Regional heterogeneity of agricultural carbon emission reduction potential in China

Shiqi Hou, Mingjie Chen, Sijie Tao, Peijia Li, Yanqiu He†

College of Management, Sichuan Agricultural University, 211 Huimin Road, Wenjiang District, Chengdu 611130, China

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ABSTRACT
Agriculture, a critical industry highly susceptible to climate change, requires thorough analysis of its carbon reduction potential and priority exploration to advance towards green and sustainable development. Therefore, this study employs a variable coefficient panel model to examine the regional heterogeneity of influencing factors. It also uses a PSO-BP neural network model to simulate changes in China’s agricultural carbon intensity and total emissions under three distinct scenarios. The findings revealed that (1) under the baseline scenario and aggressive scenario, most Chinese provinces and cities can achieve a 30% reduction in agricultural carbon intensity by 2030, and the advanced economic development in the eastern coastal regions positions them favorably for achieving peak carbon emissions. (2) Economic interventions are the main driving force for most Chinese provinces and cities to achieve their agricultural carbon intensity reduction targets, followed by technological interventions and agricultural population adjustment. (3) Eight provinces and cities can be used as emission reduction benchmarks, while Xinjiang, Inner Mongolia, and Henan are challenging points in attaining national emission reduction targets.

Keywords: Agricultural carbon emission reduction, Neural network model, Peak carbon emissions, Variable coefficient panel model

† Corresponding author
E-mail: 14063@sicau.edu.cn
Tel: +86 15928047690
ORCID: 0000-0002-0694-8789

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1. Introduction

Greenhouse gas (GHG) emissions continue to exacerbate global warming and threaten human economic and social development. In the sixth Phase I report, the Intergovernmental Panel on Climate Change (IPCC) warned of catastrophic global impacts should warming exceed 1.5°C [1]. Agriculture is a key component of carbon emissions, and the World Resources Institute (WRI) reported that emissions from agricultural activities alone accounted for 11.8% of overall emissions in 2017 and are rising sharply. Without robust measures, projections indicate a 30% increase in GHGs from agricultural activities by 2050 [2]. Recognizing the vulnerability of agriculture to climate change and its severity, the Chinese government has initiated active interventions. In addition, the Central Government's No.1 document for 4 consecutive years has proposed the green transformation of agriculture, which can augment agricultural capacity to increase foreign exchange, as well as the "double carbon" goal of carbon emissions peaking and carbon neutrality.
Therefore, important questions worth exploring are: What is the potential to attain the emissions reduction targets? Where is the focus of agricultural carbon emission reduction?

A more precise and inclusive measurement of carbon emissions is the basis for further analysis, and academics have measured agricultural carbon emissions from different viewpoints. Tieszen et al. [3] highlighted how modifications in land-use practices profoundly influence agricultural carbon emissions. Subsequently, Johnson et al. [4] measured agricultural carbon emissions more comprehensively regarding agricultural waste, enteric fermentation, manure management, agricultural energy use, rice paddies, and biocombustion. Tubiello et al. [5] and Garnier et al. [6] measured agriculture carbon emissions using the emission factor method, observing that agricultural land use emits a quarter of total GHG emissions, while this proportion reaches half in developing countries and that carbon emissions from the forestry sector are also escalating rapidly. Besides, the input-output approach has been used extensively to measure carbon emissions caused by the input-output relationship between demand and industries. Yu et al. [7] reported that the final demand promotes the growth of carbon emissions. The research indicates that ‘carbon interaction’ within the economic sectors results from the intricate input-output relationships between these sectors [8]. Moreover, carbon emissions in agricultural production primarily come from the inputs of production factors [9]. Some researchers have also employed the lifecycle approach to assess the carbon footprint, positing that this method standardizes the accounting process for agricultural carbon sources, avoiding redundant calculations [10].

Many researchers have focused on its driving forces to determine the main direction of carbon emission reduction in agriculture, among which economy, technology, population, and policy have been broadly discussed as the key influencing factors. The level of agricultural economic development is the key driver of agricultural carbon emissions, which increases when the economic level increases and falls vice versa [11], and the potential exists for significant decoupling of carbon emissions from economic growth [12]. Ghazali and Ali [13] and Wu et al. [14] demonstrated that population size affects regional carbon emissions, and that population migration spatially creates disparities in energy mix between regions, causing carbon transfers between provinces. Technology, central to emission reduction, enhances efficiency in utilizing input factors, thereby reducing emissions [15], though it can also inadvertently increase emissions due to the rebound effect [16]. Moreover, the impact of technological progress on carbon emission reduction is rather stochastic [17]. Yasseen et al. [18] and Zhao et al. [19] suggested that decreasing carbon emissions should begin with government policy reform, with emission reduction mandates at the provincial level, and the implementation of firm environmental controls will curb emissions significantly. Meanwhile, with the development of the regional economic level, environmental regulations significantly affect total factor productivity in agriculture and show a positive correlation [20,21]. Some academics believe that significant differences exist in economic development, technological progress, population, and other factors across China owing to its vast size [22-25], which, in turn, also leads to significant spatial heterogeneity in the impact of various factors on carbon emissions [26-28].

Besides the research on the historical variation pattern of carbon emissions and the influencing factors, some academics have also simulated the attainment of emission reduction targets. Zeng and Yi [20] used the STIRPAT model to project China’s carbon emissions, and they found that most metropolitan areas in China entered the saturation stage of carbon emission in 2016 yet achieving the peak carbon dioxide emission goal by 2030 remains a challenge. Based on a CGE model, Guo et al. [30] found that although China’s energy intensity and carbon emissions intensity reduced significantly, carbon emissions will continue to increase and not peak in 2030. In both scenarios, without implementing effective control measures, China faces significant obstacles in meeting its emissions reduction targets [31-33]. In addition, Zhang and Zhao [34] focused on regional heterogeneity in their projections, classifying 30 Chinese provinces into three types of regions—dominant, potential, and lagging regions—and found regional disparities in the decline of carbon emissions, influenced by variations in per capita GDP growth. Belbrute and Pereira [35] projected global CO2 emissions based on an IMA model and demonstrated that carbon emissions are less likely to peak. Later, Hamilton and Kelly [36] projected carbon emissions for the five largest economies in Sub-Saharan Africa (SSA) using an input-output model and demonstrated that none of the five countries would be able to reduce carbon emissions in 2030 to levels below those in 2012.

In summary, studies have discussed the issue of carbon emission reduction extensively, although the research on carbon emission reduction in agriculture warrants further investigation. A unified accounting system for agricultural carbon emissions is yet to be established, leading to inconsistencies in measurement results across studies. Furthermore, implementing tailored emission reduction strategies is crucial, considering China’s vast territory and regional disparities in agricultural development. Based on agricultural emission reduction, this study complements the existing literature in the following three aspects. First, we establish an accounting system for agricultural carbon emissions and consider regional differences in carbon use efficiency. Second, we set up negative, baseline, and aggressive scenarios to simulate the reduction potential of regional agricultural carbon intensity and total carbon emissions and analyze the extent of interventions required to achieve policy objectives. Third, we consider regional differences in the dominant factors of agricultural carbon emissions and estimate the potential of agricultural carbon emission reduction under four types of interventions—economic, technological, policy, and demographic, followed by exploring the differentiated reduction points. Furthermore, this study provides Chinese ideas and references for implementing heterogeneous measures in regions to attain a green transformation of agriculture.

2. Materials and Methods

2.1. Agricultural Carbon Emission

Agricultural carbon emissions encompass five categories: (i) CO2 produced by energy consumption; (ii) CO2 produced by farmland
utilization; (iii) CH₄ produced by growing rice and N₂O produced from other crops; (iv) CH₄ and N₂O produced by ruminant feeding; and (v) CO₂, CH₄, and N₂O produced by straw burning. The calculation of emissions for each category proceeds as follows:

\[ E_{ij} = \sum_{i-1}^{j} E_{ij} = \sum_{i-1}^{j} (e_i \times f_j) \]  

where \( E_i \) is the total emissions of a specific category; \( E_j \) is the emissions of source \( j \); \( e_i \) and \( f_j \) represent the activity data and emission factor, respectively. The emission factors can be found in Liu [37], Min [38], Tian [39], and Yao [40]. Upon conversion to carbon equivalents, the GHG impacts of 1 t of N₂O (equivalent to 81.2727 t C) and 1 t of CO₂ (equivalent to 6.8182 t C), respectively [41]. Activity data is shown in Table S1.

### 2.2. Variable Coefficient Panel Model

Agricultural carbon emissions also vary because of the differences in agricultural production conditions and levels in different regions. A variable coefficient panel model is used to determine the dominant factors of regional agricultural carbon emissions and lays the foundation for predicting emission reduction potential. According to previous studies, the level of agricultural economic development, level of agricultural technological progress, level of environmental governance, and level of agricultural population are the four leading factors of agricultural carbon emissions [42, 43]. The model variables are as follows.

There are three main approaches to measuring technological innovation: selecting indicators from the input perspective, selecting indicators from the perspective of the efficiency of using production materials, and comprehensively measuring the progress of agricultural technology using total factor productivity (TFP). The first two are less comprehensive than TFP; therefore, TFP in agriculture was finally chosen to measure technological progress.

The data envelopment analysis (DEA) model can consider both desired and undesired outputs and thus more comprehensively measure technological progress under green production conditions. The DEA-Malmquist productivity index is used to measure the total factor productivity of agriculture with the following equation:

\[
M(x^{m+1}, y^{m+1} ; x^{m}, y^{m}) = \frac{D^{m+1}(x^{m+1}, y^{m+1})}{D^{m}(x^{m+1}, y^{m})} \cdot \frac{D^{m+1}(x^{m+1}, y^{m+1})}{D^{m+1}(x^{m}, y^{m+1})} \cdot \frac{D^{m}(x^{m}, y^{m})}{D^{m+1}(x^{m+1}, y^{m})}
\]  

where \( M(x^{m+1}, y^{m+1} ; x^{m}, y^{m}) \) is the TFP change in agriculture, \( D^{m}(x^{m+1}, y^{m}) \) and \( D^{m+1}(x^{m+1}, y^{m+1}) \) denote respectively the \( i \)-th decision unit in period \( m \) unit in period \( t \) and period \( t+1 \) as the distance function value, and \( D^{m+1}(x^{m+1}, y^{m+1}) \) denote the distance function value of the \( i \)-th decision unit in period \( m \) and period \( m+1 \) with reference to the production technology in period \( m+1 \). The specific input-output indicators are shown in Table S2.

The final variable coefficient panel model is as follows.

\[
ACEI_{it} = a + \beta_1 AE_{it} + \beta_2 IS_{it} + \beta_3 ATP_{it} + \beta_4 EGS_{it} + \beta_5 AP_{it} + \nu_{it}
\]  

where \( i \) represents each province and city, \( t \) represents time, ACEI is agricultural carbon emission intensity, AE, IS, ATP, EGS, and AP are agricultural economic development level, industrial structure, agricultural technological progress level, level of environmental governance, and agricultural population level.

### 2.3. PSO-BP Neural Network Model

The Backpropagation (BP) Neural Network is a multilayer forward neural network. The prediction results satisfy the given error through the continuous recurrence of forward propagation of information and backward propagation of error, thus achieving more reliable simulation and prediction. Funahashi [44] has shown that a three-layer network with only one hidden layer is sufficient to represent any continuous function with arbitrary accuracy; as-

<table>
<thead>
<tr>
<th>Table 1. Model variables</th>
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<tr>
<td><strong>Variable types</strong></td>
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<tr>
<td>The dependent variable</td>
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<td>The independent variable</td>
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<td>Level of agricultural technological progress</td>
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<td>Level of environmental governance strength</td>
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<td>Level of the agricultural population</td>
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summing the number of hidden layer nodes is sufficient, its structure is as follows.

\[ p = \sqrt{(m+n)} + a \]  (4)

where: \( n \) is the number of input layer neurons, \( m \) is the number of output layer neurons, and \( a \) is a random integer from 1 to 10.

The output of the implicit layer neuron can be calculated by Eq. (5).

\[ x_i^j = f(\sum_{j=1}^{n} w_{ij}^0 x_j^0 + w_{ij}^0), \quad i = 1, 2, \ldots, m \]  (5)

where: \( x_i^j \) represents the output of the hidden layer neuron, \( \sum_{j=1}^{n} w_{ij}^0 x_j^0 + w_{ij}^0 \) represents a weighted sum of \( n \) input layer neurons, \( w_{ij}^0 \) is the weight coefficient of the degree of influence of input layer neuron \( j \) on hidden layer neuron \( i \), \( w_{ij}^0 \) is the threshold of hidden layer neuron \( i \), and \( f \) is a nonlinear excitation function with memorylessness to change the neuron's output.

Similarly, the output \( y^k \) of the output layer neurons can be calculated by Eq. (6).

\[ y^k = f(\sum_{j=1}^{m} w_{kj}^0 x_j^0 + w_{kj}^0), \quad k = 1, 2, \ldots, m \]  (6)

In addition, the error function of the output layer neurons is defined as:

\[ E = \frac{1}{2} \sum_k (d^k - y^k)^2 \]  (7)

where \( d^k \) is the target value.

(ii) Second, the results are obtained by correcting the errors. The error value of each node in the previous layers is calculated by backpropagating the error layer by layer and corrected with the following weighted correction amount formula.

\[ \Delta w_{ij}^m = \phi \eta_y \cdot y^{m-1} \]  (8)

where \( w_{ij}^m \) denotes the weight coefficient, \( y^{m-1} \) denotes the output neuron output, \( \eta \) is the learning rate, and \( \delta^r \) is the error signal.

(iii) The optimization is performed using the particle swarm optimization (PSO) algorithm. The equations for updating the position and velocity of a particle are as follows.

\[ v_i^{k+1} = v_i^k + c_1 \cdot rand() \cdot (P_{best}^k - x_i^k) + c_2 \cdot rand() \cdot (P_{pop}^k - x_i^k) \]  (9)

\[ x_i^{k+1} = x_i^k + v_i^{k+1} \]  (10)

where \( v_i^k \) and \( x_i^k \) are the velocity and position of the \( i \)-th particle at the \( k \)-th iteration in \( D \)-dimensional space, \( v_i^{k+1} \) and \( x_i^{k+1} \) refer to the meaning of the generation analogously. \( P_{best}^k \) and \( P_{pop}^k \) are the own optimal value and population optimal value of the \( i \)-th particle at the \( k \)-th iteration. \( c_1 \) and \( c_2 \) are both learning factors, also called acceleration constants. Rand () is a random function that produces a random number between (0,1).

(iv) In the final step, we identify the dominant factors influencing carbon emissions, guided by empirical data from the variable coefficient panel model. These factors are then employed to establish various scenarios, facilitating robust predictions of potential reductions in agricultural emissions.

2.4. Data Sources

In estimating agricultural carbon emissions, energy consumption data were obtained from the China Energy Statistics Yearbook, and four types of data, including farmland utilization, were obtained from the China Rural Statistical Yearbook. In the process of building the variable coefficient panel model, three types of data, namely, the level of agricultural economics, the industrial structure, and the level of agricultural population, were obtained from the China Rural Statistical Yearbook, the level of environmental governance was obtained from the China Environmental Statistical Yearbook, and the level of agricultural technological progress was obtained from the China Rural Statistical Yearbook and the China Human Resources Statistical Yearbook. In addition, the PSO-BP neural network model used the same variables as the variable coefficient panel model, and the data required for the PSO-BP neural network model were also obtained from the China Rural Statistical Yearbook, China Human Resources Statistical Yearbook, and China Environmental Statistical Yearbook.
3. Results and Discussion

3.1. The Characteristics of Agricultural Carbon Emissions in China

Fig. 2 illustrates that, beginning in 2007, agricultural carbon emissions in China have exhibited a consistent upward trend, increasing from $1.52 \times 10^9$ tons in 2007 to $1.57 \times 10^9$ tons in 2020, an escalation reflected by an average annual growth rate of 0.25%. In contrast, there has been a significant decrease in China’s carbon emission intensity during the same period. Carbon emission intensity has decreased from 5.55 ton/10^4 yuan RMB (3.76 ton/10^3 USD) in 2007 to 1.90 ton/10^4 yuan RMB (1.29 ton/10^3 USD) in 2019, with an average annual growth rate of -7.92%.

Fig. S1(a) shows the differences in total carbon emissions between the eastern, middle, and western regions. In the eastern region, a significant reduction is noted, with emissions decreasing from $0.48 \times 10^9$ tons in 2007 to $0.44 \times 10^9$ tons in 2020, representing an average annual decrease of 0.65%. Conversely, the middle region experienced heightened emissions, accompanied by substantial year-to-year fluctuations in carbon emission from $0.72 \times 10^9$ tons in 2007 to $0.75 \times 10^9$ tons in 2020, with an average annual growth rate of 0.36%. The western region remains at a lower carbon emission level, with an average annual growth rate of 1.09%.

From the carbon emission intensity in Fig. S1(b), the western region has the largest decline, from 5.85 ton/10^4 yuan RMB (3.96 ton/10^3 USD) in 2007 to 1.87 ton/10^4 yuan RMB (1.27 ton/10^3 USD) in 2020, a decline of 68.02%; followed by the middle region, from 6.32 ton/10^4 yuan RMB (4.28 ton/10^3 USD) to 2.33 ton/10^4 yuan RMB (1.58 ton/10^3 USD), a decline of 63.13%; the eastern region has the relatively smallest decline, from 4.10 ton/10^4 yuan RMB (2.78 ton/10^3 USD) to 1.52 ton/10^4 yuan RMB (1.07 ton/10^3 USD), a decline of 62.90%.

Table S3 demonstrates that the middle region of China exhibits the highest levels of agricultural carbon emissions, and the differences between the eastern and western regions are small. The proportion of agricultural carbon emissions in the middle region is as high as 46.01% of the national agricultural carbon emissions, with Heilongjiang and Henan provinces accounting for more than 8%. This trend can be attributed to these two provinces’ extensive agricultural activities and developed primary industries. Agricultural carbon emissions in the eastern region account for 27.77% of the national agricultural carbon emissions, with Shandong accounting for the highest proportion and Beijing the smallest, with a difference of 6.47% between the two provinces.

The western region produces relatively the least agricultural carbon pollution, accounting for only 24.22%.

3.2. Analysis of Regional Differences in Influencing Factors of Agricultural Carbon Emissions

Table 2 demonstrates that the agricultural carbon intensity decreases with the improvement of agricultural economic development, indicating that most provinces and cities have crossed the inflection point of the Kuznets curve in terms of agricultural industry development in China. This finding aligns with the research conducted by Liu and Feng [45], which illustrates that agricultural carbon emissions and the economy in China display decoupling, and agriculture is developing in a sustainable and green direction.

Table S4 demonstrates that the industrial structure influences the intensity of agricultural carbon emissions in 6 provinces and cities. The coefficients of Beijing and Chongqing are positive, suggesting that the increase in the proportion of traditional agriculture would aggravate carbon pollution [46]. Beijing largely has tertiary
industry, and Chongqing has a more developed industry, while neither has the advantage of developing traditional agriculture. In contrast, Hebei, Henan, Xinjiang, and Anhui are large agricultural provinces; the scale effect of traditional agriculture is noticeable, and the percentage of planting and animal husbandry is high. China's agricultural green transformation strategy promotes upgrading agricultural technology and reducing emission reduction costs [47]. Therefore, carbon pollution slows down with the increase in the percentage of traditional agriculture.

Table S5 demonstrates that the agricultural carbon emission intensity of over one-third of Chinese provinces and cities is influenced by the level of agricultural technology, and the estimated coefficients are positive in all regions except for Beijing, suggesting that technological progress does not exert the emission reduction effect, but further aggravates regional carbon pollution. The reason is that agricultural input factor utilization efficiency increases with technological progress. However, under the rebound effect [48], the increase in emissions due to the expansion of agricultural production scale completely offsets the emission reduction due to technological progress and carbon pollution increases.

Table S6 demonstrates that environmental governance strength significantly impacts seven provinces and cities in China. However, the coefficients of all other provinces and cities are negative, except for Shanghai, suggesting that increasing government environmental governance is conducive to emission reduction. Shanghai mainly has a tertiary industry, where pollution control investment is more concentrated in secondary and tertiary industries, and agriculture is subjugated by high-value-added, low-carbon characteristics, thereby limiting the agricultural emission reduction potential. Hence, the increase in environmental management is not conducive to agricultural emission reduction.

Table S7 demonstrates that the share of the agricultural population influences agricultural carbon emissions in one-third of Chinese provinces and cities. Of these, the increase in agricultural population in Hainan, Anhui, and Beijing will exacerbate the agricultural carbon emission problem. This is because tropical cash crops and tourism agriculture dominate Hainan, and Anhui is the chief distribution area of China's plantation industry, and the percentage of agricultural population in both places is already as high as 46.77% and 52.37%, respectively. Thus, further escalating the agricultural population will only decrease the economic efficiency of agriculture, which is not conducive to emission reduction. However, as the representative of economically developed regions, Beijing is dominated by the development of tertiary industries, and the percentage of agriculture is only 0.26%. Here, the increase in agricultural population may lead to inefficiencies in agricultural production, potentially hindering efforts toward emission reduction. The remaining 7 provinces and cities are vast, with a small population density and a population share of only around 10% of the country and are the main production areas of planting and animal husbandry. Therefore, the growth of the agricultural population is conducive to driving the advantageous agricultural industries to become bigger and stronger and then realize the green transformation of agriculture. Hence, increasing the agricultural population share is beneficial to carbon emission reduction.

3.3. Forecast of Chinese Agricultural Carbon Reduction Potential

3.3.1. Scenario setting

First, based on the estimation results of each factor in the panel variable coefficient model above, the provinces and cities are systematically clustered. If the coefficients are not significant, the variables are defined as 0; if the coefficients are significant, the variables are defined as 1, 2, and 3, respectively, per the degree of significance defined by the number of *, marked by the degree of significance, the degree of significance ** is defined as 3, and so on, by which the agricultural carbon emissions of each province and city can be classified into economy-led, technology-led, policy-led, and population-led.

Then, when setting the agricultural carbon emission projection scenarios, three categories of baseline, aggressive, and negative scenarios are set for the four types of regions based on economic, technical, policy, and demographic indicators, respectively. Of these, the baseline scenario denotes the average rate of change of indicators in the past 10 years; the aggressive scenario denotes the ideal value of indicators in the past 10 years; the negative scenario denotes the unsatisfactory value of indicators in the past 10 years. Fig. 3 presents the clustering results.

![Fig. 3. Results of cluster analysis](image)

3.3.2. Forecast of carbon intensity reduction potential

(1) Comparative analysis of four types of regions

Fig. 4 shows differences in the emission reduction effects of the four types of regions. While the aggressive scenario can better stimulate agricultural emission reduction potential and attain agricultural carbon emission reduction, the negative scenario exerts a limited effect on emission reduction and could even increase carbon pollution. Under the negative scenario, the carbon intensity of economy-led regions increases rather than decreases, while the carbon intensity of the other three types of regions decreases to a lesser extent. For most regions in China, if the agricultural economic development level and the agricultural industry structure are adjusted toward low carbonization at a slower rate, the issue of agricultural carbon pollution cannot be solved. Under the baseline
scenario, technology-led regions have the best emission reduction effect, with agricultural carbon intensity declining by 39.31% in 2030 compared with 2020, whereas policy-led regions have the worst emission reduction effect, with the agricultural carbon intensity declining by only 12.57%, suggesting that the technology reduction effect is still strong even if agriculture is developed at a conventional rate. Under the aggressive scenario, the decline in agricultural carbon intensity in 2030 compared with 2020 is >10% higher in the economy-led and technology-led regions than in the other two dominant regions.

(2) Comparative analysis of provinces and cities within the four types of regions

Fig. S2 demonstrates that the degree of carbon intensity target attainment varies broadly among provinces and cities within the economy-led regions. Under the aggressive scenario, around 90% of the regions can accomplish the 30% reduction in carbon intensity target, and only Anhui and Tianjin do not. Under the baseline scenario, 52.63% of provinces and cities can meet the target, with Guizhou displaying the largest decrease and Tianjin the smallest. Under the negative scenario, only four provinces and cities accomplish the target, and 50% of the provinces and cities increase their agricultural carbon intensity rather than decrease it, indicating that for economy-led regions, an aggressive agricultural economic development strategy is more conducive to attaining the carbon intensity reduction target [49].

Fig. S3 shows that the carbon intensity targets in the negative scenario are poorly achieved in technology-led regions, and the gap between the targets in the baseline and aggressive scenarios is small.

Under the baseline and aggressive scenarios, only Henan failed to meet the carbon intensity reduction target. Under the negative scenario, all provinces and cities failed to meet the target, indicating that the focus of emission reduction in technology-led regions is Henan. Henan’s agriculture total factor productivity remains lower than the national average; thus, the emission reduction effect of agricultural technology progress has not yet been fully played.

Fig. S4 shows that the carbon intensity in the aggressive scenario in the policy-led region decreases much more than in the other two scenarios. The carbon intensity of agriculture declines by 13% and 9% under the baseline and negative scenarios, respectively, which are far from the emission reduction target, while the carbon intensity declines by 45% under the aggressive scenario. Overall, Shanghai’s agricultural economy is developing toward green and low-carbon, and administrative forces should be the main force in decreasing emissions.

Fig. S5 shows that some provinces and cities failed to attain the target under the three scenarios in population-led regions. Inner Mongolia is the focus of emission reduction, whose agricultural emission reduction is more challenging because of its vast natural pastures, main livestock production base in China, and outstanding advantages in scale, along with an already low proportion of the agricultural population, making it more problematic to stimulate emission reduction potential through the agricultural population [50].

3.3.3. Forecast of total carbon emission reduction potential

(1) Comparative analysis of four types of regions

The potential reduction of total agricultural carbon emissions in
China was further explored. Based on the average annual growth rate of agricultural value added from 2007 to 2020, the agricultural total carbon emissions are predicted based on the agricultural carbon intensity under the three scenarios, as shown in Fig. S6. Carbon emissions differ markedly among the three scenarios. In the negative scenario, total agricultural carbon emissions continue to rise. In the baseline scenario, after a minor decrease until 2030, carbon emissions increase again, indicating that it is tougher to attain "peak carbon dioxide emissions" in Chinese agriculture without any positive intervention. On the contrary, the aggressive scenario declines from 1.64 × 10⁹ tons in 2020 to 1.22 × 10⁹ tons in 2030, a decrease of 25.61%, suggesting that the aggressive scenario effectively reduces emissions.

We further explored the differences in carbon emissions of each dominant type from the perspective of carbon emission pollution (Fig. 5). Economy-led regions, as depicted in Fig. 5(a), exhibit the highest levels of carbon emissions. Both negative and baseline scenarios negatively impact the national carbon reduction, with the total carbon emissions increasing by 35.5% and 0.19% in 2030 compared with 2020, respectively. Under the aggressive scenario, carbon emissions decline significantly from 0.96 × 10⁹ tons in 2020 to 0.68 × 10⁹ tons in 2030, a decline of 29.17%, which is 3.56% higher than the national carbon emissions decrease in the same period, suggesting that the aggressive scenario effectively reduces emissions.

Next is the technology-led regions. From Fig. 5(b), technology-led regions positively impact the national carbon reduction under the baseline scenario, whereas the positive role is heightened in the aggressive scenario. Under the negative scenario, agricultural carbon emissions will increase by 27.76% in 2030 compared with 2020. Under the baseline scenario, carbon emissions decrease by 3.07%. However, due to the inherently lower emissions within technology-led regions, their contribution to national emission reduction is comparatively minor, rendering the positive effects less discernible. Under the aggressive scenario, carbon emissions decline from 0.31 × 10⁹ tons in 2020 to 0.24 × 10⁹ tons in 2030, a reduction of 22.58%, which is 3.56% lower than the national carbon emission decrease rate in the same period, indicating that the technology-led type plays a weaker positive role on the national carbon emission.

The third is the population-led regions. From Fig. 5(d), the population-led regions have relatively small changes in the three scenarios and play a smaller role in the national carbon emissions. Under the negative scenario, agricultural carbon emissions in 2030 declined by 6.65% compared with 2020, which is much lower than the national carbon emissions growth rate in the same period, and the negative effect is smaller. Under the baseline scenario, carbon emissions rise by 5.4%, which is higher than the carbon emissions growth rate in the same period. Under the aggressive scenario, carbon emissions decline markedly, from 0.36 × 10⁹ tons in 2020 to 0.3 × 10⁹ tons in 2030, a decline of 16.67%, which is lower than the national carbon emissions decrease rate in the same period.

The lowest carbon pollution is in the policy-led regions. From Fig. 5(c), policy-led regions have the lowest carbon emission values. Under all three scenarios, agricultural carbon emissions in 2030...
are 27.27%, 30.22%, and 51.35% lower than those in 2020. Given that Shanghai is the sole policy-led region, its total carbon emissions are significantly low, thereby rendering its positive impact on national carbon reduction relatively negligible.

(2) Comparison of time of carbon peak in provinces and cities

We conducted an in-depth analysis of the projected timelines for reaching peak carbon emissions in each Chinese province and city, delineated across three predefined scenarios (Fig. S7). Provinces were categorized based on their anticipated timelines for peaking agricultural carbon emissions: regions not meeting the target, regions achieving the target by 2025, and regions accomplishing the target by 2030.

The aggressive scenario forecasts the most favorable conditions for reaching emission peaks, whereas the negative scenario presents the least favorable projections. Among them, Xinjiang, Inner Mongolia, and Henan do not reach the peak under the three scenarios because these three areas are highly dependent on traditional agriculture and are the major provinces of animal husbandry and plantation in China, making agricultural emission reduction tougher [51].

In the negative scenario, the agricultural carbon emissions in Jilin, Liaoning, Shanxi, Hubei, and Hainan will peak before 2025, while the agricultural carbon emissions in Qinghai, Beijing, and Zhejiang will peak before 2030. In the baseline scenario, Anhui, Zhejiang, and Jiangxi will be added to the list of regions that will attain peak carbon emissions by 2025; Yunnan, Guizhou, Sichuan, Chongqing, and Shandong, Jiangsu, Shanghai, and Fujian on the eastern coast will also be added to this list. This suggests that these regions can attain China’s "peak carbon" by 2030 under conventional development and could serve as emission reduction benchmarks, establish a regional alliance of emission reduction pioneers, and promote China’s overall agricultural carbon emission reduction. Under the optimistic projections of the positive scenario, Ningxia and Shaanxi are anticipated to reach peak emissions before 2025. Concurrently, Hunan, Guangdong, Guangxi, and northern Gansu are projected to follow suit before 2030, underscoring the imperative for targeted emission reduction strategies in these areas.

3.4. The Test of The Model’s predictive Effect

Carbon intensity from 2007 to 2015 was used as a training sample, and carbon intensity from 2016 to 2020 was used as a test sample to test the applicability and accuracy of the model. The simulation was conducted with MATLAB software, the Levenberg-Marquardt (L-M) algorithm was selected, and particle swarm optimization (PSO) was used to optimize the algorithm. Taking "TANSIG" as the transfer function of the neural network and "Train LM" as the training function. The results are shown in Table 3. The difference between actual and predicted carbon intensity was small, with an average error of 2.61%, indicating that the model’s overall prediction result is good.

3.5. Sensitivity Analysis

Sensitivity analysis is further utilized to examine the impact of uncertainty in economic, demographic, technological, and policy factors on the forecast results. Sensitivity analysis is a method to assess the importance of each input parameter of the output parameter. We declined and increased the initial values for each input parameter by 20%, while the other input parameter data were kept unchanged [52]. The results are shown in Fig. S8.

It can be seen that the industrial structure has the greatest impact on the predicted value. When the industrial structure decreases by 20% compared to the actual value, the predicted carbon intensity decreases by 52% compared to the original value, and when the industrial structure rises by 20% compared to the actual value, the predicted carbon intensity rises by 83% compared to the original value. Next is the agricultural population and the

Table 3. Comparison of predicted and actual annual average carbon intensity from 2016 to 2020

<table>
<thead>
<tr>
<th>Area</th>
<th>Predicted values</th>
<th>Actual value</th>
<th>Area</th>
<th>Predicted values</th>
<th>Actual value</th>
</tr>
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<tbody>
<tr>
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<td>2.80</td>
<td>Henan</td>
<td>3.03</td>
<td>2.90</td>
</tr>
<tr>
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<td>3.68</td>
<td>Hubei</td>
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<td>1.84</td>
</tr>
<tr>
<td>Hebei</td>
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<td>2.45</td>
<td>Hunan</td>
<td>2.46</td>
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</tr>
<tr>
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<td>4.18</td>
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<td>1.25</td>
</tr>
<tr>
<td>Inner Mongolia</td>
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<td>4.78</td>
<td>Guangxi</td>
<td>1.72</td>
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<tr>
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<td>2.50</td>
<td>Hainan</td>
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<td>0.94</td>
</tr>
<tr>
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<td>5.11</td>
<td>Chongqing</td>
<td>1.69</td>
<td>1.63</td>
</tr>
<tr>
<td>Heilongjiang</td>
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<td>4.10</td>
<td>Sichuan</td>
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<td>1.93</td>
</tr>
<tr>
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<td>1.61</td>
<td>Yunnan</td>
<td>2.68</td>
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<tr>
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<td>Qinghai</td>
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</table>
level of environmental governance, whose rise or fall will make the carbon intensity prediction fluctuate within 10% around the original value. The fluctuations of the remaining factors all have a smaller impact on the predicted value of carbon intensity, and when these factors fluctuate, the predicted value of carbon intensity only fluctuates within 4%-5% of the original value. This indicates that the final prediction results are more sensitive to changes in industrial structure, changes in agricultural population, and changes in the level of environmental governance, of which industrial structure adjustment is slow, but with the development of the agricultural economy, the progress of agricultural technology and changes in the level of environmental governance may fluctuate considerably, resulting in a certain degree of uncertainty in the final prediction results.

After that, each parameter’s impact on carbon intensity prediction was identified. Fig. 13 shows the results of the sensitivity analysis using the PSO-BP network, where the industrial structure (IS) has the greatest effect on the carbon intensity prediction, after which agricultural population (AP), environmental governance strength (EGS), agricultural economic (AE) and agricultural technological progress (ATP) are effective respectively.

3.6. Discussion

(1) This study aimed to estimate the potential for carbon emission reduction in agriculture within the framework of China’s double carbon goals. It focused on strategies for achieving a transition to environmentally sustainable and low-emission agricultural practices. Previous studies have usually focused on the emission reduction potential of secondary and tertiary industries, arguing that the industry, as a representative of high-energy-consuming industries, must improve its emission reduction capacity by formulating emission reduction strategies tailored to local conditions and optimizing its energy structure [53]. Moreover, the emission reduction potential of each subindustry is different. In the case of intervention, the power industry, the steel industry, the construction industry, the air transport industry, and the tourism industry can achieve the carbon peak at different times. Among these, the tourism industry’s peak emissions timeline aligns with China’s overall carbon peak objectives [54-57]. To attain the peak carbon target in China, the potential of each sector must be stimulated, and agriculture is markedly different from the secondary and tertiary sectors in terms of its ability to decrease carbon emissions, which warrants additional government support [58] and could be more optimistic than industry, construction, and transportation [59]. Based on the differences in the emission reduction potential of agriculture under different levels of interventions, we predicted the emission reduction of agriculture in 30 provinces and cities in China under the negative, baseline, and aggressive scenarios, making the findings more detailed than previous studies and facilitating the setting of differentiated emission reduction promotion measures by region. Our findings reveal that only 23.3% of Chinese provinces and cities can attain a 30% reduction in the agricultural carbon intensity under the negative scenario, and as the level of intervention increases, the number of provinces and cities attaining the target reduction in the agricultural carbon intensity increases to 56.7% and 86.7% under the baseline and aggressive scenarios, respectively.

(2) This study used cluster analysis to classify regions into four categories—economy-led, technology-led, policy-led, and population-led—based on the differences in the dominant factors of agricultural carbon emissions among Chinese provinces and cities. In addition, we explored the impact of differences in intervention types on the reduction potential of agricultural carbon intensity and total carbon emissions, which differs from previous carbon emission simulations based on the international [60], national [61], or regional levels [62-64] that did not fully reflect on the differences in the dominant factors of carbon emissions. Our findings facilitate the adoption of nonhomogeneous agricultural carbon emission reduction interventions across regions. Existing literature confirms that strategies such as industrial restructuring, improved energy efficiency, advancement in low-carbon technologies, and stringent environmental regulations are crucial for mitigating high-carbon trends and achieving emission reduction goals. Nonetheless, the primary factors influencing agricultural emissions can vary regionally, influenced by diverse resource endowments, production capabilities, and policy frameworks. The research suggests that employing uniform interventions may not effectively achieve the desired emission reductions due to regional disparities. This study demonstrates that 12 Chinese provinces and cities, including Fujian and Guangdong on the southern coast, Jiangsu on the eastern coast, Shandong, Hebei, and Beijing on the northern coast, Hunan in the middle reaches of the Yangtze River, Shaanxi in the middle reaches of the Yellow River, Ningxia and Guangxi in the southwest, and Xinjiang and Gansu in the northwest, all need to reinforce economic interventions to decrease agricultural carbon emissions. In addition, Chongqing in the southwest, Jiangxi in the middle reaches of the Yangtze River, and Shanxi in the middle reaches of the Yellow River require stronger technical interventions. Furthermore, Shanghai on the eastern coast needs stronger environmental regulation. However, Hainan on the southern coast, Heilongjiang and Jilin in the northeast, and Qinghai in the southwest should work on agricultural population adjustment.

(3) In this study, the PSO-BP neural network model is used for carbon emission intensity prediction, in which the DEA model is used to calculate the technical index of total factor productivity in agriculture. The BP algorithm is local, and the PSO algorithm is global. The combination of these two algorithms can improve computational efficiency and overcome the shortcomings of traditional BP neural networks, such as poor stability, low reliability, and easy-to-reach local minima [65,66]. DEA is an efficient tool for measuring the efficiency of various agricultural products. The Malmquist productivity index (MPI) is a useful approach for determining the productivity changes of decision-making units [67]. Existing MPI methods are usually based on an optimistic view and affect the results somewhat [68,69].

(4) Agriculture is a vital carbon source and a crucial carbon sink. However, this study does not consider the dual attributes of agriculture to examine its net carbon emissions and does not estimate the potential of agricultural carbon sequestration. Owing to the national performance assessment, promoting agricultural carbon emission reduction in each region would generate learning, imitation, competition, and other behaviors, causing inter-regional
interaction in emission reduction. In addition, this study does not consider the interaction between regions when forecasting the potential of agricultural emission reduction. Besides, the impact of inter-regional interactions is not considered. Thus, in future research, we should construct a complete model that covers both agricultural carbon emissions and carbon sequestration, as well as include the interference factors of regional interactions to obtain more realistic simulation results of agricultural emission reduction potential.

4. Conclusions
Zonal simulations reveal that most Chinese provinces could reduce agricultural carbon intensity by 30% by 2030 under baseline and aggressive scenarios. Particularly, economic growth along the eastern coast appears conducive to these reductions. Economic strategies are crucial for carbon intensity reduction, with technological advancements and demographic adjustments also playing significant roles. Notably, eight provinces— including Yunnan, Guizhou, Sichuan, Chongqing, Shandong, Jiangsu, Shanghai, and Fujian—have emerged as leaders, potentially serving as benchmarks in emission reduction efforts. Conversely, Xinjiang, Inner Mongolia, and Henan face substantial challenges meeting the national emission reduction benchmarks.

Thus, we suggest that regions with economic-led agricultural carbon emissions should adopt more aggressive economic interventions, actively promote agricultural economic growth, increase the agricultural added value, and optimize the agricultural industrial structure. Regions with technology-led agricultural carbon emissions should increase investment in agricultural research, fast-track the efficiency of agricultural technology transformation, guide the optimal allocation of agricultural resources, and build an agricultural technology transfer platform to share the success of technology emission reduction. Regions with policy-led agricultural carbon emissions should improve agricultural environmental management and adopt the idea of "development while management." In regions with population-driven agricultural carbon emissions, we should focus on increasing the urbanization rate and promoting the transformation of rural communities into urban communities. Finally, we should establish benchmarks for emission reduction and give full play to the leading role of benchmark regions in overall agricultural carbon emission reduction.

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Author Contributions
Based on Contribution Roles Taxonomy: T.S.J. (MA student) and L.P.J. (MA student) conducted data curation. C.M.J. (MA student) supported data analysis. H.S.Q. (MA student) wrote an original manuscript. H.Y.Q. (Associate Professor) wrote and revised the manuscript.

Conflict-of-Interest Statement
The authors declare that they have no conflict of interest.

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