Agricultural Energy Rebound Effect and Its Key Drivers in China: New Evidence from Machine Learning Model

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With the transformation of agricultural production methods, it was expected that the enhancement of energy utilization efficiency would lead to a decrease in energy consumption. However, contrary to expectations, energy consumption has increased. This study delves into the mechanisms behind China's agricultural energy rebound effect. By employing a systematic generalized method of moments (GMM) model, the agricultural energy rebound effect in China from 2003 to 2022 is quantified, and various models are utilized to verify contributing factors. The findings indicated that Random Forest and Gradient Boosted Regression Tree models outperformed others in forecasting the factors influencing China's agricultural energy rebound effect. Among all the characteristic variables, the most influential factors were residents' income (RLI) levels, advancements in agricultural technology, the structure of the agricultural industry, and the degree of urbanization. The prediction patterns of the above four influences on the rebound effect of China's agricultural energy were further inferred through the accumulated local effects (ALE) Plot, respectively, and the results show distinctly different nonlinear characteristics.

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INTRODUCTION

With the profound changes in global energy supply and demand patterns, agricultural production has become increasingly energy-dependent, and global agricultural energy consumption has shown a significant increase (Zohuri 2023), which continues to rise with the spread of agricultural mechanization, greenhouse cultivation, irrigation technology and modern agricultural facilities (Zaman *et al.* 2012; Mihov and Ivanov 2017; Kalita 2019; Ceylan 2020). For instance, the volume of agricultural machinery inputs witnessed a staggering 21-fold increase by 2005 compared to 1950. The growing proportion of energy utilization in agriculture has triggered adverse repercussions on land resources and the environment, manifesting as water contamination and emissions of greenhouse gases (Ghorbani *et al.* 2011; Soni *et al.* 2013). Climate change exacerbates the situation, with the energy demand in greenhouse agriculture mounting swiftly (Gawel *et al.* 2024). The widespread deployment of artificial lighting and heating systems to counter temperature fluctuations has posed challenges in significantly curbing energy consumption in agriculture. In response, the European Commission is actively formulating strategies for fostering a greener transition in the agricultural sector (Cheba *et al.* 2022). In addition, sustained growth in world population and consumption is further fueling demand for agricultural products (Godfray *et al.* 2010). According to the World Bank, the average percentage of annual gross domestic product (GDP) accounted for by agriculture between 2010 and 2016 was about 9.49%, while some countries, such as Niger, Ethiopia, Kenya and Sudan, have agriculture accounting for more than 30% of total national GDP (Chen *et al.* 2020) The world's population is expected to grow by 25% over the next 20 years, which will lead to a sharp rise in demand for food and energy and a need to rely on more workers and agricultural land to meet the growing global demand for food (Taloba and Rayan 2025).

Against the backdrop of the global energy transition and agricultural modernization, improving energy use efficiency in agriculture has been considered a key strategy for reducing energy consumption and carbon emissions in the sector. However, energy efficiency improvement does not always bring about the expected reduction in energy consumption. It may instead lead to a rebound in energy consumption, a phenomenon that is particularly complex in the agricultural sector and involves multiple influences such as technological advances, production restructuring, and changes in market demand (Fei *et al.* 2021; Ghaedi *et al.* 2024). Based on data from the National Bureau of Statistics of China, the total power of agricultural machinery in China grew from 526 million kilowatts (kW) to 1.056 billion kW between 1999 and 2020, a period marked by the country's transition toward agricultural modernization. However, the average annual growth rate of agricultural energy consumption remained at 3.13% between 2009 and 2017. As a major global agricultural producer and consumer, China's energy consumption dynamics not only influence the sector's development, but they also have far-reaching implications for national energy security, food security, environmental management, and the attainment of the objectives to achieve "carbon peaking by 2030 and carbon neutrality by 2060" (Yin *et al.* 2024). Over the past few years, China has increasingly invested in technological advancements aimed at enhancing agricultural energy efficiency, but does improved efficiency mean a green transition in energy use in agriculture? If not, what are the obstacles? Addressing this question is vital for mitigating the rebound effect in agricultural energy consumption, thereby improving the policy performance of agricultural development and ensuring that agriculture achieves the goal of achieving "carbon peaking by 2030 and carbon neutrality by 2060" on schedule.

In view of the important position of agriculture in national development, the mitigation of energy consumption is paramount for the sustainable progression of this sector. Existing research predominantly centers on the rebound effect of energy within the industrial and residential sectors, but there is a notable scarcity of studies about agriculture. Hence, there are three questions to be further explored about the rebound effect of agricultural energy (AERE): First, what constitutes the formation mechanism of the AERE? Second, what are the patterns of existence and development of the AERE in China? Third, what factors influence the AERE? Compared with the previous studies, the contributions of this study are as follows: (1) The formation mechanism of AERE is expounded from the perspectives of output and consumption, which addresses the gaps in theoretical research. (2) Compared with traditional metrology research methods, the machine learning method is used to explore the influencing factors, which have obvious advantages in high-dimensional data analysis and complex nonlinear relationship modeling.

Literature Review

The concept of the rebound effect was first introduced by the British economist William Stanley Jevons in 1865. In his research, he found that improvements in steam engine technology raised coal utilization efficiency and reduced usage costs yet ultimately led to an increase in total coal consumption, a phenomenon known as the "Jevons Paradox" (York and McGee 2016). Under the framework of neoclassical economics, the rebound effect is regarded as a manifestation of the price mechanism: improvements in energy efficiency lower the effective price of energy, which in turn stimulates the growth of energy demand (Brookes 1978, 1990). Emerging disciplines such as behavioral economics and institutional economics have further supplemented the role of consumer behavior, institutional policies, and other factors in shaping the rebound effect (Khazzoom 1980). In the 1990s, Greening *et al.* classified the energy rebound effect into three categories: direct effect, indirect effect, and macroeconomic effect. However, due to its complexity and diverse application scenarios, a universally accepted measurement method has not yet been established (Greening *et al.* 2000). At present, four mainstream approaches are widely adopted to measure the energy rebound effect: first, the direct measurement method, which takes energy efficiency as the independent variable and changes in energy service demand as the dependent variable (Sorrell *et al.* 2009; Hens *et al.* 2010); second, the price elasticity method, which estimates the magnitude of the rebound effect by calculating the price elasticity of energy services; third, the computable general equilibrium (CGE) model, which links various sectors of the macroeconomic structure through price mechanisms (Khosroshahi and Sayadi 2020; Bataille and Melton 2017); and fourth, the economic growth method, which uses a production function to estimate the contribution of energy efficiency to economic growth and then measures the rebound effect accordingly (Shao *et al.* 2014; Lin *et al.* 2017). Existing studies have confirmed that the rebound effect exists widely in many industries and sectors, especially in energy-intensive industries such as manufacturing in the United States, the steel industry in Europe, the transportation sector in Germany, and road freight in China (Frondel *et al.* 2012; Dasgupta and Roy 2015; Flues *et al.* 2015; Wang *et al.* 2012; Bentzen 2004), and it is also prevalent in household energy consumption (Wang *et al.* 2014; Chitnis *et al.* 2013). The manifestations and influencing factors of the energy rebound effect differ significantly across sectors: in the steel industry, the rebound effect shows distinct regional characteristics, with factor substitution and capacity expansion as core drivers (Wu and Lin 2022); in manufacturing, the application of industrial robots contributes to carbon emission reduction but significantly increases energy consumption, particularly in western China (Wang *et al.* 2023); and research in agricultural production remains relatively scarce, with only a few studies noting that technological spillover and scale spillover from agricultural technological progress exert negative impacts on the energy rebound effect, yet lack in-depth analysis of its formation mechanism (Han *et al.* 2024).

Overall, existing studies have mostly focused on the energy rebound effect in industrial, transportation, and residential sectors, while systematic research on the agricultural sector is notably insufficient. Significant research gaps exist, especially regarding the formation mechanism, dynamic evolution characteristics, and multi-dimensional influencing factors of the agricultural energy rebound effect. Moreover, most studies adopt traditional econometric methods, which are inadequate for processing high-dimensional data and complex nonlinear relationships. Therefore, this study focuses on the crucial agricultural sector and deeply analyzes the formation mechanism of the agricultural energy rebound effect from the dual perspectives of output and consumption, so as to fill the gaps in relevant theoretical research. Meanwhile, this study breaks through the limitations of traditional econometric methods by introducing machine learning to explore influencing factors, improving the accuracy of high-dimensional data analysis and nonlinear relationship modeling, thereby addressing the core deficiencies of existing studies in research perspective, content dimension, and methodological application.

Formation Mechanism of the Energy Rebound Effect

Mechanism in the Production End

(1) Factor Substitution Effect

The improvement of energy efficiency reduces the energy input cost per unit product, which incentivizes agricultural producers to substitute non-energy factors with energy-based inputs. The advancement of agricultural mechanization enables farmers to decrease their reliance on manual labor by incorporating more electric or oil-powered agricultural machinery (Shao *et al.* 2014; Kuboń *et al.* 2024). In addition, the high efficiency of agricultural chemicals such as fertilizers and pesticides may also prompt farmers to increase their investment to optimize land use, thus leading to an increase in energy consumption in agricultural production (Pellegrini and Fernández 2018). As shown in Fig. 1, in the initial state, the equilibrium point of agricultural production is A, and energy consumption is E. With the improvement of energy efficiency, agricultural producers allocate a greater portion of energy-based resources to preserve non-energy elements like land or labor, thereby establishing a new equilibrium point at A' with a corresponding energy consumption level of E'.

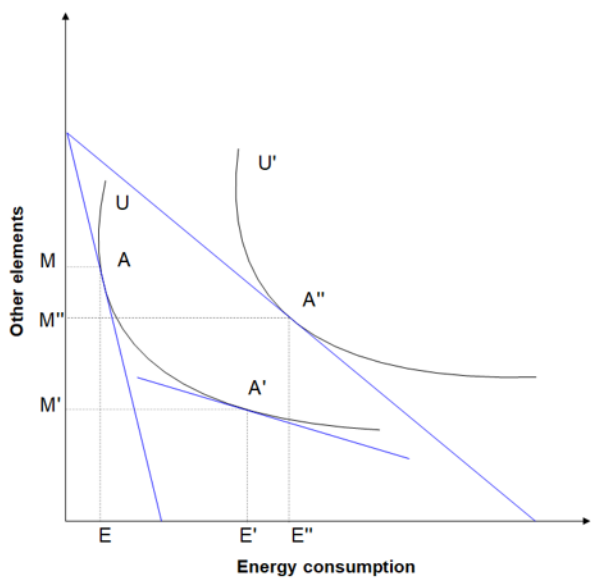

Fig. 1. Mechanism in the production end

(2) Cost Reduction Effect

The improvement of energy efficiency can reduce the overall production costs. With the decrease in production cost, farmers have the incentive to expand production scale and improve the supply of agricultural products, which will push up the demand for agricultural energy (Chen *et al.* 2020). For instance, the adoption of precision agriculture technologies not only optimizes energy utilization but also reduces the marginal cost of output per unit. This reduction encourages farmers to expand cultivated areas or scale up livestock operations, leading to a rise in total agricultural energy consumption. As shown in Fig. 1, post the energy efficiency enhancement, agricultural producers observe a reduction in production costs, an increase in output, a shift in the Iso-Quant curve from U to U', a modification in the production equilibrium point from A' to A", and a corresponding alteration in energy consumption to point E".

Mechanism in the End of Consumption

(1) Consumption growth effect

Enhancement of energy efficiency reduces the production cost associated with agricultural commodities, which in turn can lead to a decrease in market prices. Amidst this trend of declining prices, there is a notable increase in consumers' purchasing power, particularly for energy-intensive agricultural products such as meat, dairy, and greenhouse-grown vegetables (Priyatna and Suryadi 2025; Težak *et al.* 2009). This surge in demand is likely to stimulate an increase in agricultural energy consumption, potentially resulting in the phenomenon known as the energy rebound effect. As shown in Fig. 2, under the constraint of a fixed consumption budget, the equilibrium point for energy consumption is denoted as B, with the total energy consumption amounting to E_1+E_1'. However, when consumption levels escalate, the equilibrium point shifts to a new position, denoted as B', and the total energy consumption increases to E_2+E_2'.

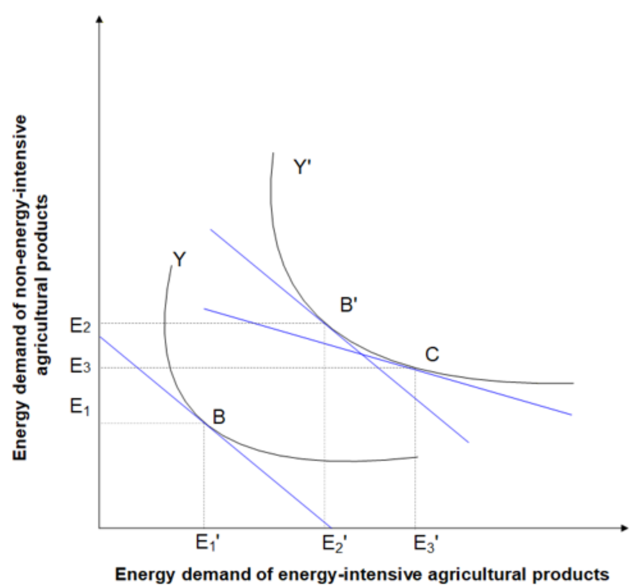

Fig. 2. Mechanism in the consumption end

(2) Structural substitution effect

Due to fluctuations in agricultural product prices, consumers may exhibit a tendency to opt for agricultural products with higher energy requirements. For instance, when the cost of farming decreases, consumers might escalate their consumption of meat products while decreasing their demand for less energy-intensive products like grains or vegetables (He *et al.* 2019; Cecchini *et al.* 2018). This change in consumption preference has enabled the agricultural sector to increase investment in energy-intensive industries and further amplify the rebound effect of agricultural energy. As shown in Fig. 2, within the confines of consumer preferences, the new equilibrium point shifts to C, and the new total energy consumption is E_3+E_3'.

EXPERIMENTAL

Spatio-temporal Analysis of Agricultural Energy Efficiency and Agricultural Energy Rebound Effect

Measurement of agricultural energy efficiency

The agricultural energy efficiency assessment was conducted based on the methodology proposed by Tone and Tsutsui (2009), which employed the Slacks-based Measure model. This model incorporated slack variables associated with both input and output factors, and efficiency metrics were established based on these components. The input variables encompassed asset input, labor input, and energy input, while the output variable was represented by agricultural value added. Specifically, Asset input was quantified using agricultural fixed asset outlay, whereas labor input was determined by the number of workers engaged in primary industry activities within the region. Energy input was calculated as the total agricultural energy consumption, including both direct and indirect energy usage. Agricultural output was defined as the value added in the primary industry across different regions.

Assume that the input set of decision-making units is $x=(x_1,...x_N)\in R_+^N$ and the desirable output is $y=(y_1,...y_M)\in R_+^M$; the SBM model is specified as follows:

$$\min(\theta-\varepsilon\sum_{i=1}^{N}\frac{\omega_i^- s_i^-}{x_{i0}})$$

$$s.t.\begin{cases}\sum_{k=1}^{K}\lambda_k x_{ik}+s_i^-=\theta x_{io}(i=1,2,...N)\\ \sum_{k=1}^{K}\lambda_k y_{mk}\geq y_{mo}(m=1,2,...M)\\ \sum_{k=1}^{K}\lambda_k b_{jk}=b_{jo}(j=1,2,...J)\\ \lambda\geq o, s_i^-\geq 0\end{cases} \tag{1}$$

This model can be adopted to calculate the optimal agricultural energy input E_{it}^* of region i in year t, where E_{it} denotes the actual agricultural energy input of region i in year t. Accordingly, the agricultural energy efficiency is defined as follows:

$$\tau_{it}=\frac{\mathrm{E}_{it}^*}{E_{it}} \tag{2}$$

The value of τ_{it} ranges from 0 to 1, with a larger value corresponding to a higher level of energy utilization efficiency.

Formula derivation process of agricultural energy rebound effect

The calculation of the rebound effect of agricultural energy is based on agricultural energy consumption and agricultural energy efficiency, drawing upon the findings of Pan and *et al.* (2021). This study employed a sophisticated two-stage estimation method to quantify the rebound effect of energy consumption, specifically in the context of China. The calculation is as follows,

$$\ln E_{it}^*=f(\ln P_{it},\ln Y_{it},\ln\tau_{it})+\varepsilon_{it}+\varphi_i \tag{3}$$

where E_{it}^* is the optimal energy input, P_{it} the energy consumption price, Y_{it} the added value of the primary industry, τ_{it} the agricultural energy efficiency, ε_{it} the error term, and φ_i the intercept term.

The energy elasticity relationship can be expressed as follows.

$$\sigma_{it} = \frac{d \ln E_{it}}{d \ln \tau_{it}} \tag{4}$$

Due to the inability of energy consumption to reach its optimal state within a certain period of time, it is posited that energy consumption undergoes dynamic adjustments in two cycles.

$$\ln E_{it} - \ln E_{it-1} = (1-\theta)(\ln E_{it}^* - \ln E_{i,t-1}) \tag{5}$$

Building upon this premise, a Formula approximating energy consumption is derived:

$$\ln E_{it} = \theta \ln E_{it-1} + (1-\theta) f(\ln P_{it}, \ln Y_{it}, \ln \tau_{it}) + (1-\theta)\varphi_i + (1-\theta)\mu_{it} \tag{6}$$

This formula is approximated as a quadratic polynomial by using the second-order Taylor expansion,

$$\begin{aligned} \ln E_{it} &= \theta \ln E_{it-1} + \gamma_1 \ln P_{it} + \gamma_2 \ln Y_{it} + \gamma_3 \ln \tau_{it} + \frac{\gamma_4}{2!} \ln P_{it} \ln \tau_{it} + \frac{\gamma_5}{2!} \ln Y_{it} \ln \tau_{it} \\ &+ \frac{\gamma_6}{2!} \ln P_{it} \ln Y_{it} + \frac{\gamma_7}{2!} (\ln \tau_{it})^2 + \frac{\gamma_8}{2!} (\ln Y_{it})^2 + \frac{\gamma_9}{2!} (\ln P_{it})^2 + \delta_{it} + \upsilon_{it} \end{aligned} \tag{7}$$

where γ_i is the parameter to be estimated, and $\delta_{it} = (1-\theta)\varphi_i, \upsilon_{it} = (1-\theta)\mu_{it}$. The elasticity of agricultural energy efficiency to energy consumption can be obtained by taking the derivative of ln, as shown in Eq. 6

$$\sigma_{it} = \gamma_3 + \frac{\gamma_4}{2!} \ln P_{it} + \frac{\gamma_5}{2!} \ln Y_{it} + \gamma_7 \ln \tau_{it} \tag{8}$$

Finally, the rebound effect of the value of agricultural energy is:

$$R_{it} = 1 + \sigma_{it} \tag{9}$$

When $R_{it} = 1$, a full rebound effect is observed; when $0 < R_{it} < 1$, there exists a partial rebound effect; when $R_{it} = 0$, the rebound effect equals zero. A larger value of R_{it} corresponds to a weaker energy-saving effect.

Rebound effect calculation methodology for agricultural energy efficiency

The estimation of the agricultural energy rebound effect was conducted using the generalized method of moments (GMM), fixed effects (FE), and random effects (RE) models, leading to the formulation of its calculation equation. The estimation results are summarized in Table 1, where Model 1 reports the GMM estimates, Model 2 presents the FE model results, and Model 3 provides the RE model findings. The results of each model indicated a significantly positive regression coefficient for the optimal energy input at the 1% confidence level, while the benefit of the primary industry exhibited a significantly negative impact with a negative regression coefficient at the same confidence level. Considering that the explanatory variables might have endogenous issues, the results estimated by the GMM model were substituted into Formula (8) to obtain the elasticity value of agricultural energy efficiency to energy consumption. Subsequently, the energy rebound effect across various Chinese provinces was derived based on Formula (9).

Table 1. Model Estimation Results

Variable	Model 1	Model 2	Model 3
	GMM	FE	RE
LnEit-1	0.995***	0.265***	0.334***
	(0.014)	(0.059)	(0.069)
LnPit	-1.810	-1.189	-1.770
	(1.527)	(2.167)	(1.949)
LnYit	0.245**	0.835***	0.678***
	(0.109)	(0.154)	(0.157)
$Ln\tau_{it}$	0.390	0.033	-0.084
	(0.681)	(0.498)	(0.516)
LnPit *LnYit	-0.019	0.010	0.017
	(0.017)	(0.021)	(0.021)
LnYit*$Ln\tau_{it}$	0.007	-0.000	-0.003
	(0.014)	(0.018)	(0.017)
LnPit * $Ln\tau_{it}$	-0.110	-0.045	-0.009
	(0.142)	(0.092)	(0.098)
$(LnPit)^2$	0.212	0.124	0.183
	(0.165)	(0.228)	(0.205)
$(LnYit)^2$	-0.011***	-0.010***	-0.007***
	(0.004)	(0.002)	(0.002)
$(Ln\tau_{it})^2$	-0.024	-0.022	-0.033
	(0.053)	(0.068)	(0.059)
constant	3.315	1.400	3.126
	(3.534)	(5.347)	(4.788)
N	569	569	569
R^2	0.996	0.973	

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Analysis of agricultural energy efficiency and energy rebound effect

Figure 3 illustrates the average distribution of agricultural energy efficiency and energy rebound effects across Chinese provinces from 2003 to 2022, constructed based on the aforementioned methodology. The data presented in this figure are calculated based on Formula (2) and Formula (9) mentioned above, respectively. The results reveal significant regional disparities in agricultural energy efficiency. The top four provinces were Hainan, Jiangsu, Shanghai, and Zhejiang, with energy efficiency values of 0.971, 0.953, 0.941, and 0.882, respectively. Conversely, the provinces with the lowest rankings were Shaanxi, Ningxia, Qinghai, and Yunnan, corresponding to energy efficiency values of 0.487, 0.502, 0.511, and 0.521. For the energy rebound effect, the regions with the smallest values were Shanghai, Hainan, Tianjin, and Beijing, recorded as 0.916, 0.925, 0.929, and 0.932, respectively. In contrast, the regions exhibiting the largest rebound effects showed values of 0.965, 0.962, 0.961, and 0.959. These differences were mainly determined by the combined effects of regional economic development levels and agricultural structural variations. Economically developed eastern regions, represented by Shanghai, achieved higher agricultural energy efficiency through greater investment in technology, intensive production, and advanced agricultural machinery and facilities. Meanwhile, urbanization and industrial structural optimization effectively suppressed the energy rebound effect. Hainan delivered a strong performance in both efficiency and rebound control by relying on tropical high-efficiency agriculture and green production models. By contrast, central and western provinces such as Shaanxi, Ningxia, Qinghai, and Yunnan had relatively weak economic foundations, extensive agricultural production methods, and insufficient technological inputs, resulting in lower energy efficiency. Furthermore, during the process of efficiency improvement, these provinces tended to experience expansion of production scale and rebound in energy demand, thereby forming a relatively strong energy rebound effect.

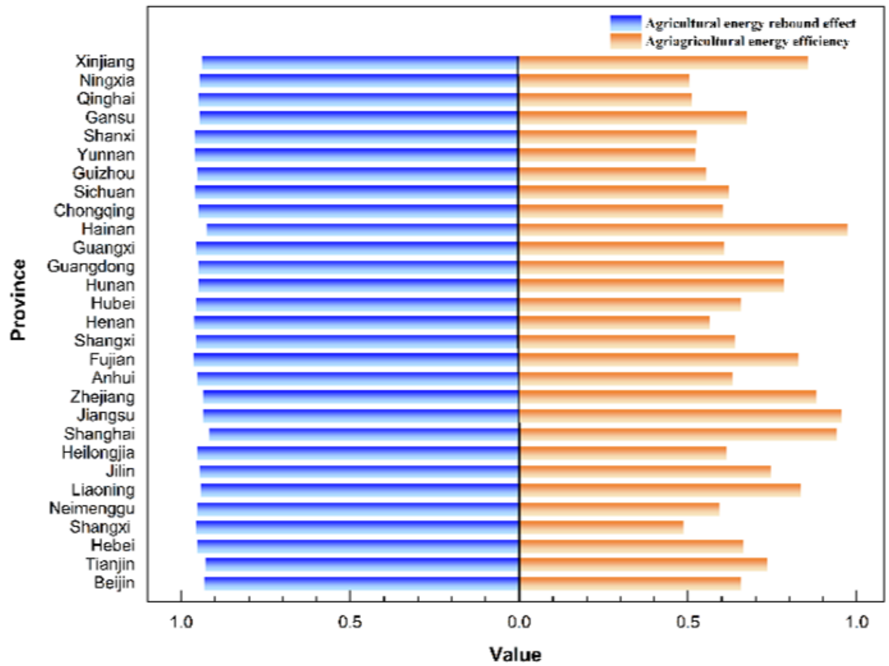

Fig. 3. The average distribution of agricultural energy efficiency and energy rebound effects

Influencing Factors of Agricultural Energy Rebound Effect

As the intensive agricultural production paradigm gains momentum, the allocation of production factors is experiencing significant structural transformations (Groenewold *et al.* 2008; Cheng *et al.* 2021). Academics are generally concerned that in the process of dynamic substitution of labor-capital-energy ternary elements, technology-driven efficiency improvement may lead to the phenomenon of "energy efficiency paradox", that is, the enhancement of energy utilization efficiency not only fails to reduce total energy consumption but also exacerbates energy consumption intensity through various transmission channels (Kounetas and Tsekouras 2008). Furthermore, a multitude of empirical studies have identified evidence suggesting that the abundance of energy resources can indirectly impede economic growth (James and Aadland 2011; Hu *et al.* 2020). To elucidate the factors that influence the energy rebound effect, this analysis will systematically examine the following dimensions.

The level of residents income (RLI)

An uptick in income is frequently linked to a rise in consumers' purchasing power, particularly in the realm of agricultural products. This surge in buying power often translates into heightened demand for energy-intensive agricultural goods like meat and greenhouse vegetables, subsequently propelling overall energy consumption (Ahunov *et al.* 2022; Xu and Zhong 2023). As income levels climb, farmers may opt to invest in more energy-efficient equipment in a bid to boost production efficiency. Paradoxically, while this move towards efficiency enhancement can be beneficial in some respects, it can also drive farmers to expand their production capacity, which in turn escalates aggregate energy consumption.

The level of urbanization (URB)

The urbanization process has catalyzed a substantial migration of the labor force, leading to a progressive increase in the urban population's share of the total population, which has eventually reached a state of equilibrium. This migration has had two principal effects on agriculture. On one hand, the consequent reduction in agricultural labor has necessitated the adoption of higher mechanization levels, which in turn has increased the elasticity of agricultural energy demand (Sun *et al.* 2021). On the other hand, the migration of farmers to urban areas has spurred the circulation and leasing of rural land, thereby enhancing land utilization rates and consequently leading to a growth in agricultural energy demand (Xu *et al.* 2020).

Regional industrial structure (RIS)

As economic development progresses, capital availability increases. The rising share of secondary and tertiary sectors in the economy signifies a transition towards higher value-added and technology-intensive industries. Technological advancements contribute to enhanced energy efficiency, optimizing energy utilization per unit of output and diminishing energy consumption per unit output – a phenomenon known as structural dividends (Li and Lin 2014). Nonetheless, distortions in industrial structure can adversely affect energy intensity (Luan *et al.* 2021; Shen and Lin 2021; Guo *et al.* 2022).

The structure of the agricultural industry (AIS)

The intensive and refined management of agriculture is accompanied by the investment in more energy-efficient automation equipment. Although these pieces of equipment contribute to enhancing energy efficiency in a single production process, their energy-saving effects may be counteracted by emerging demand driven by the expansion of overall production scale, ultimately leading to increased energy consumption (Fei and Lin 2017). In addition, after the production efficiency is improved, farmers tend to expand the production scale and further amplify energy demand, thus producing a "rebound effect" of energy consumption (Shi *et al.* 2022). The optimization and adjustment of the structure of the AIS may improve energy efficiency in the immediate term, but the rebound effect may aggravate the energy consumption intensity over the long term and scale expansion.

Agricultural planting structure (APS)

The cultivation of cash crops frequently necessitates a higher energy input, notably during greenhouse cultivation and extensive irrigation processes. The expansion of the cultivation area for such crops typically results in elevated energy consumption. Additionally, the substantial profit margins associated with cash crops incentivize farmers to expand their cultivation areas to maximize their income, consequently contributing to heightened energy usage. Consequently, while short-term enhancements in energy efficiency have been achieved through adjustments in agricultural cultivation practices, the rebound effect of energy consumption has become increasingly discernible considering escalating production scales and mounting market demands (Han and Wu 2018).

Agricultural technology level (ATL)

The enhancement of energy efficiency driven by technological progress encourages producers to gradually invest in more efficient production factors, replacing outdated and high-cost ones. This phenomenon is referred to as the factor substitution effect (Zhang *et al.* 2014). However, a reduction in unit energy costs can enhance producers' incomes, thereby stimulating greater energy consumption demand—a phenomenon known as the income effect (Huang *et al.*2017). Both effects have the potential to intensify the rebound of energy consumption.

Agricultural disaster level (ADL)

Natural disasters lead to the loss of agricultural production, prompting farmers to rehabilitate their production capabilities by augmenting their investment in energy-intensive technologies and machinery (Zhao *et al.* 2022; Fang *et al.* 2024). Concurrently, within the post-disaster recovery phase, there is a notable escalation in the expenditure on fertilizers and pesticides by farmers, which consequently drives an increase in energy demand (Lin and Wang 2024). Thus, while the severity of agricultural disasters has catalyzed the adoption of high-efficiency technologies, an emergent phenomenon of energy consumption rebound has become increasingly apparent amidst the backdrop of production resumption and scale expansion.

Natural resource endowment (NRE)

The larger the effective irrigation area, the greater the energy demand for production, such as the power needed for using water pumps and irrigation systems (Hamidov *et al*. 2022). Furthermore, a high irrigation ratio can facilitate the cultivation of crops that are inherently energy-intensive, such as rice and greenhouse vegetables. The production demands of these crops contribute significantly to the overall energy consumption, thereby exacerbating the energy demands of the agricultural sector.

Indicators and Variables

In this study, the energy rebound effect served as the dependent variable, while the independent variables encompassed various socioeconomic and environmental factors, including RLI level, URB, RIS, AIS composition, cropping structure, agricultural technological advancement, agricultural disaster severity, and the NRE. Specifically, the RLI level was represented by per capita disposable income, while URB level was measured by the proportion of the urban population to the total population. The RIS was quantified by the share of value-added from secondary and tertiary industries in regional GDP, whereas the AIS composition was indicated by the proportion of non-crop output value within the total output of agriculture, forestry, animal husbandry, and fisheries. Cropping structure was assessed by the ratio of cash crop sown area to total crop sown area. The level of agricultural technology was evaluated based on the total power of agricultural machinery (10,000 kilowatts). Agricultural disaster severity was represented by the ratio of affected crop area to total cultivated land in each province, while the NRE was reflected by the proportion of irrigated land to total cultivated land.

Models and Algorithms

Drawing on the research by Feng *et al*. (2025), this study conducted an exploratory analysis of eight potential influencing factors using various mainstream machine learning methods. In contrast to traditional explanatory studies of causal relationships, machine learning algorithms excel in handling high-dimensional data, dynamic economic environments, and complex dependency relationships among multiple variables (Sun *et al.* 2024). Predictive research within machine learning could effectively capture nonlinear relationships and interactions within complex economic systems, thereby offering highly accurate predictions in the absence of a clear theoretical framework or prior assumptions. The specific model formulas are provided as follows.

Multiple linear regression model

$$\mathrm{aere}_i = \alpha + \beta^T X_\mathrm{i} + \varepsilon_i \tag{10}$$

where aere_i represents the rebound effect of agricultural energy, α is an intercept term, X_i denotes a series of response variables, β^T refers to an influence coefficient of each response variable, and ε_i is an error term.

Penalty regression model

The penalty regression methods employed in this study include LASSO regression and ridge regression. The principle behind it is to add a regular term to the objective function of the ordinary least squares (OLS) method to constrain the regression coefficients of the model, limit the complexity of the model, and prevent overfitting. Here, N represents the total sample size, Formula (9) corresponds to LASSO regression, characterized by the L1 regularization term, $\lambda\sum_{j=1}^{p}|\beta_j|$, which represents the sum of the absolute values of the parameters. Formula (10) represents ridge regression, featuring the L2 regularization term $\lambda\sum_{j=1}^{p}\beta_j^2$, that is, the sum of the squares of the parameters.

$$\min_\beta\left(\frac{1}{2n}\sum_{i=1}^{n}(aere_i - \beta^T X_i - \alpha)^2 + \lambda_1\sum_{j=1}^{p}\left|\beta_j\right|\right) \tag{11}$$

$$\min_\beta\left(\frac{1}{2n}\sum_{i=1}^{n}(aere_i - \beta^T X_i - \alpha)^2 + \lambda_2\sum_{j=1}^{p}\beta_j^2\right) \tag{12}$$

where aere_i represents the rebound effect of agricultural energy, α is an intercept term, X_i denotes a series of response variables, β^T is the influence coefficient of each response variable, λ is a regularization parameter, and ε_i is an error term.

Support vector machine

Support Vector Machine (SVM) is a specialized method for addressing statistical learning in small-sample scenarios. Its core principle involves identifying an optimal hyperplane that maximizes the margin between different classes, thereby achieving effective data classification. Consider a sample dataset $\{x_i, y_i\}$, where $x_i \in \mathrm{R}^\mathrm{D}$, each x_i contains D features. $y_i \in R, F = \{f \mid f : R^D \to R\}$. If the regression function $f(x_i)$ is nonlinear, the original input training samples are mapped into a high-dimensional feature space through a nonlinear mapping x_i, The training samples must satisfy the following constraints $y_i(x_i \cdot \omega + b) - 1 + \varphi_i \geq 0, \varphi_i \geq 0$, with φ being slack variables. The optimization problem for maximizing the support vector machine margin is then formulated as:

$$\min \frac{1}{2}\|\omega\|^2 + c\sum_{i=1}^{n}\varphi_i$$
$$y_i(x_i \cdot \omega + b) - 1 + \varphi_i \ge 0, \varphi_i \ge 0, i = 1,...n \qquad (13)$$

where $c > 0$ is the penalty parameter that controls the model complexity? The solution yields the decision function, $f(x) = \mathrm{sgn}(\sum_{i=1}^{n} a_i y_i K(x_i, x) + b)$, $K(x_i, x)$ where denotes the kernel function. In this study, the radial basis function (RBF) kernel was defined as $K(x_i, x) = \exp(\frac{-\|x - x_i\|^2}{2\sigma^2}), \sigma > 0$.

Random Forest

Random Forest is an ensemble learning technique built upon the Bagging (Bootstrap Aggregating) approach. By constructing multiple decision trees and integrating their prediction results, the generalization ability of the model is improved. First, a predetermined number of subsets $D1, D2,..., Dm$, denoted as m , are randomly selected from the training set $D = \{(x1, y1), (x2, y2),...,(xn, yn)\}$, and the size of each subset is n. During the node-splitting process, a random selection of k features is made from the total pool of p features ($k = \sqrt{p}$). The prediction is then formulated by computing the average of the predictions from all constituent trees, denoted as $\hat{y} = \frac{1}{m}\sum_{i=1}^{m} T_i(x)$.

Gradient lifting

Gradient boosting is an amalgamated learning technique grounded in the principles of Boosting, where a robust learner is iteratively built by sequentially adjusting the residuals. The magnitude of adjustment at each step is constrained through a technique known as Shrinkage to avert the issue of over-fitting. The fundamental premise of this algorithm involves the initialization of a rudimentary base model, followed by the computation of the initial prediction value: $f_0(x) = \arg\min_{\rho} \sum_{i=1}^{m} L(y_i, \rho)$, where $\mathrm{L}(y_i, \rho)$ is the loss function. When $\rho = f_0(x)$ $\sum_{i=1}^{m} L(y_i, \rho)$ yields the smallest value. Then, the iterative process ($(d = 1, 2..., D)$) is repeated for D times, and after D iterations, the final prediction model $f_D(x)$ is obtained. First, compute the negative gradient of the loss function $\Psi_{i,d} = -\frac{\partial L(y_i, f(x))}{\partial x}$, where $f(x) = f_{d-1}(x)$. Second, fit a new regression tree $g_d(x) = E(\Psi \mid x)$ with $\Psi_{i,d}$ the residuals as the approximation, and iteratively fit the residuals.

Third, choose the gradient descent that minimizes the error, that is, $\tau = \arg\min_{\tau} \sum_{i=1}^{N} L(y_i, f_{d-1}(\mathrm{x}) + \tau g_d(\mathrm{x}))$; Fourth, compute the new prediction function, $f_d(x) = f_{d-1}(x) + \upsilon\tau g_d(x)$, where υ is the shrinkage function.

Model Performance Evaluation Methods

To evaluate the performance of different machine learning algorithms, this study focused on the explanatory power and prediction accuracy of the model, and the following data were chosen as the foundation for evaluating these metrics. The in-sample goodness-of-fit, R^2_{Is}, was used to measure how well different algorithms fit the sample, and the closer its value is to 1, the better the fit. The out-of-sample goodness-of-fit, R^2_{oos}, reflected the model's ability to generalize, and the larger its value, the better the prediction. Explainable variance, expressed as EVS_{oos} measures the proportion of variance in the target variable explained by the model, reflecting the predictive stability of the model. The out-of-sample means square error, expressed as MSE_{oos}, measures the divergence between the predicted and actual values. Given the susceptibility of the mean square error to the influence of outliers, which may skew the results, this study adopted the mean absolute error MAE_{oos} and the absolute median difference $MedAE_{oos}$ to assist in assessing the accuracy of the model prediction.

RESULTS AND DISCUSSION

Prediction Effect Evaluation Based on Different Models

The efficacy of various machine learning techniques in modeling the energy rebound effect was assessed through a suite of statistical metrics, including in-sample goodness-of-fit (R^2_{Is}), out-of-sample goodness-of-fit (R^2_{oos}), explanatory variance (EVS), and prediction error indicators (MSE, MAE, MedAE). The tabulated findings, as presented in Table 2, delineate the performance of diverse models. Specifically, column (1) of Table 2 shows that the ensemble learning method exhibits high adaptability to training data. The goodness-of-fit between random forest (R^2=0.928) and gradient boosting regression tree (GBRT, R^2=0.889) is obviously higher than that of multiple linear regression and regularized linear model (LASSO, Ridge regression), indicating that the traditional variable selection method has limited improvement on the model complexity. In columns (2) and (3), the generalization ability and stability of the random forest and asymptotic gradient regression are observed to be inferior to those of the linear models, which accords with the theory of "Bias-variance Tradeoff". While ensemble learning techniques enhance training accuracy by diminishing bias, they may concurrently amplify variance due to the increased model complexity. Despite this, the ensemble learning methods, as exemplified by the random forest and GBRT, exhibit superior prediction error metrics (MSE, MAE, MedAE) when juxtaposed with linear models. Thus, ensemble learning approaches, particularly those represented by the random forest and gradient boosting regression tree, are more adept at forecasting the repercussions of the energy rebound effect.

Table 2. Model Fitting Results

Model	R^2_{Is}	R^2_{oos}	EVS	MSE	MAE	MedAE
Linear Regression	0.4116	0.1143	0.1146	0.0010	0.0119	0.0084
LASSO	0.4107	0.1139	0.1141	0.0010	0.0119	0.0085
Ridge Regression	0.4115	0.1147	0.1150	0.0010	0.0119	0.0085
SVM	0.6578	0.1092	0.1093	0.0010	0.0118	0.0083
Random Forest	0.9280	0.0921	0.0922	0.0010	0.0114	0.0078
GBRT	0.8888	0.0961	0.0962	0.0010	0.0113	0.0077

Importance Ranking of Feature Variables

The technique of determining the relative importance of features serves as a valuable tool in assessing the significance of various features within a model. Given the notable efficacy demonstrated by random forest and GBRT in forecasting the key drivers of the energy rebound effect, this study delved deeper into discerning varying influence levels of different variables on this phenomenon through the application of these two machine learning methodologies. Analysis of the results, detailed in Table 3, reveals comparable predictive performances between random forest and GBRT, with the top four feature variables ranked in terms of significance being the level of RLI, the level of agricultural technology, the structure of the AIS, and the level of URB. These outcomes underscore the strong predictive capabilities of these aforementioned feature variables concerning the agricultural energy rebound effect.

Table 3. Ranking of Variable Importance

Ranking	Random Forest		GBRT	
	Variable	Relative Importance (%)	Variable	Relative Importance (%)
1	RLI	0.2858	RLI	0.2901
2	ATL	0.1870	AIS	0.2370
3	AIS	0.1644	ATL	0.1584
4	URB	0.1375	URB	0.1189
5	ADL	0.0694	APS	0.0587
6	APS	0.0531	NRE	0.0573
7	RIS	0.0525	ADL	0.0541
8	NRE	0.0502	RIS	0.0255

Influence of Main Feature Variables on the Rebound Effect of Agricultural Energy

The accumulated local effects (ALE) diagram is a method used to scrutinize the impact of an individual feature on model predictions, effectively circumventing issues associated with multicollinearity among features (Apley and Zhu 2020). In this study, four significant feature variables were chosen for analysis: the level of RLI, the level of agricultural technology, the structure of the AIS, and the level of URB. A corresponding set of ALE diagrams was constructed. The y-axis depicts the local cumulative effect, reflecting the average degree of influence of the feature variables on the model's prediction output, while the x-axis illustrates the spectrum of characteristic variables.

Figure 4 is the corresponding ALE diagram depicting the relationship between the level of the RLI and the rebound effect of agricultural energy (AERE). With the change of the level of the RLI, the rebound effect of agricultural energy in China first experiences a slow increasing stage and then increases rapidly over a period. This phenomenon can be attributed to the potential linkage between higher income levels and increased consumption of agricultural goods. Consequently, agricultural producers respond by expanding their production capacities, enhancing product quality, and diversifying their offerings to meet evolving market demands. Throughout this process, these producers may adopt more mechanized and modernized production techniques that are energy-intensive, thereby amplifying the agricultural energy rebound effect. With the further increase of the level of th RLI, the energy rebound effect gradually slows down and then begins to decline after reaching a certain threshold. This phenomenon can be attributed to the saturation of demand, which, in turn, intensifies market competition among agricultural producers. Consequently, these producers are compelled to embrace more energy-efficient and productive technologies to enhance the quality of their products and to mitigate production expenses.

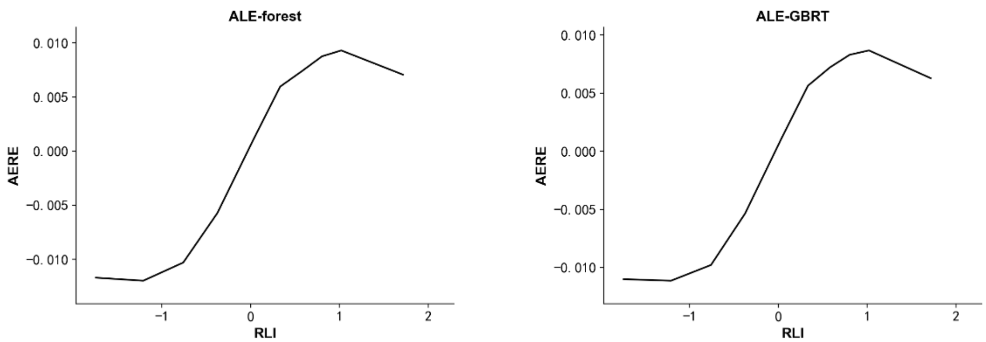

Fig. 4. The relationship between the RLI and AERE

Figure 5 is the corresponding ALE diagram depicting the relationship between the ATL and the rebound effect of the AERE. With the increase in the level of agricultural technology, the rebound effect of agricultural energy exhibits an increasing trend. The increase in the level of agricultural machinery, on the one hand, drives the energy consumption of equipment to increase. The demand for energy, such as diesel and electricity, has increased. However, the improvement of machinery level stimulates the expansion of production scale, drives the energy consumption of other agricultural activities such as irrigation, fertilization, and land reclamation, and further increases energy consumption, thus increasing the rebound effect of agricultural energy.

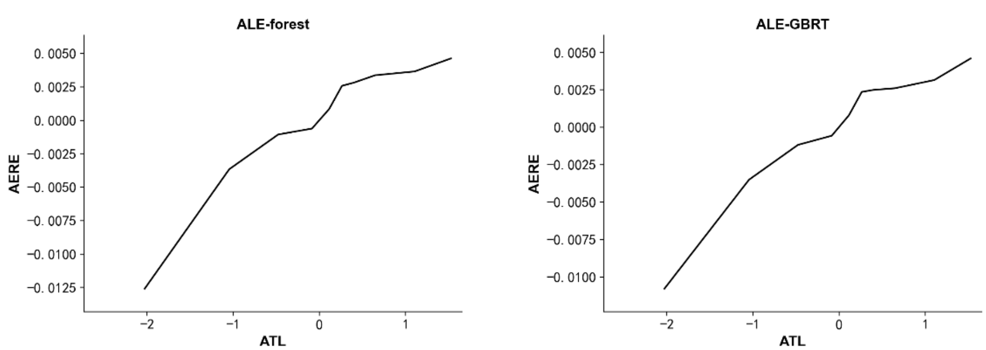

Fig. 5. The relationship between the ATL and AERE

Figure 6 is the corresponding ALE diagram depicting the relationship between the structure of the AIS and the rebound effect of the AERE. With the constant change of the structure of the AIS, the rebound effect of agricultural energy is stimulated in the initial stage, and subsequently, the strategic optimization of the AIS's structure acts to mitigate the escalating trend in energy utilization post-peak. This trend stems from the pronounced energy demand within energy-intensive sectors such as greenhouse vegetable cultivation, intensive aquaculture, and large-scale farming, all of which have the potential to exacerbate the energy rebound effect. In recent years, the Chinese government has encouraged low-energy consumption and low-emission production methods and technologies through policies and measures such as subsidies and tax incentives. The rapid development of ecological agriculture and organic agriculture has reduced unnecessary energy waste and emissions to some extent, thereby effectively attenuating the energy rebound effect.

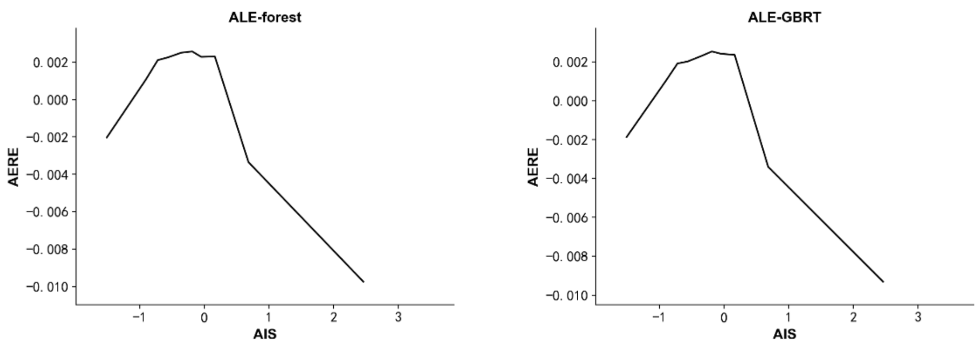

Fig. 6. The relationship between the AIS and AERE

Figure 7 is the corresponding ALE diagram depicting the relationship between the level of the URB and the rebound effect of the AERE. As shown in the figure, the progression of urbanization can significantly enhance the rebound effect of agricultural energy. As the level of urbanization improves, a substantial portion of the agricultural labor force migrates to urban and non-agricultural sectors, leading to a labor shortage in rural areas. Consequently, agricultural producers are compelled to embrace more efficient and mechanized production techniques to enhance productivity, which facilitates the specialization and scaling up of agricultural operations, thereby boosting energy efficiency. Moreover, the urbanization process creates a wider scope for agricultural innovation and development. In this context, renewable energy sources like solar power and wind energy are increasingly being applied in agricultural practices, including solar-powered pumps and wind turbine electricity generation. The integration of these sustainable energy alternatives not only curbs carbon emissions in agricultural activities but also elevates energy efficiency levels.

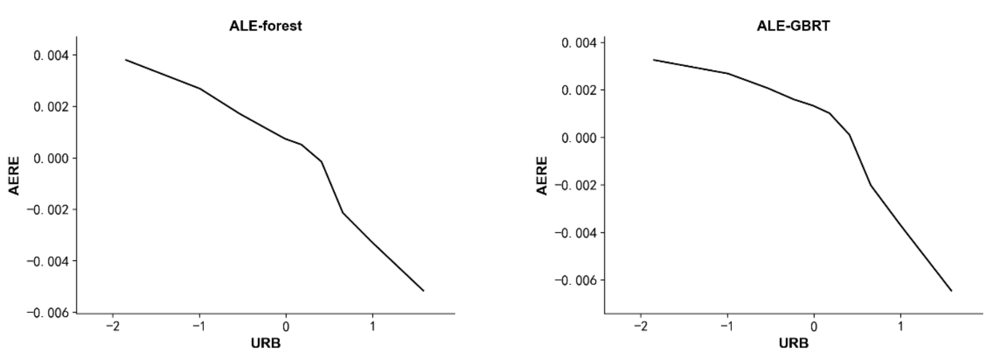

Fig. 7. The relationship between the URB and AERE

Robustness Analysis

Alternative measurement of the response variable

In the initial calculation of the agricultural energy rebound effect, the results estimated by the GMM model were incorporated into the formula to address potential endogeneity issues in the explanatory variables. To validate the robustness of the findings, the results from the RE model were substituted into the formula to generate a new response variable. As demonstrated in Table 4, both Random Forest and GBRT methods maintained superior predictive performance for the energy rebound effect, further confirming the robustness of the conclusions.

Table 4. Model Fitting Results

Model	R^2_{ls}	R^2_{oos}	EVS	MSE	MAE	MedAE
Linear Regression	0.1618	0.0140	0.0413	0.0003	0.0129	0.0104
LASSO	0.1596	0.0338	0.0629	0.0003	0.0128	0.0104
Ridge Regression	0.9190	0.4029	0.4228	0.0002	0.0096	0.0068
SVM	0.6021	0.3495	0.3626	0.0002	0.0104	0.0089
Random Forest	0.9190	0.4029	0.4228	0.0002	0.0096	0.0068
GBRT	0.8861	0.3649	0.3763	0.0002	0.0098	0.0080

Variable Ranking Using Feature Importance Measures

Following the replacement of the response variable, the relative importance of each influencing factor was reassessed through feature importance analysis. As shown in Table 5, when employing the Random Forest method, the top four variables by importance were AIS, ATL, RLI, and URB. For the GBRT method, the ranking yielded AIS, URB, LI and NRE as the top four, with ATL ranking fifth. These results align substantially with the importance of rankings derived in the earlier analysis, thereby further corroborating the robustness of the conclusions.

Table 5. Ranking of Variable Importance

Ranking	Random Forest		GBRT	
	Variable	Relative Importance (%)	Variable	Relative Importance (%)
1	AIS	0.1851	AIS	0.1811
2	ATL	0.1534	URB	0.1726
3	RLI	0.1513	RLI	0.1619
4	URB	0.1362	NRE	0.1181
5	NRE	0.1203	ATL	0.1166
6	ATI	0.1043	APS	0.1071
7	RIS	0.0758	RIS	0.1016
8	ADL	0.0738	ADL	0.0410

Policy Recommendations

Based on the research findings, the following targeted policy recommendations are proposed to effectively address the rebound effect of energy consumption in Chinese agriculture, optimize energy efficiency, and promote the development of sustainable agriculture.

First, to optimize income distribution and consumption guidance, the government should develop a "Low-Energy Agricultural Product" standard, clearly defining agricultural production methods with low energy input, such as open-field cultivation, water-saving dryland agriculture, and free-range livestock farming. Certification labels should be issued for such products. In addition, a priority procurement policy should be established to encourage schools, government offices, and state-owned enterprises to prioritize the purchase of low-energy agricultural products, such as open-field vegetables and free-range eggs, thereby creating a stable market demand. Furthermore, it is important to promote the consumption of low-energy agricultural products by encouraging the use of energy labels on packaged agricultural products. These labels should indicate the energy consumption level during the production process, and products with lower energy consumption should be eligible for additional subsidies, guiding consumers toward more sustainable choices.

To promote green transformation through agricultural technological innovation, it is necessary to advance renewable energy substitution projects in agriculture. This can be achieved by implementing "Agriculture-Photovoltaic Complementary" pilot projects, focusing on the promotion of models such as photovoltaic greenhouses and photovoltaic farming. Additionally, constructing centralized biogas supply projects using crop straw and promoting energy utilization technologies for livestock manure should be prioritized, alongside the development of biomass fuel processing equipment. The application of digital technologies in agriculture should also be strengthened, including smart irrigation systems, precision farming technologies, intelligent agricultural machinery, digital greenhouse management, and smart cold chain logistics. These measures will enable efficient energy use across agricultural production, management, and operations, thus reducing dependency on traditional energy sources. Finally, a robust technical promotion and support system should be established, with special policy support and demonstration zones guiding the implementation of green technologies. It is also crucial to cultivate talent for digital agriculture and create platforms for school-enterprise cooperation to support the application of research and development outcomes.

To encourage the optimization of the AIS structure, it is important to limit the expansion of high-energy-consuming agricultural sectors. This can be achieved by setting energy consumption caps for energy-intensive industries, such as greenhouse farming and intensive livestock production, and increasing their environmental costs through mechanisms such as carbon taxes or emissions trading systems. At the same time, support should be provided for ecological agriculture and the circular economy, offering subsidies, certifications, and market access policies. Encouraging low-carbon farming models, such as organic farming and integrated crop-livestock systems, will help reduce the rebound effect of energy consumption across the entire agricultural value chain.

Finally, to deepen the synergy between urbanization and agricultural modernization, it is essential to promote coordinated development of urbanization and the green energy transition, with a focus on strengthening rural renewable energy infrastructure, such as distributed photovoltaic and small wind power systems. Supporting the electrification of agricultural machinery is also crucial, with a priority on promoting low-carbon equipment such as solar-powered water pumps and electric smart farming machines. Furthermore, land consolidation incentive mechanisms should be established to guide the transfer of farmland to new agricultural business entities, promoting the "full mechanization + digital management" model to reduce per-unit energy consumption through scaled production. Finally, strengthening the training systems for green skills among farmers is essential. This can be achieved by offering courses on renewable energy applications, smart machinery operations, and digital management, thus enhancing their ability to apply low-carbon technologies and reducing the inertia of traditional high-energy-consuming practices.

Research Prospects

This study systematically investigated the factors influencing the rebound effect of energy consumption in Chinese agriculture using machine learning methods. Additionally, interpretability techniques such as SHAP values and ALE plots have been employed to further analyze the predictive power and patterns of various feature variables, revealing insights that traditional explanatory modeling could not achieve. However, the causal inferences drawn from the conclusions still require further strengthening. In the future, it will be important to combine the methods used in this study with causal inference techniques to complement each other's functionality and objectives, thereby enriching the research conclusions. The study relied on provincial-level data, which provided a macro-level observation of the energy rebound effect. However, this approach inevitably overlooked micro-level influencing factors, such as group preferences, regional culture, and resource endowments. Therefore, it will be necessary to conduct a more detailed discussion of the mechanisms driving the energy rebound effect at a more micro-level in future research.

CONCLUSIONS

1. Various machine learning algorithms (including random forest, gradient boosting regression tree, support vector machine, and traditional linear regression model) were applied to evaluate the impact of different variables on the rebound effect of agricultural energy.
2. Empirical analysis showed that ensemble learning methods (such as random forest and GBRT) are superior to traditional linear regression models in prediction accuracy and generalization ability, especially in out-of-sample fitting and prediction error indicators (MSE, MAE, MedAE). Further analysis of feature importance reveals that RLI level, ATL, AIS structure, and URB level are the key factors influencing the rebound effect of agricultural energy.
3. Through the analysis of the ALE diagram, the level of RLI, the level of agricultural technology, the structure of AIS, and the level of urbanization have different influence paths on the rebound effect of agricultural energy. Specifically, an increase in RLI initially correlates with higher energy consumption in agricultural production, but the growth rate slows down after reaching a certain threshold.
4. The enhancement of agricultural technology consistently leads to increased energy consumption, which indicates that technological progress may aggravate the energy rebound effect in the short term.
5. The intricate relationship between the optimization of the AIS's structure and energy consumption necessitates a thorough analysis. While an initial increase in energy consumption is observed, the energy rebound effect diminishes as the AIS structure becomes more sophisticated.
6. The urbanization process significantly contributes to the excessive growth of the energy

rebound effect by enhancing agricultural modernization and the implementation of sustainable energy practices.

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Conflicts of Interest

The authors declare that they have no competing interests.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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