Agriculture, as a crucial source of food for human survival, also profoundly affects the carbon cycle of ecosystems and greenhouse gas (GHG) emissions [3, 4]. Agriculture is not only a significant source of carbon emissions but also has the potential to function as a carbon sink [5]. Reducing agricultural carbon emissions helps control global climate change, protect the environment, and enhance sustainable agricultural development [6]. In the global context of responding to climate change, low-carbon agriculture characterized by "low energy consumption, low emissions, low pollution, and high carbon sequestration" will become the inevitable trend for the future development of agricultural economics [7]. China has actively contributed to addressing global climate change and has made significant contributions to emissions reduction. In 2020, it set forth an ambitious goal of striving to peak carbon dioxide emissions by 2030 and achieve carbon neutrality by 2060 [8].

In modern agriculture, fertilizers and pesticides play an indispensable role in increasing crop yields and ensuring food security [9, 10]. However, their use also constitutes a significant source of carbon emissions [11, 12]. Excessive application of fertilizers and pesticides not only promotes GHG emissions from the soil but also accelerates the process of global climate change [13]. The reasonable and scientific use of fertilizers and pesticides is crucial for ensuring the sustainability and environmental friendliness of agricultural production [14]. The intensity of pesticide and fertilizer use in China far exceeds the world average, being about three times and 2.5 times the global average, respectively [15, 16]. In 2015, the Ministry of Agriculture and Rural Affairs issued the "Zero Growth Action Plan for Fertilizer and Pesticide Use by

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2020," aiming to achieve zero growth in fertilizer use for major crops by 2020 [17]. Recently, the Chinese government issued the "Opinions on Deepening the Fight Against Pollution," which puts forward new requirements for controlling agricultural non-point source pollution and monitoring rural ecosystems [18]. Against the backdrop of "zero growth" in fertilizer and pesticide use and the "dual carbon targets," studying the impact of agricultural carbon emissions on the environment holds significant practical importance.

As one of China's key agricultural production regions, Shandong Province has abundant water and soil resources. Shandong plays a significant role in ensuring national food security due to its high agricultural output [19]. However, for a long time, agricultural production in Shandong has been constrained by the high-input, high-output, high-emission model of chemical agriculture [20]. Since the "zero growth" initiative for fertilizer and pesticide use was introduced in 2015, Shandong has achieved remarkable results, leading the nation in fertilizer reduction with a total decrease of 826,000 tons of fertilizer and 42,800 tons of pesticides. In Shandong's efforts to establish a pioneering zone for green, low-carbon, and high-quality development, exploring pathways to low-carbon and high-quality agricultural development is crucial.

Accurate carbon emission measurement is essential for achieving the "dual carbon" targets [21, 22]. Scholars have conducted considerable research on agricultural carbon emissions, focusing primarily on carbon emission measurement [23, 24], spatiotemporal characteristics [25], and influencing factors [26], with scales ranging from national and provincial to county levels [27, 28]. Recent studies have further expanded the literature from multiple perspectives. Yang et al. [29] investigated the effects of agricultural practices on agricultural carbon emission efficiency in China, finding that fertilizer and pesticide inputs may benefit from economies of scale, whereas agricultural machinery and irrigation tend to generate diseconomies of scale. Their study further identified significant spatial spillover effects across regions. Similarly, Wang et al. [30] examined the spatiotemporal evolution of agricultural carbon emission efficiency in the Yangtze River Economic Belt, identifying pronounced spatial clustering and positive spillover effects. Their results further pinpoint pesticide use as a major constraint on efficiency gains. Beyond the Chinese context, Balogh [31] examined the effects of agricultural development and trade on CO_2 emissions across 152 non-EU countries, finding that agricultural development generally drives emissions upward, whereas the environmental implications of agricultural trade and trade agreements prove more nuanced. In addition, Raihan and Tuspekova [32], using Brazil as a case study, found that agricultural value added contributed to CO_2 emissions, whereas renewable energy consumption and forested area served to alleviate environmental pressure. Collectively, these studies indicate that agricultural carbon emissions and carbon efficiency are influenced not only by direct input use but also by spatial interactions, trade structures, and broader economic and ecological contexts. Relative to other sectors, the heterogeneous nature of agricultural production substantially complicates the sources of carbon emissions [33].

Methods for measuring agricultural carbon emissions primarily include life cycle assessment (LCA) theory and the Intergovernmental Panel on Climate Change (IPCC) methodology. Schueler et al. [28] examined the utility of the IPCC Tier 1 methodology in distinguishing the carbon footprints (CFs) of milk production across different Norwegian dairy farms. Using data from 20 dairy farms, the authors evaluated the uncertainties associated with emissions by conducting Monte Carlo simulations. Rahman et al. [34] performed an LCA of conventional rice farming in Malaysia, adopting a cradle-to-gate framework to examine GHG emissions across the main stages of rice production. All inputs—including fertilizers, soil conditioners, pesticides, and fuel—were accounted for throughout the production chain, from seed cultivation and land preparation through to seeding, field maintenance, and harvesting. The findings show that producing one ton of un-milled rice grain generates 1.39 tons of CO_2 equivalent, with CH_4 emissions from field cultivation accounting for 76.85% of the total [34]. Yao et al. [35] explored the feasibility of coupling LCA with the RothC model to estimate the CF of wheat production systems incorporating green manure in China. Their work centered on assessing current and future CF mitigation potential through the replacement of summer fallow with leguminous green manure (LGM) on the Loess Plateau, a semi-arid region of the country. The findings indicate that while LGM treatments initially entail higher GHG emissions from agricultural inputs, they substantially increased soil organic carbon stocks by 14%–24% over an eight-year period. As a result, the CF was reduced by 25%–51% relative to conventional fallow systems [35].

Research on the relationship between agricultural input resources and carbon emissions in the agricultural sector remains comparatively scarce. As a leading agricultural province, Shandong Province offers a valuable case for characterizing carbon emission patterns and trajectories, with important strategic implications for the green transformation of agriculture in both the province and the country at large [36]. This study adopts the carbon emission coefficient method, with a focus on agricultural inputs, to estimate agricultural carbon emissions in Shandong Province. On this basis, carbon emissions are treated as an undesirable output, and the epsilon-based measure–global Malmquist–Luenberger (EBM–GML) model is employed to measure green total factor productivity (GTFP) in Shandong's agricultural sector. Furthermore, the STIRPAT model is utilized to examine the determinants of emissions and to project agricultural carbon emissions in Shandong for 2035, with the goal of furnishing policy-relevant insights for the province's low-carbon agricultural transition.

2. Research Content and Methodology

2.1. Overview of the study area

Shandong Province (114°47.5'E to 122°42.3'E, 34°22.9'N to 38°24.0'N) is bordered by the sea on its north, east, and south sides, facing the Bohai Sea and Yellow Sea, and located in the lower reaches of the Yellow River. It is one of China's key economic provinces. Centered around its capital, Jinan, Shandong comprises 16 prefecture-level cities, including Jinan, Qingdao, Yantai, and Weifang, covering a total area of approximately 157,900 square kilometers, with a resident population of 101.23 million in 2023. Shandong has a warm temperate monsoon climate, characterized by four distinct seasons and mild conditions, with an annual average temperature of 11–14 °C, 2290–2890 h of sunlight, and 550–950 mm of precipitation. The main soil types for cultivated land are fluvo-aquic soil, brown soil, and cinnamon soil.

As a major agricultural province in China, Shandong is an essential agricultural production base, with cultivated land accounting for 6.17% of the national total, ranking third nationwide, and its agricultural value added consistently ranks first. Shandong's total grain output has been among the top three in the country for many years, with leading production volumes in grains, vegetables, fruits, meat, eggs, milk, and aquatic products. In 2023, the total output value of agriculture, forestry, animal husbandry, and fisheries was 1.25319 trillion yuan, with a total grain output of 56.553 million tons. With the rapid development of agriculture and the advancement of agricultural modernization, the use of chemical inputs such as fertilizers and pesticides has increased significantly, leading to notable agricultural environmental pollution and substantial GHG emissions, which pose serious challenges to achieving the "dual carbon" targets [37]. Reasonably and accurately estimating agricultural carbon emissions in Shandong is crucial for devising effective agricultural emission reduction measures and promoting sustainable agricultural development.

2.2. Methodology

The IPCC is an international organization founded by the United Nations Environment Programme and the World Meteorological Organization. The mission of the IPCC is to evaluate scientific, social, and economic information pertaining to climate change. Among the tools it provides, the IPCC methodology is extensively employed for estimating GHG emissions and features prominently in research on agricultural carbon emissions [38]. The IPCC methodology follows a basic computational procedure that begins with identifying the principal sources of agricultural carbon emissions and then multiplies the activity data for each source by its corresponding emission factor to derive GHG emissions from individual agricultural categories. These emissions are subsequently converted into carbon dioxide equivalents using the global warming potential values assigned to different gases, thereby producing an aggregate carbon emission total. Here, the emission factor refers to the amount of GHG emissions generated per unit of activity or energy use [39]. The specific calculation formula is as follows:

$$C_T = \sum_{i=1}^{6} c_i f_i \tag{1}$$

Based on existing studies, this research identifies chemical fertilizers, pesticides, agricultural diesel, agricultural plastic film, irrigation, and tillage as the six primary carbon sources in agricultural production in Shandong Province [40–42]. In Equation (1), C_T represents the total carbon emissions, c_i (where $i = 1, 2, \ldots, 6$) denotes the usage quantity of each input factor, and f_i represents the carbon emission factor for each input factor. The carbon emission factors involved in the calculation of agricultural carbon emissions for Shandong Province are organized in Table 1.

To address issues such as the inclusion of undesirable outputs and the simultaneous presence of radial and non-radial factors, Tone et al. [41] proposed the Epsilon-based measure (EBM) model. The input-oriented EBM model under variable returns to scale is as follows:

$$\gamma^* = \min \frac{\theta - \varepsilon_x \sum_{i=1}^{m} \frac{w_i^- s_i^-}{x_{i0}}}{\varphi + \varepsilon_y \sum_{r=1}^{s} \frac{w_r^+ s_r^+}{y_{r0}}}$$
$$s.t\begin{cases} \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{i0} \\ \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = \varphi y_{r0} \\ \lambda_j \ge 0, \sum \lambda = 1, s_i^-, s_r^+ \ge 0 \end{cases} \tag{2}$$

In Equation (2), γ^* represents the comprehensive efficiency value; x and y denote inputs and desirable outputs, respectively; m and s represent the number of input and desirable output indicators; and w_i^- and w_r^+ are the weights for the i-th input and the r-th desirable output, respectively. s_i^- and s_r^+ are the slack variables for the i-th input and the r-th desirable output, respectively. θ and φ denote the parameters for the radial part; ε represents the importance parameter for the non-radial part, and n indicates the number of decision-making units.

Färe et al. [42] developed the data envelopment analysis–based Malmquist productivity index, which can be decomposed into technical efficiency change and technical progress. However, the Malmquist index may encounter infeasibility in linear programming. Following Oh [43], this study adopts the global Malmquist–Luenberger (GML) index to measure GTFP. This approach further decomposes GTFP into green technical efficiency change (GEC) and green technical progress (GTC). The formula is given as follows:

$$\begin{aligned} & GML^{t,t+1}\left(x^t, y^t, x^{t+1}, y^{t+1}, z^{t+1}\right) \\ & = \frac{E^{G,t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}\right)}{E^{G,t}\left(x^t, y^t, z^t\right)} \\ & = \frac{E^{G,t}\left(x^{t+1}, y^{t+1}, z^{t+1}\right)}{E^{G,t}\left(x^t, y^t, z^t\right)} \\ & \times \frac{E^{G,t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}\right)/E^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}\right)}{E^{G,t}\left(x^t, y^t, z^t\right)/E^{t}\left(x^t, y^t, z^t\right)} \\ & = GEC^{t,t+1} \times GTC^{t,t+1} \end{aligned} \tag{3}$$

Table 1
Carbon emission factors for different inputs

Item	Emission parameter	Unit	Reference source
Nitrogen fertilizer	2.116	kg C/kg	Chen et al.
Phosphate fertilizer	0.636	kg C/kg	Chen et al.
Potassium fertilizer	0.18	kg C/kg	Chen et al.
Compound fertilizer	1.772	kg C/kg	CLCD v0.7
Pesticides	12.44	kg C/kg	Ecoinvent v2.2
Agricultural diesel	0.59	kg C/kg	IPCC
Agricultural plastic film	2.58	kg C/kg	Sun et al.
Irrigation	266.48	kg C/hm-2	IPCC
Tillage	312.6	kg C/hm-2	IPCC

GEC reflects the extent to which a production unit moves closer to the production frontier from period t to $t + 1$. GTC captures the outward shift of the production frontier over time. Values of GTFP, GEC, and GTC greater than 1 indicate growth or improvement, whereas values below 1 indicate decline or deterioration.

The STIRPAT model is a variant of the IPAT model, which is widely used to examine the environmental impacts of human activities. In the IPAT framework, environmental impact (I) is determined by three key factors: population (P), affluence (A), and technology (T). The basic expression of the IPAT model is as follows:

$$I = \alpha P^n A^m T^z \varepsilon \tag{4}$$

In Equation (4), α is the constant term, n is the exponent for the population variable, m is the exponent for the affluence variable, and z is the exponent for the technology variable. After taking the logarithm, the equation can be transformed into Equation (5):

$$\ln I = \ln \alpha + n \ln P + m \ln A + z \ln T + \ln \varepsilon \tag{5}$$

The basic concept of the IPAT model is that increases in population, economic development, and the use and innovation of technology all impact the environment. Population growth and economic development tend to drive up resource consumption and intensify environmental pressures. Technological progress can, to a certain degree, lower the environmental footprint per unit of output; however, when technological advances are over-relied upon or misapplied, they may still give rise to environmental problems. The STIRPAT model incorporates stochastic components, which enable it to accommodate the uncertainty and variability inherent in environmental impacts, thereby offering a more realistic representation of actual conditions. In this study, we employ an extended version of the STIRPAT framework and conduct the analysis using a multiple linear regression model, as specified below:

$$\begin{aligned} \ln I &= \ln \alpha + \beta_1 \ln\ x_1 + \beta_2 \ln\ x_2 + \beta_3 \ln\ x_3 + \beta_4 \ln\ x_4 \\ &\quad + \beta_5 \ln\ x_5 + \beta_6 \ln\ x_6 + \beta_7 \ln\ x_7 + \beta_8 \ln\ x_8 \\ &\quad + \beta_9 \ln\ x_9 + \ln \varepsilon \end{aligned} \tag{6}$$

In Equation (6), x_1–x_9 represent pesticide input, fertilizer input, agricultural diesel input, agricultural plastic film input, effective irrigation area, mechanical power, urbanization level, industrial structure, and the level of agricultural economic development, respectively.

Ridge regression is a linear regression method that can be used to address multicollinearity in a dataset. Ridge regression applies a constraint on the model's regression coefficients to reduce their variance, thereby improving the model's stability and predictive performance. This is achieved by introducing an adjustment term known as the ridge parameter or regularization parameter. The ridge parameter controls the strength of regularization; a larger ridge parameter results in stronger shrinkage of the regression coefficients, reducing the impact of multicollinearity on the coefficient estimates. When multicollinearity is present, using ordinary least squares (OLS) estimation does not yield a unique solution. To obtain a unique solution for the parameter vector, regularization is applied by adding a penalty term to the loss function:

$$\min_{\beta} L(\beta) = \underbrace{(y - X\beta)^{'}(y - X\beta)}_{SSR} + \underbrace{\lambda \|\beta\|_2^2}_{penalty} \tag{7}$$

In Equation (7), the sum of squared residuals (SSR) and the penalty term are included. This regularization term effectively prevents model overfitting and addresses the difficulty of inversion in cases of rank deficiency. The advantage of ridge regression is that it can effectively reduce the impact of multicollinearity on the estimation of regression coefficients and improve the model's generalization ability.

2.3. Data sources

The agricultural input and output data related to this study mainly come from the Shandong Statistical Yearbook (2000–2022), China Rural Statistical Yearbook, statistical yearbooks of various prefecture-level cities in Shandong Province, and statistical websites. A descriptive statistical analysis of the main agricultural carbon sources in Shandong Province is shown in Table 2. A list of abbreviations used in this study is provided in Appendix Table A1.

3. Results

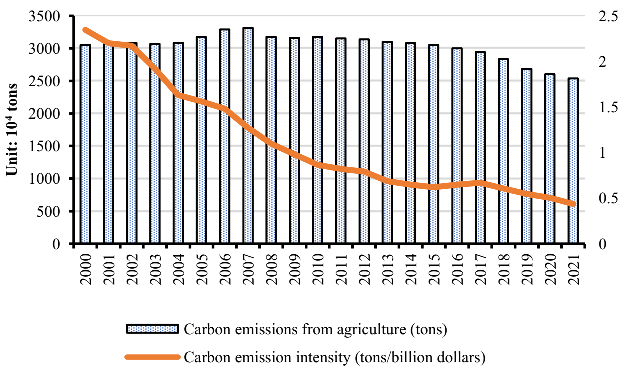
3.1. Carbon emissions and carbon intensity

Based on the calculation results, Figure 1 presents the trends in agricultural carbon emissions and carbon emission intensity

Table 2
Descriptive statistical analysis of agricultural inputs and outputs

Variable	Mean	Std. Dev	Min	Max	Unit
Agricultural output value	215.58	13.68	29.72	630.35	Billion Yuan
Nitrogen fertilizer	34.92	18.23	5.26	76.12	10^4 Tons
Compound fertilizer	19.58	17.15	5.07	86.39	10^4 Tons
Potassium fertilizer	6.91	38.7	0.65	15.81	10^4 Tons
Phosphate fertilizer	14.91	10.08	1.84	47.85	10^4 Tons
Pesticides	0.94	0.49	0.22	2.47	10^4 Tons
Agricultural diesel	10.45	8.02	1.09	35.12	10^4 Tons
Agricultural plastic film	1.87	1.69	0.21	8.29	10^4 Tons
Irrigation area	312.03	148.02	98.57	689.89	10^3 Hectares
Crop area	69.39	35.63	19.06	155.79	10^4 Hectares

Figure 1
Agricultural carbon emissions and carbon emission intensity in Shandong Province, 2000–2021



in Shandong Province over the period 2000–2021. Agricultural carbon emissions in the province followed an inverted-V trajectory over these years. From 2000 to 2007, emissions rose from 30.52 million tons to 33.18 million tons, representing an increase of 2.66 million tons (8.70%). After 2008, emissions began to decline, falling from 31.79 million tons in 2008 to 25.41 million tons in 2021—a reduction of 6.38 million tons, or 20.10%.

In terms of input factors, in 2000, fertilizers, tillage, and pesticides contributed the most to agricultural carbon emissions, accounting for 22.50 million tons, 3.49 million tons, and 1.75 million tons, respectively, representing 73.70%, 11.40%, and 5.70% of total emissions. When agricultural carbon emissions peaked in 2007, the carbon emissions from fertilizers, tillage, and pesticides reached 24.25 million tons, 3.56 million tons, and 2.06 million tons, accounting for 73.10%, 10.70%, and 6.20%, respectively. By 2021, following the zero-growth initiative for fertilizer and pesticide use, the top three contributors to agricultural carbon emissions were fertilizers, tillage, and irrigation, with contributions of 17.83 million tons, 3.42 million tons, and 1.42 million tons, representing 70.20%, 13.50%, and 5.60%, respectively. Pesticides became the fourth-largest contributor to carbon emissions, with emissions of 1.35 million tons, accounting for 5.30%.

Across prefecture-level cities in Shandong, the top five cities in agricultural carbon emissions in 2000 were Weifang, Linyi, Heze, Jining, and Dezhou, with emissions of 3.50 million, 2.95 million, 2.72 million, 2.55 million, and 2.52 million tons, respectively. In 2007, the top five cities were Weifang, Linyi, Heze, Jining, and Dezhou, with emissions of 3.78 million, 3.30 million, 3.12 million, 2.83 million, and 2.77 million tons, respectively. In 2021, following the zero-growth initiative for fertilizer and pesticide use, the top five cities were Heze, Weifang, Linyi, Dezhou, and Jining, with emissions of 2.88 million, 2.62 million, 2.34 million, 2.18 million, and 2.13 million tons, respectively.

From 2000 to 2021, the intensity of agricultural carbon emissions in Shandong showed a "rapid decline—stable decline" trend. From 2000 to 2013, the intensity of agricultural carbon emissions declined rapidly, decreasing from 2.34 million tons of carbon emissions per 100 million yuan of agricultural output in 2000 to 0.69 million tons per 100 million yuan in 2013, with an average annual decrease of 8.40%. From 2014 to 2021, the intensity continued to decline at a stable rate, falling from 0.65 million tons per 100 million yuan in 2014 to 0.44 million tons per 100 million yuan in 2021, with an average annual decrease of 2.40%.

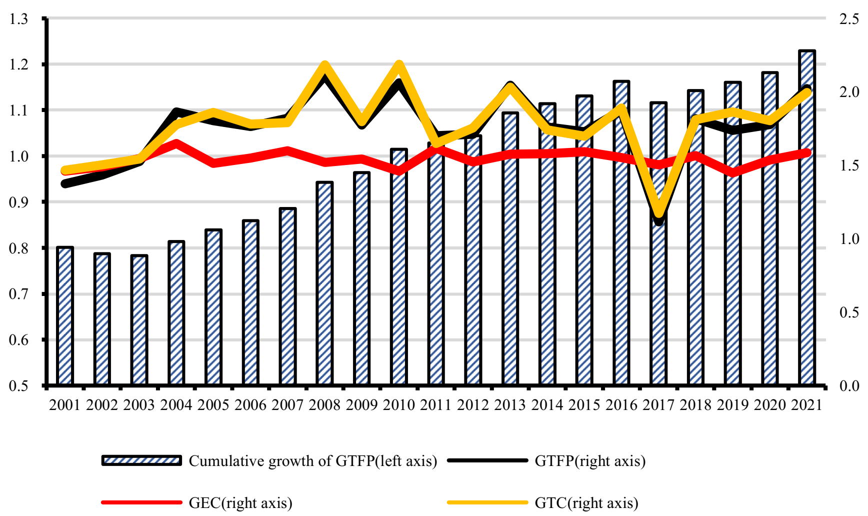
3.2. Green agriculture total factor productivity in Shandong Province

Based on agricultural panel data from Shandong Province from 2000 to 2021, the EBM–GML model was used to measure and decompose the province's agricultural GTFP (Figure 2). Overall, agricultural GTFP in Shandong showed an upward trend during this period, with growth primarily driven by agricultural green technological progress, while agricultural green technical efficiency hindered productivity growth. The average agricultural GTFP in Shandong from 2000 to 2021 was 1.061, with a cumulative productivity index of 2.279, indicating an average annual growth rate of 6.10% and a cumulative increase of 127.90%.

Decomposing the agricultural GTFP, the average agricultural green technical efficiency from 2000 to 2021 was 0.994, while the average agricultural green technological progress was 1.068. This indicates that agricultural green technical efficiency decreased by an average of 0.60% per year, while agricultural green technology advanced by an average of 6.80% per year.

By phases, agricultural GTFP in Shandong Province has experienced three stages: "steady growth—M-shaped fluctuating growth—steady growth." From 2001 to 2007, agricultural GTFP

Figure 2
Green total factor productivity in agriculture and its trends, Shandong Province, 2001–2021

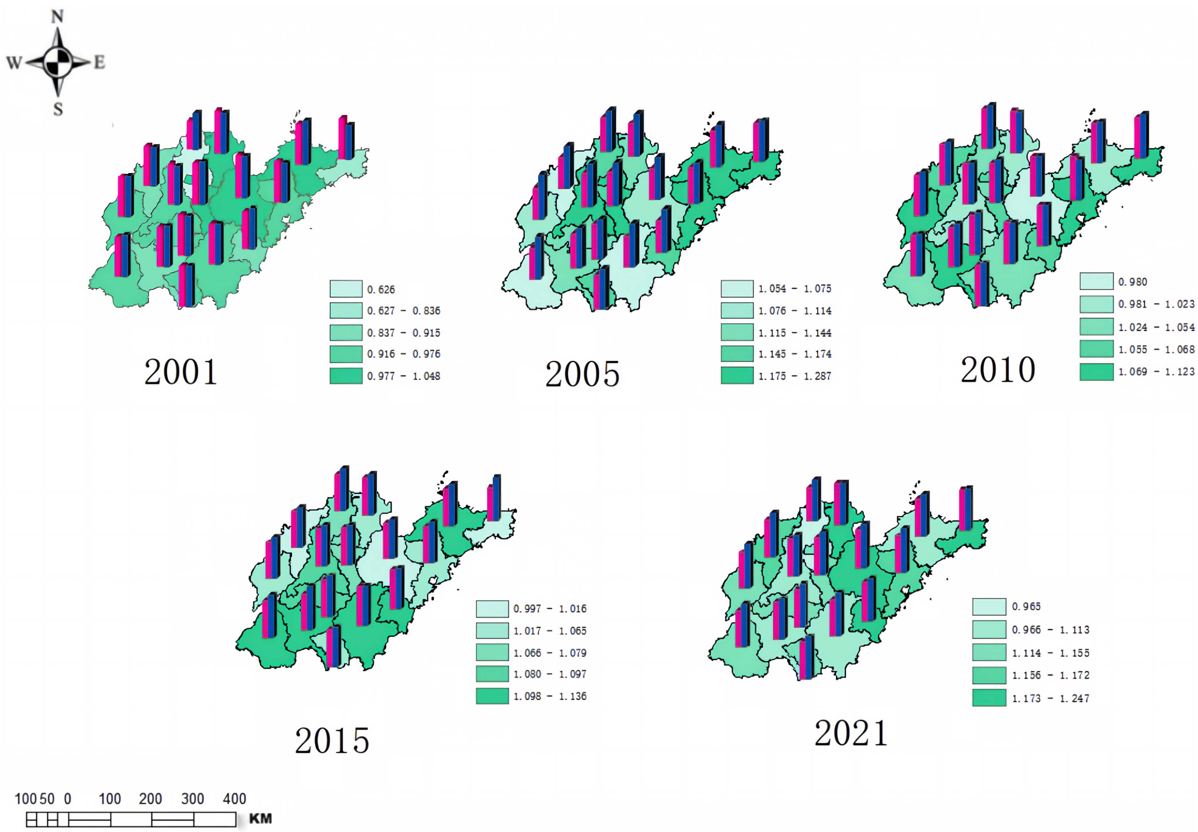


in Shandong grew steadily, with an average productivity value of 1.029, an average green technical efficiency of 0.994, and an average green technological progress of 1.036. This indicates an average annual growth rate of 2.90% in total factor productivity, an annual decline of 0.60% in green technical efficiency, and an annual growth of 3.6% in green technological progress during this period. Between 2007 and 2018, agricultural GTFP in Shandong underwent two "M-shaped fluctuation" phases, with an average productivity value of 1.074, an average green technical efficiency of 0.997, and an average green technological progress of 1.079. This signifies an annual growth rate of 7.40% in total factor productivity, a 0.30% annual decrease in green technical efficiency, and a 7.90% annual increase in green technological progress. Notably, extreme weather events during this period led to rapid declines in agricultural GTFP. From 2018 to 2021, GTFP returned to steady growth, with an average productivity value of 1.088, an average green technical efficiency of 0.991, and an average green technological progress of 1.098. During this period, total factor productivity grew at an average annual rate of 8.80%, green technical efficiency declined by 0.90% per year, and green technological progress increased by 9.80% per year.

Figure 3 reports the evolution of agricultural GTFP and its decomposition across prefecture-level cities in Shandong Province from 2001 to 2021. During this period, GTFP increased across all sample cities. The top five cities in terms of agricultural GTFP were Yantai (1.078), Zibo (1.077), Liaocheng (1.075), Dongying (1.072), and Jining (1.071). Heze (1.046), Rizhao (1.046), and Weihai (1.049) ranked lower in agricultural GTFP. In addition, this study compares agricultural green technical efficiency across prefecture-level cities in Shandong. Cities with improved agricultural green technical efficiency (efficiency greater than 1) include Dongying, Jining, and Yantai. Cities where agricultural technical efficiency remained unchanged (efficiency of 1) include Zaozhuang, Jinan, and Zibo, while Binzhou, Dezhou, Heze, Liaocheng, Linyi, Qingdao, Rizhao, Tai'an, Weihai, and Weifang showed continuous declines in agricultural green technical efficiency. Agricultural green technology also showed an overall improvement trend across the sample cities. The top five cities in agricultural green technological progress were Liaocheng (1.087), Binzhou (1.078), Dezhou (1.078), Zibo (1.077), and Yantai (1.074). Conversely, Zaozhuang (1.051), Rizhao (1.057), Tai'an (1.061), Jinan (1.062), and Weifang (1.062) ranked relatively lower in terms of agricultural green technological progress.

From 2001 to 2021, agricultural GTFP recorded positive growth across all prefecture-level cities in Shandong, driven largely by advances in green agricultural technology. Although improvements in green technical efficiency were observed in Dongying, Jining, and Yantai, the average green technical efficiency in most regions remained at or below 1, which limited their contribution to overall productivity gains. When examined by individual year, the regions with the highest annual growth rates varied over time: Yantai (4.80%), Dongying (3.40%), and Weifang (3.10%) led in 2001; Weihai (13.60%), Linyi (13.20%), and Rizhao (13.10%) topped the list in 2005; Weihai (28.70%), Qingdao (24.30%),

Figure 3
City-level comparison of agricultural green total factor productivity and its decomposition in Shandong Province



and Zibo (23.50%) recorded the largest increases in 2010; Qingdao (12.30%), Liaocheng (10.10%), and Weihai (9.90%) regained the lead in 2015; and by 2021, Rizhao (24.70%), Dongying (24.50%), and Weifang (21.60%) emerged as the fastest-growing cities.

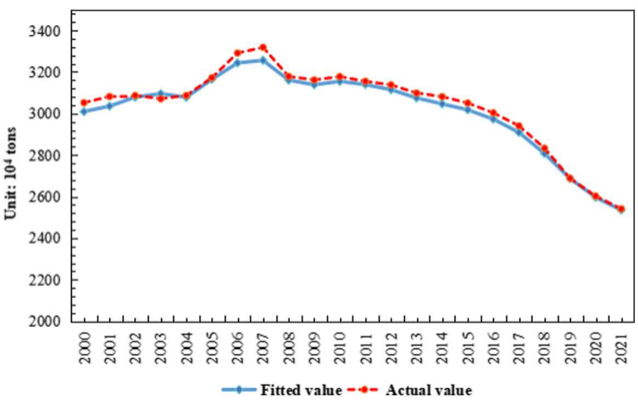
4. Scenario Forecasting and Analysis

Before estimating Equation (6), multicollinearity testing was conducted, revealing that several variables had variance inflation factors greater than 10, indicating a severe multicollinearity problem. Consequently, ridge regression, as shown in Equation (7), was applied to estimate Equation (6), yielding the following fitted equation:

$$\begin{aligned} \ln I &= 4.13 + 0.395 \ln\ x_1 + 0.081 \ln\ x_2 + 0.175 \ln\ x_3 \\ &\quad - 0.013 \ln\ x_4 - \ 0.069 \ln\ x_5 + 0.011 \ln\ x_6 - 0.023 \ln\ x_7 \\ &\quad + 0.013 \ln\ x_8 - 0.021 \ln\ x_9 \\ R^2 &= 0.998, lambda = 0.0679 \end{aligned} \tag{8}$$

The accuracy of this equation was tested using ten-fold cross-validation, yielding a goodness-of-fit of 99.28%. Figure 4 shows the changes in the simulated and fitted values of carbon emissions in Shandong Province. The simulated values are only slightly lower than the actual values in some years, indicating a good fit that effectively reflects the trends and characteristics of agricultural carbon emissions in Shandong Province.

Figure 4
Actual versus fitted carbon emissions (2000–2021)



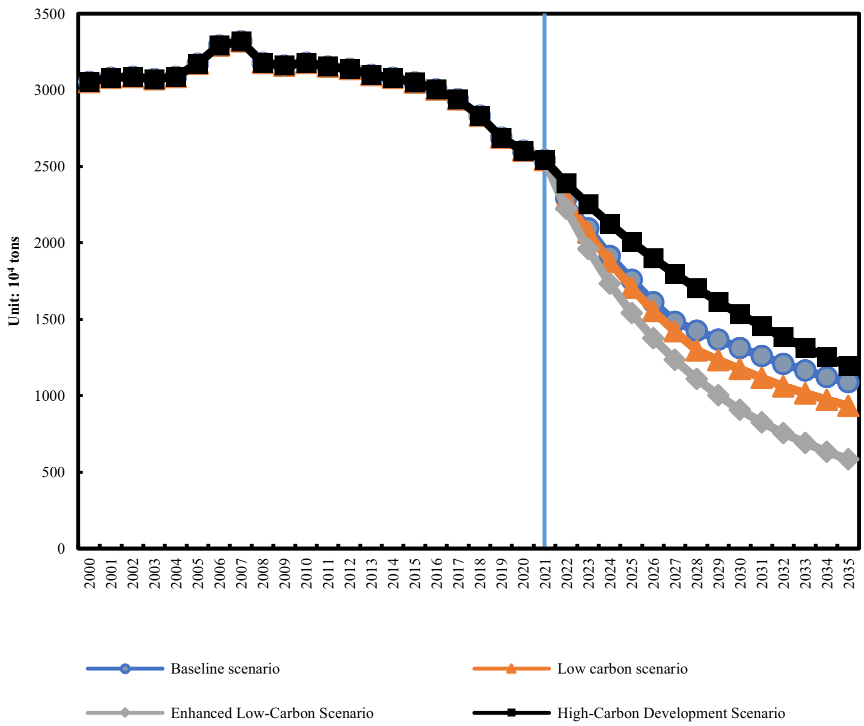
Scenario analysis is a decision-making method used to evaluate various possible scenarios and outcomes associated with a specific decision or event. This approach involves the construction of multiple scenarios, each subjected to quantitative or qualitative analysis, so as to facilitate a more thorough understanding and assessment of the potential risks and opportunities associated with a given decision. In this study, scenario analysis is employed to project agricultural carbon emissions in Shandong Province over the period 2022–2035 (Table 3 and Figure 5). On the basis of existing data and relevant research, the following four scenarios are established:

1) Baseline Scenario: Under this scenario, only the reductions in pesticide and fertilizer inputs are taken into account with respect to their effects on agricultural carbon emissions. Based on the average growth rate of fertilizer usage over the past five years, the growth rate is set at −3.20% for 2022–2027 and −1.60% for 2028–2035. For pesticides, the average growth rate over the past five years suggests a rate of −5.40% for 2022–2027 and −2.70% for 2028–2035. This parameter setting is based on the premise that the rapid reduction in fertilizer and pesticide use cannot be sustained long-term and should be moderately reduced to ensure food security. Thus, the growth rate in the latter period is set at 50% of the previous period's rate.
2) Low-Carbon Scenario: This scenario considers not only the reductions in pesticide and fertilizer inputs but also the impact of changes in agricultural diesel, plastic film, and effective irrigation area on agricultural carbon emissions. Unlike the baseline scenario, the reduction rate for pesticides and fertilizers in 2028–2035 remains high, at 75% of the past five years' rate. For agricultural diesel, plastic film, and effective irrigation area, the growth rate is set to match the past five years' average for 2022–2027 and the average growth rate from 2001–2021 for 2028–2035.
3) Enhanced Low-Carbon Scenario: This scenario represents a more proactive approach to achieving low-carbon goals, with strengthened measures to reduce GHG emissions. It includes changes in agricultural diesel, plastic film, and effective irrigation area, with the growth rates for 2022–2027 and

Table 3
Basic parameter settings for different scenarios

Scenario type	Year	Fertilizer growth rate (%)	Pesticide growth rate (%)	Diesel growth rate (%)	Plastic film growth rate (%)	Irrigation area growth rate (%)
Baseline scenario	2022–2027	–3.2	–5.4	–	–	–
	2028–2035	–1.6	–2.7	–	–	–
Low-carbon scenario	2022–2027	–2.4	–4.05	–3.8	–2.1	0.45
	2028–2035	–1.6	–2.7	–1.1	–1.05	0.55
Enhanced low-carbon scenario	2022–2027	–3.2	–5.4	–3.8	–2.1	0.55
	2028–2035	–3.2	–5.4	–3.8	–2.1	0.55
High-carbon development scenario	2022–2027	–1.6	–2.7	–1.1	0.6	0.45
	2028–2035	–1.6	–2.7	–1.1	0.6	0.45

Figure 5
Carbon emissions prediction (2022–2035)



2028–2035 aligned with the past five years, maintaining a consistent rate of reduction.

4) High-Carbon Development Scenario: This scenario prioritizes rapid agricultural growth with minimal emphasis on emissions reduction. Here, the growth rates of agricultural input factors for 2022–2027 and 2028–2035 are set to maintain only a low growth level.

5. Farm-Level Evidence on Chemical Input Use and Ecological Efficiency

The province- and city-level analyses document the evolution of agricultural green productivity and the projected decline in carbon emissions under alternative fertilizer- and pesticide-reduction scenarios. However, aggregate evidence alone cannot determine whether lower chemical input use is compatible with efficient production at the farm level. To provide complementary micro-level evidence, we use survey data from wheat-producing households in Shandong Province to examine the relationship between chemical input intensity, farm ecological efficiency, and agricultural performance. Specifically, we assess whether farms with lower fertilizer and pesticide use achieve higher ecological efficiency and whether input reduction is associated with losses in wheat yield or farm returns. Given the cross-sectional nature of the data, the estimates are interpreted as conditional associations rather than causal effects.

5.1. Data and empirical specification

The farm-level analysis draws on a survey of 176 wheat-producing households located in Changle County of Weifang, Gaotang County of Liaocheng, and Yanzhou District of Jining. The survey records wheat production during the 2023 agricultural year and covers 5 townships and 12 villages. It contains detailed information on fertilizer application, pesticide expenditure and application frequency, wheat yield, production costs, output prices, household characteristics, and land conditions. After excluding two households with missing ecological-efficiency scores, the estimation sample contains 174 observations.

Farm ecological efficiency is measured using the EBM. The EBM approach explicitly accounts for input and output slacks and therefore provides a more flexible assessment of inefficient input use. The efficiency score ranges from zero to one, with a higher value indicating that a household operates closer to the ecological production frontier. The mean EBM efficiency score in the estimation sample is 0.626, suggesting considerable heterogeneity in farm-level ecological performance. Descriptive statistics for the farm-level variables are reported in Appendix Table A2.

To examine the farm-level relationship between chemical input use and ecological efficiency, we estimate the following specification:

$$EcoEff_i = \alpha + \beta_1 lnFertilizer_i + \beta_2 ln\left(Pesticide_i\right) + X_i + \varepsilon_i \quad (9)$$

where $EcoEff_i$ denotes the ecological-efficiency score of household i. $Fertilizer_i$ is fertilizer application per mu, while $Pesticide_i$ is pesticide expenditure per mu. The vector X_i includes the age and age squared of the household head, years of education, self-rated health, household farm labor, part-time farming status, planted area, number of plots, land quality, irrigation convenience, high-standard farmland status, machinery ownership, and exposure to weather shocks. All models are estimated using ordinary least squares (OLS) with heteroskedasticity-robust standard errors.

Because fertilizer and pesticide inputs may also enter the construction of the EBM score, the coefficients should not be interpreted as causal effects. Instead, the regressions characterize whether the micro-level efficiency pattern is consistent with the input-reduction relationship identified in the aggregate analysis.

5.2. Chemical inputs and farm ecological efficiency

Table 4 reports the relationship between chemical input intensity and farm-level EBM ecological efficiency. Column (1) includes fertilizer and pesticide inputs only. Column (2) adds household characteristics, while Column (3) further controls for farm and land conditions. The coefficients on fertilizer quantity and pesticide expenditure remain negative and statistically significant across all three specifications.

In the preferred specification reported in Column (3), the coefficient on log fertilizer quantity is −0.2120, while that on log pesticide expenditure is −0.0637. Both coefficients are statistically significant at the 1% level. These estimates imply that a 10% increase in fertilizer use is associated with an approximately 0.021-point decline in the EBM efficiency score, whereas a 10% increase in pesticide expenditure is associated with an approximately 0.006-point decline. The stability of the coefficients after adding household and farm controls indicates that the negative input-efficiency relationship is not driven solely by observable differences in farmer characteristics or production conditions.

Table 4
Chemical input intensity and farm-level EBM ecological efficiency

	(1)	(2)	(3)
	Inputs only	+ Household controls	+ Farm controls
Log fertilizer quantity	–0.226***	–0.219***	–0.212***
	(0.023)	(0.022)	(0.026)
Log pesticide expenditure	–0.064***	–0.063***	–0.063***
	(0.006)	(0.005)	(0.006)
Age		0.001	0.002
		(0.003)	(0.003)
Age squared		0.000	–0.000
		(0.000)	(0.000)
Years of education		0.002	0.004*
		(0.002)	(0.002)
Self-rated health		0.027***	0.017**
		(0.008)	(0.008)
Farm labor		–0.041***	–0.034***
		(0.013)	(0.012)
Part-time farming		0.011	0.003
		(0.016)	(0.017)
Log planted area			0.005
			(0.012)
Number of plots			–0.000
			(0.000)
Land quality			0.008
			(0.006)
Irrigation convenience			0.007
			(0.009)
High-standard farmland = 2			–0.080***
			(0.027)
High-standard farmland = 3			0.016
			(0.020)
Owns agricultural machinery			–0.041
			(0.028)
Weather shocks			–0.002
			(0.011)
Constant	0.629***	0.506***	0.427***
	(0.007)	(0.124)	(0.137)
Observations	174	174	174
Adjusted R-squared	0.621	0.702	0.712

Note: Asterisks denote statistical significance at the 10% level, 5% level (**), and 1% level (***).

Several control variables also display meaningful associations with ecological efficiency. Education and self-rated health are positively associated with the EBM score, whereas the number of household members engaged in farming is negatively associated with ecological efficiency. These estimates should nevertheless be interpreted cautiously because the cross-sectional specification cannot eliminate unobserved differences in managerial ability or production conditions.

Table 5 examines the robustness of the main results to alternative measures of chemical input intensity and potential outliers. We replace fertilizer quantity with fertilizer expenditure, replace pesticide expenditure with pesticide application frequency, and winsorize the chemical input variables at the 1st and 99th percentiles. The fertilizer and pesticide coefficients remain negative and statistically significant at the 1% level in all specifications. These results confirm that the negative association between chemical input intensity and EBM ecological efficiency is not sensitive to a particular input measure or a small number of extreme observations.

5.3. Yield and profitability trade-offs

A central concern surrounding fertilizer and pesticide reduction is that lower chemical input use may compromise food production or farm income. Table 6 therefore examines the relationships between chemical inputs, wheat yield, and net returns per mu. Columns (1) and (2) use log wheat yield as the dependent variable, while Columns (3) and (4) examine net returns per mu. The specifications in Columns (2) and (4) include quadratic input terms to allow for diminishing or negative marginal returns.

The estimates indicate a nonlinear relationship between fertilizer use and agricultural performance. In the yield equation, the squared fertilizer term is negative and statistically significant at the 1% level. The fertilizer terms are also jointly significant. The estimated turning point is approximately 121 jin per mu, with a 95% confidence interval of 104–138 jin per mu. Because average fertilizer application in the sample is approximately 150 jin per mu, this result suggests that a substantial share of farms may operate beyond the fertilizer level associated with maximum predicted wheat yield.

A similar pattern emerges for farm profitability. The squared fertilizer term is negative and statistically significant, and the fertilizer terms are jointly significant. The estimated fertilizer level associated with maximum predicted net returns is approximately 103 jin per mu, which is lower than the yield-maximizing level. This difference is economically intuitive: additional fertilizer may generate some output but cease to be profitable once its cost is taken into account.

The evidence for pesticide use is less consistent. Pesticide expenditure is positively associated with yield and net returns in the linear specifications, but the coefficients become statistically insignificant once nonlinear terms are introduced. The pesticide terms are jointly significant in the yield equation but not in the net-return equation. We therefore do not find robust evidence that additional pesticide expenditure improves farm profitability.

Table 5
Robustness checks for farm-level EBM ecological efficiency

	(1)	(2)	(3)	(4)
	Baseline	Input expenditure	Pesticide frequency	Winsorized inputs
Log fertilizer quantity	–0.212***		–0.230***	
	(0.026)		(0.032)	
Log fertilizer expenditure		–0.146***		
		(0.015)		
Winsorized log fertilizer quantity				–0.218***
				(0.025)
Log pesticide expenditure	–0.063***	–0.073***		
	(0.006)	(0.006)		
Log pesticide frequency			–0.121***	
			(0.021)	
Winsorized log pesticide expenditure				–0.062***
				(0.006)
Controls	Yes	Yes	Yes	Yes
Constant	0.427***	0.393**	0.403***	0.419***
	(0.137)	(0.153)	(0.148)	(0.135)
Observations	174	174	174	174
Adjusted R–squared	0.712	0.658	0.635	0.717

Note: Asterisks denote statistical significance at the 10% level, 5% level (**), and 1% level (***).

Table 6
Chemical inputs, wheat yield, and net returns

	(1)	(2)	(3)	(4)
	Log yield	Log yield	Net return/mu	Net return/mu
Log fertilizer quantity	–0.074*	–0.082**	–196.465***	–210.179***
	(0.042)	(0.041)	(68.208)	(70.010)
Log fertilizer quantity squared		–0.256***		–324.857***
		(0.077)		(121.306)
Log pesticide expenditure	0.035***	0.002	47.871**	11.885
	(0.012)	(0.031)	(21.819)	(51.480)
Log pesticide expenditure squared		–0.009		–9.900
		(0.009)		(15.900)
Controls	Yes	Yes	Yes	Yes
Constant	6.305***	6.361***	–390.350	–326.593
	(0.224)	(0.224)	(353.078)	(363.346)
Observations	176	176	176	176
Adjusted R-squared	0.493	0.522	0.544	0.557

Note: Asterisks denote statistical significance at the 10% level, 5% level (**), and 1% level (***).

Taken together, the farm-level results are consistent with the aggregate scenario analysis. They suggest that reducing excessive fertilizer use may improve ecological efficiency without necessarily compromising wheat production or farm returns. However, the estimated turning points should be interpreted as sample-based statistical thresholds rather than agronomic recommendations or causal policy targets.

The micro-level evidence thus provides a behavioral and production-level foundation for the fertilizer-reduction pathways considered in the provincial carbon-emission scenarios.

6. Conclusion and Policy Implications

This study combines province- and city-level evidence with farm-level survey data to examine the evolution of agricultural carbon emissions, green productivity, and chemical input use in Shandong Province. Agricultural carbon emissions followed an inverted V-shaped trajectory between 2000 and 2021, increasing from 30.52 million tons in 2000 to a peak of 33.18 million tons in 2007 before declining to 25.41 million tons in 2021. Agricultural GTFP increased over the study period, although its growth was driven primarily by green technological progress, while improvements in green technical efficiency remained comparatively limited. The scenario simulations further project that, relative to 2020, fertilizer and pesticide use will decline by 0.85–1.13 million tons and 0.04–0.05 million tons, respectively, by 2035. The corresponding reduction in agricultural carbon emissions is projected to range from 14.09 to 20.18 million tons. These projections indicate the potential contribution of sustained chemical input reduction and improvements in production technology to Shandong's low-carbon agricultural transition.

The farm-level analysis provides complementary evidence on whether chemical input reduction is compatible with agricultural performance. Based on survey data from 174 wheat-producing households, the EBM regressions show that fertilizer quantity and pesticide expenditure are negatively associated with farm ecological efficiency after household and farm characteristics are controlled for. These relationships remain stable when fertilizer expenditure and pesticide application frequency are used as alternative input measures and when extreme observations are winsorized. The nonlinear estimates further suggest that wheat yield and net returns reach their predicted maxima at fertilizer application levels of approximately 121 jin per mu and 103 jin per mu, respectively. Beyond these levels, additional fertilizer application is associated with diminishing and eventually negative marginal performance. The micro-level evidence is therefore consistent with the aggregate results: reducing excessive chemical input use need not necessarily compromise agricultural productivity or farm profitability.

These findings should nevertheless be interpreted with appropriate caution. The emission projections depend on assumed future trajectories of agricultural inputs and should be regarded as scenario-based simulations rather than unconditional forecasts. In addition, the farm-level analysis is based on cross-sectional survey data, and the EBM indicator is constructed from observed production inputs and outputs. The estimated relationships therefore represent conditional associations rather than causal effects. Future research could use longitudinal farm data and stronger identification strategies to assess the longer-term effects of input reduction on emissions, productivity, and household income.

Several policy implications follow. First, fertilizer and pesticide policies should focus on improving input-use efficiency rather than imposing uniform reductions across farms. Soil testing, formula fertilization, precision application, and integrated pest management can help identify and reduce excessive input use while protecting yields and farm returns. The farm-level results also suggest that input recommendations should account for crop type, soil conditions, and existing application intensity.

Second, greater emphasis should be placed on converting green technological progress into farm-level efficiency gains. Investment in water-saving irrigation, energy-efficient machinery, low-carbon agricultural inputs, and agricultural plastic-film recycling should be accompanied by practical technical guidance and farmer training. This combination can reduce the gap between the availability of green technologies and their effective adoption in agricultural production.

Third, emission-reduction strategies should reflect the substantial differences in resource endowments, production structures, and green productivity across Shandong's prefecture-level cities. Regions with relatively low green technical efficiency should prioritize technology diffusion and improvements in farm management, whereas regions with higher efficiency but greater emission intensity should focus more directly on input substitution and emission control.

Finally, policy implementation should incorporate regular monitoring of chemical input use, crop yields, farm income, and carbon emissions. Scenario assumptions and input-reduction targets should be periodically updated in response to observed production outcomes. Such an adaptive approach would help Shandong pursue agricultural emission reduction without undermining food security or farmers' economic incentives.

Ethical Statement

The farm household survey conducted in this study was a non-interventional socioeconomic survey involving minimal risk to participants. The survey did not involve clinical trials, biological sample collection, invasive procedures, or experimental interventions. Participants were informed of the purpose of the survey, the voluntary nature of participation, and the confidentiality of the information collected, and informed consent was obtained prior to participation. The Institutional Review Board of the Institute of Agricultural Economics and Development, Chinese Academy of Agricultural Sciences, confirms that this study is exempt from formal ethical review and approval.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data are available from the corresponding author upon reasonable request.

Author Contribution Statement

Chenyang Liu: Conceptualization, Methodology, Validation, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration. **Wei Guo:** Software, Validation, Formal analysis, Resources, Data curation, Writing – original draft, Visualization.

References

[1] Chandio, A. A., Jiang, Y., Rehman, A., & Rauf, A. (2020). Short and long-run impacts of climate change on agriculture: An empirical evidence from China. *International Journal of Climate Change Strategies and Management*, *12*(2), 201–221. https://doi.org/10.1108/IJCCSM-05-2019-0026

[2] Lee, C.-C., Zeng, M., & Luo, K. (2024). How does climate change affect food security? Evidence from China. *Environmental Impact Assessment Review*, *104*, 107324. https://doi.org/10.1016/j.eiar.2023.107324

[3] Hasegawa, T., Sakurai, G., Fujimori, S., Takahashi, K., Hijioka, Y., & Masui, T. (2021). Extreme climate events increase risk of global food insecurity and adaptation needs. *Nature Food*, *2*(8), 587–595. https://doi.org/10.1038/s43016-021-00335-4

[4] Guo, W., Dong, S., & Qian, J. (2023). The green productivity of broiler production in China: Considering the resource utilization of manure. *Heliyon*, *9*(12), e22759. https://doi.org/10.1016/j.heliyon.2023.e22759

[5] Yang, H., Wang, X., & Bin, P. (2022). Agriculture carbon-emission reduction and changing factors behind agricultural eco-efficiency growth in China. *Journal of Cleaner Production*, *334*, 130193. https://doi.org/10.1016/j.jclepro.2021.130193

[6] Chen, R., Zhang, R., Han, H., & Jiang, Z. (2020). Is farmers' agricultural production a carbon sink or source? – Variable system boundary and household survey data. *Journal of Cleaner Production*, *266*, 122108. https://doi.org/10.1016/j.jclepro.2020.122108

[7] Ridzuan, N. H. A. M., Marwan, N. F., Khalid, N., Ali, M. H., & Tseng, M.-L. (2020). Effects of agriculture, renewable energy, and economic growth on carbon dioxide emissions: Evidence of the environmental Kuznets curve. *Resources, Conservation and Recycling*, *160*, 104879. https://doi.org/10.1016/j.resconrec.2020.104879

[8] Wu, Q., He, Y., Madramootoo, C. A., Qi, Z., Xue, L., Bukovsky, M., & Jiang, Q. (2023). Optimizing strategies to reduce the future carbon footprint of maize under changing climate. *Resources, Conservation and Recycling*, *188*, 106714. https://doi.org/10.1016/j.resconrec.2022.106714

[9] Wang, Y., Guo, C., Chen, X., Jia, L., Guo, X., Chen, R., . . . , & Wang, H. (2021). Carbon peak and carbon neutrality in China: Goals, implementation path and prospects. *China Geology*, *4*(4), 720–746. https://doi.org/10.31035/cg2021083

[10] Penuelas, J., Coello, F., & Sardans, J. (2023). A better use of fertilizers is needed for global food security and environmental sustainability. *Agriculture & Food Security*, *12*(1), 5. https://doi.org/10.1186/s40066-023-00409-5

[11] Liu, L., Zheng, X., Wei, X., Kai, Z., & Xu, Y. (2021). Excessive application of chemical fertilizer and organophosphorus pesticides induced total phosphorus loss from planting causing surface water eutrophication. *Scientific Reports*, *11*(1), 23015. https://doi.org/10.1038/s41598-021-02521-7

[12] Wang, R., Zhang, Y., & Zou, C. (2022). How does agricultural specialization affect carbon emissions in China? *Journal of Cleaner Production*, *370*, 133463. https://doi.org/10.1016/j.jclepro.2022.133463

[13] Khan, Z. A., Koondhar, M. A., Ma, T., Khan, A., Nurgazina, Z., Liu, T., & Ma, F. (2022). Do chemical fertilizers, area under greenhouses, and renewable energies drive agricultural economic growth owing the targets of carbon neutrality

in China? *Energy Economics*, *115*, 106397. https://doi.org/10.1016/j.eneco.2022.106397

[14] Tian, M., Zheng, Y., Sun, X., & Zheng, H. (2022). A research on promoting chemical fertiliser reduction for sustainable agriculture purposes: Evolutionary game analyses involving 'government, farmers, and consumers'. *Ecological Indicators*, *144*, 109433. https://doi.org/10.1016/j.ecolind.2022.109433

[15] Xin, L. (2022). Chemical fertilizer rate, use efficiency and reduction of cereal crops in China, 1998–2018. *Journal of Geographical Sciences*, *32*(1), 65–78. https://doi.org/10.1007/s11442-022-1936-2

[16] van Wesenbeeck, C. F. A., Keyzer, M. A., van Veen, W. C. M., & Qiu, H. (2021). Can China's overuse of fertilizer be reduced without threatening food security and farm incomes? *Agricultural Systems*, *190*, 103093. https://doi.org/10.1016/j.agsy.2021.103093

[17] Wang, R., Wang, Q., Dong, L., & Zhang, J. (2021). Cleaner agricultural production in drinking-water source areas for the control of non-point source pollution in China. *Journal of Environmental Management*, *285*, 112096. https://doi.org/10.1016/j.jenvman.2021.112096

[18] Niu, S., Lyu, X., Gu, G., Zhou, X., & Peng, W. (2021). Sustainable intensification of cultivated land use and its influencing factors at the farming household scale: A case study of Shandong Province, China. *Chinese Geographical Science*, *31*(1), 109–125. https://doi.org/10.1007/s11769-021-1178-8

[19] Yang, W., Zhang, L., & Liang, C. (2023). Agricultural drought disaster risk assessment in Shandong Province, China. *Natural Hazards*, *118*(2), 1515–1534. https://doi.org/10.1007/s11069-023-06057-z

[20] Huang, R., Zhang, S., & Wang, P. (2022). Key areas and pathways for carbon emissions reduction in Beijing for the "Dual Carbon" targets. *Energy Policy*, *164*, 112873. https://doi.org/10.1016/j.enpol.2022.112873

[21] Kamyab, H., SaberiKamarposhti, M., Hashim, H., & Yusuf, M. (2024). Carbon dynamics in agricultural greenhouse gas emissions and removals: A comprehensive review. *Carbon Letters*, *34*(1), 265–289. https://doi.org/10.1007/s42823-023-00647-4

[22] Liu, M., & Yang, L. (2021). Spatial pattern of China's agricultural carbon emission performance. *Ecological Indicators*, *133*, 108345. https://doi.org/10.1016/j.ecolind.2021.108345

[23] Liu, D., Zhu, X., & Wang, Y. (2021). China's agricultural green total factor productivity based on carbon emission: An analysis of evolution trend and influencing factors. *Journal of Cleaner Production*, *278*, 123692. https://doi.org/10.1016/j.jclepro.2020.123692

[24] Jebli, M. B., & Youssef, S. B. (2017). The role of renewable energy and agriculture in reducing CO_2 emissions: Evidence for North Africa countries. *Ecological Indicators*, *74*, 295–301. https://doi.org/10.1016/j.ecolind.2016.11.032

[25] Zheng, X., Tan, H., & Liao, W. (2025). Spatiotemporal evolution of factors affecting agricultural carbon emissions: Empirical evidence from 31 Chinese provinces. *Environment, Development and Sustainability*, *27*(5), 10909–10943. https://doi.org/10.1007/s10668-023-04337-z

[26] Wang, G., Liao, M., & Jiang, J. (2020). Research on agricultural carbon emissions and regional carbon emissions reduction strategies in China. *Sustainability*, *12*(7), 2627. https://doi.org/10.3390/su12072627

[27] Nemecek, T., Roesch, A., Bystricky, M., Jeanneret, P., Lansche, J., Stüssi, M., & Gaillard, G. (2024). Swiss agricultural life cycle assessment: A method to assess the emissions and environmental impacts of agricultural systems and products. *The International Journal of Life Cycle Assessment*, *29*(3), 433–455. https://doi.org/10.1007/s11367-023-02255-w

[28] Schueler, M., Hansen, S., & Paulsen, H. M. (2018). Discrimination of milk carbon footprints from different dairy farms when using IPCC Tier 1 methodology for calculation of GHG emissions from managed soils. *Journal of Cleaner Production*, *177*, 899–907. https://doi.org/10.1016/j.jclepro.2017.12.227

[29] Yang, X., Liu, Y., Bezama, A., & Thrän, D. (2024). Agricultural carbon emission efficiency and agricultural practices: Implications for balancing carbon emissions reduction and agricultural productivity increment. *Environmental Development*, *50*, 101004. https://doi.org/10.1016/j.envdev.2024.101004

[30] Wang, M., Jiang, Q., Xue, T., Xiao, Y., Shan, T., Liu, Z., . . . , & Hu, C. (2025). Spatial and temporal pattern changes and spatial spillover effects of agricultural carbon emission efficiency in the Yangtze River economic belt of China. *Environment, Development and Sustainability*, 1–29. https://doi.org/10.1007/s10668-025-06036-3

[31] Balogh, J. M. (2022). The impacts of agricultural development and trade on CO_2 emissions? Evidence from the Non-European Union countries. *Environmental Science & Policy*, *137*, 99–108. https://doi.org/10.1016/j.envsci.2022.08.012

[32] Raihan, A., & Tuspekova, A. (2022). Dynamic impacts of economic growth, energy use, urbanization, tourism, agricultural value-added, and forested area on carbon dioxide emissions in Brazil. *Journal of Environmental Studies and Sciences*, *12*(4), 794–814. https://doi.org/10.1007/s13412-022-00782-w

[33] Aliyu, G., Luo, J., Di, H. J., Lindsey, S., Liu, D., Yuan, J., . . . , & Ding, W. (2019). Nitrous oxide emissions from China's croplands based on regional and crop-specific emission factors deviate from IPCC 2006 estimates. *Science of the Total Environment*, *669*, 547–558. https://doi.org/10.1016/j.scitotenv.2019.03.142

[34] Rahman, M. H. A., Chen, S. S., Razak, P. R. A., Bakar, N. A. A., Shahrun, M. S., Zawawi, N. Z., . . . , & Talib, S. A. A. (2019). Life cycle assessment in conventional rice farming system: Estimation of greenhouse gas emissions using cradle-to-gate approach. *Journal of Cleaner Production*, *212*, 1526–1535. https://doi.org/10.1016/j.jclepro.2018.12.062

[35] Yao, Z., Zhang, D., Yao, P., Zhao, N., Liu, N., Zhai, B., . . . , & Gao, Y. (2017). Coupling life-cycle assessment and the RothC model to estimate the carbon footprint of green manure-based wheat production in China. *Science of the Total Environment*, *607–608*, 433–442. https://doi.org/10.1016/j.scitotenv.2017.07.028

[36] Zhang, Y., Zhu, J., Wang, K., & Zhang, J. (2024). Are governmental policies an effective way to reduce agricultural carbon emissions? An empirical study of Shandong in main grain producing areas of China. *Agriculture*, *14*(11), 1940. https://doi.org/10.3390/agriculture14111940

[37] Chao, Z., Zhu, Z., & Li, Y. (2025). Spatial-temporal characteristics and influencing factors of farmland carbon emissions in Guangdong Province, China. *Frontiers in Environmental Science*, *12*, 1515571. https://doi.org/10.3389/fenvs.2024.1515571

[38] Pedersen, J. S. T., Santos, F. D., van Vuuren, D., Gupta, J., Coelho, R. E., Aparício, B. A., & Swart, R. (2021). An

assessment of the performance of scenarios against historical global emissions for IPCC reports. *Global Environmental Change*, *66*, 102199. https://doi.org/10.1016/j.gloenvcha.2020.102199

[39] Long, D. J., & Tang, L. (2021). The impact of socio-economic institutional change on agricultural carbon dioxide emission reduction in China. *PLOS One*, *16*(5), e0251816. https://doi.org/10.1371/journal.pone.0251816

[40] Sun, T., Li, H., Wang, C., Li, R., Zhao, Z., Guo, B., . . . , & Gao, X. (2024). The carbon footprint and influencing factors of the main grain crops in the North China Plain. *Agronomy*, *14*(8), 1720. https://doi.org/10.3390/agronomy14081720

[41] Tone, K., & Tsutsui, M. (2010). An epsilon-based measure of efficiency in DEA–A third pole of technical efficiency. *European Journal of Operational Research*, *207*(3), 1554–1563. https://doi.org/10.1016/j.ejor.2010.07.014

[42] Färe, R., Grosskopf, S., Norris, M., & Zhang, Z. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. *The American Economic Review*, *84*(1), 66–83.

[43] Oh, D. (2010). A global Malmquist-Luenberger productivity index. *Journal of Productivity Analysis*, *34*(3), 183–197. https://doi.org/10.1007/s11123-010-0178-y

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Appendix

Table A1
List of Abbreviations

Abbreviation	Full Term
IPCC	Intergovernmental Panel on Climate Change
GTFP	Green Total Factor Productivity
EBM	Epsilon-Based Measure
GML	Global Malmquist–Luenberger Index
GEC	Green Technical Efficiency Change
GTC	Green Technical Progress
STIRPAT	Stochastic Impacts by Regression on Population, Affluence, and Technology
IPAT	Impact = Population × Affluence × Technology
CO_2	Carbon Dioxide
LCA	Life Cycle Assessment

Table A2
Descriptive statistics for the farm-level sample

	Observations	Mean	Std. Dev.
Ecological efficiency	174	0.626	0.151
Fertilizer quantity (jin/mu)	176	150.124	50.192
Pesticide expenditure (yuan/mu)	176	45.261	25.209
Pesticide applications	176	2.568	1.245
Wheat yield (jin/mu)	176	1066.477	199.356
Net return (yuan/mu)	176	779.571	357.150
Age	176	51.881	13.162
Years of education	176	9.290	3.389
Self-rated health	176	4.568	0.714
Farm labor	176	2.159	0.867
Part-time farming	176	0.483	0.501
Planted area (mu)	176	42.839	121.929
Number of plots	176	4.551	9.403
Land quality	176	3.580	1.202
Irrigation convenience	176	4.301	1.119
High-standard farmland	176	2.068	0.995
Owns agricultural machinery	176	0.159	0.367
Weather shocks	176	0.403	0.669