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Re-Measurement of Agriculture Green Total Factor Productivity in China from a Carbon Sink Perspective

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Abstract: Accurate measurement of agricultural total factor productivity (AGTFP) is crucial to measure the level of sustainable agricultural development, and agricultural carbon sink is an important element to leverage the development of green transformation. Few studies have incorporated agricultural carbon sink into the measurement framework of AGTFP, and the evolutionary dynamics and related spatial effects of Chinese AGTFP from the perspective of carbon sinks are unclear. On this basis, the paper used a provincial-level agricultural panel data set of China from 2000 to 2019 to measure the provincial indicators of agricultural carbon sinks, CO_2 emissions and agricultural non-point source pollution. Then, we incorporated these environmental factors into the measurement framework of AGTFP and used the SBM-DEA model to calculate the Chinese AGTFP from the perspective of carbon sinks. We further analyzed the spatial and temporal divergence and convergence of AGTFP in China using Moran'I and spatial econometric models. We found that after measuring AGTFP, including agricultural carbon sinks, 28 out of 30 Chinese provinces showed an increased trend, but the development gap between regions was obvious. The spatial econometric model showed a significantly positive spatial correlation between the AGTFP of each province and did not have absolute α-convergence and absolute β-convergence characteristics. After adding the control variables of resource endowment of each province, it showed conditional β-convergence characteristics, and the spatial spillover effect of China's AGTFP was increasing. Finally, the paper proposed policy recommendations for the sustainable and coordinated development of China's agricultural regions in response to the research findings.

Keywords: carbon sink; agriculture green total factor productivity in China; re-measurement

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1. Introduction

Since the reform and opening up, Chinese agriculture has made great progress in ensuring food security and economic stability. However, Chinese agricultural production has long relied on the traditional factor-driven pattern, and the overuse of production factors has contributed to the deterioration of carbon emissions and the increase in agricultural surface pollution while promoting agricultural development [1]. According to the bulletin of the first national pollution source census, the emissions of the three main agricultural water pollutants in China account for a large proportion of total pollution, including chemical oxygen demand (COD) accounting for 43.71%, total nitrogen (TN) accounting for 57.19% and total phosphorus (TP) accounting for 67.27%. COD emissions from agricultural pollution exceed those from the industrial sector, becoming the main source of COD emissions. Energy consumption and CO_2 emissions are increasing year by year [2]. Various phenomena, such as overconsumption of resources and energy, and gradual deterioration of ecological badlands, are seriously limiting the sustainable development of Chinese agriculture, and the changes in production methods around agriculture are imminent. Total factor productivity (TFP) is not only the main tool to study economic growth but also a key method to determine the quality of economic growth [3]. There is a great potential for synergy between TFP and sustainable agricultural development and ecological resilience [4]. The improvement of agricultural green total factor productivity (AGTFP) is a vital indicator to guarantee the green development of agriculture and even economic development [5,6]. Therefore, to clarify how to maintain sustainable agricultural development, exploring the level of green productivity of Chinese agriculture under resource and environmental constraints by measuring AGTFP is crucial.

In addition, global climate problems are becoming increasingly serious, and climate warming threatens global food security by affecting agricultural production [7–10], and climate change has long been a common challenge for people around the world to face. As a major contributor to climate change, the development of agriculture must join the action to cope with the global climate crisis. Agriculture contains not only carbon sources but also the function of the carbon sink in its production process. Therefore, agriculture is a large carbon sink system, and a healthy agroecosystem can offset up to 80% of global greenhouse gas emissions released due to agricultural production processes [11]. Therefore, taking into full consideration the role of agricultural carbon sinks, grasping the development process of low-carbon agriculture, re-measuring the green total factor productivity (AGTFP) of China from the perspective of carbon sinks and releasing the huge potential of agricultural emission reduction will become the keys to promoting the green and sustainable development of agriculture, to achieving China's carbon peaking and carbon neutrality goals and to completing the transformation of the economy to a low-carbon development.

How to improve agricultural productivity has been the focus of scholars' research [12–14], and agricultural total factor productivity (ATFP) is also considered as a measure of agricultural productivity. There are currently three main methods to calculate ATFP. The first method is the growth accounting method, which was used by Fan (1991) [15] to measure ATFP in China, and Wen (1993) [16] also used the Solow residual method and reached similar conclusions as Fan (1991) [15]. The second method is stochastic frontier analysis (SFA), which can construct a frontier surface suitable for the characteristics of agricultural production [17], but it requires a predetermined production function. Coelli et al. (2003) [18] calculated the ATFP of Bangladesh using the SFA approach and found a U-shaped agricultural technology progress. Chen and Gong (2021) [19] estimated four AGTFPs under different forms of production functions. The third method is the data envelope method analysis (DEA), which does not require a predetermined functional form and is used to determine productivity levels by creating a piecewise linear production frontier and comparing it with the optimal frontier surface [20]. DEA is capable of handling multiple inputs and outputs. Po-Chi et al. (2008) [14] used sequential DEA to calculate the output-oriented Malmquist productivity index and its decomposition; they found that the main source of productivity growth is technological progress. In recent years, along with global climate change and ecological deterioration, green growth in agriculture has become an essential element to improve agricultural productivity, and it is the key to sustainable agricultural development [20,21]. Agricultural green total factor productivity (AGTFP) is an objective indicator of sustainable agricultural development [22], revealing the sustainable growth component beyond input factors under environmental pressure. Since SFA is difficult to meet the needs of multiple outputs in agricultural production [1], the advantages of DEA methods, such as measuring multiple inputs and multiple outputs, are widely used in the assessment, especially when incorporating environmental factors into the measurement framework of AGTFP [23–28]. The specific measurement method is to attribute environmental factors, such as carbon source pollution and non-point source pollution, generated from the agricultural production process as non-desired outputs to the output side and then use the DEA method to measure AGTFP [2,20,24,29]. However, the agricultural production process includes not only carbon emissions but also carbon sinks, and a healthy agroecosystem can effectively reduce the CO_2 released from the agricultural production process [30]. Currently, scholars' research focuses on CO_2 and non-point source pollution emissions [2]. Zhang et al. (2017) [31] established a method and estimated the carbon footprint of grain production in China based on life cycle analysis (LCA). The results showed that grain production had a high carbon footprint in 2013. Cheng et al. (2015) [32] also conducted similar studies as Zhang et al. (2017) [31]. Some scholars have estimated and studied carbon sinks. For example, Lin (2018) [33] calculated the green production efficiency of forests based on carbon sinks. Zhang et al. (2022) [34] measured the efficiency of net carbon sinks in 285 Chinese cities from 2012 to 2017. Chen et al. (2021) [35] estimated the carbon sink of crop production systems from four aspects: tree; soil organic carbon; fertilizer application; and no-till management. Chen estimated the carbon footprint of farmers' agricultural production through a multi-system boundary scenario approach and included agricultural carbon sinks in the research framework to judge the contribution of farmers' agricultural production to climate change Chen (et al. (2020)) [36]. There is still a great lack of studies that include carbon sink, carbon emissions and non-point pollution jointly in the measurement framework of AGTFP. Hence, in order to accurately measure China's AGTFP from the perspective of carbon sink, as well as to grasp the sustainable development level of agriculture under environmental constraints, we used the DEA method to add carbon sink to the environmental factors to measure China's AGTFP. On the other hand, another key aspect to assess the sustainable development level of agriculture at this stage is to study the spatial effect of agricultural AGTFP [37]. Wei et al. (2018) [38] studied the factors affecting agriculture using a spatial error model (SEM) and found that factors such as industrial agglomeration and the level of science and technology had positive effects on agricultural green production efficiency. Therefore, to further grasp the level of sustainable agricultural development in China, we used a spatial econometric model to study the relevant spatial effects of AGTFP after completing the measurement of AGTFP that incorporates agricultural carbon sink factors.

Previous studies on the measurement of AGTFP and its spatial effects provide the basis for this paper. However, few studies have included carbon sink factors in the measurement framework of AGTFP, and there is a lack of research on the spatial effects of AGTFP in China from the perspective of carbon sinks. The marginal contributions of this paper are as follows. First, agricultural ecosystems are an essential part of global terrestrial ecosystems, an important source and sink of atmospheric carbon. Agricultural soils have a great carbon sink potential, which has a large impact on mitigating climate change. Relatively few scholars have measured the data on carbon sink as well as net carbon emission indicators. This paper measured agricultural carbon sink, CO_2 emissions and non-point source pollution emissions in Chinese provinces from 2000 to 2019 and included them as non-expected outputs in the calculation framework of AGTFP, which enriches the measurement of AGTFP. Second, based on the previous measured data, we used the global Moran'I index, absolute α convergence, absolute β convergence, conditional β convergence and spatial Durbin model (SDM) to study the spatial autocorrelation, convergence and other spatial effects of China's AGTFP from multiple perspectives to reveal the spatial and temporal convergence of China's AGTFP from a dynamic perspective. Third, this research focused on the agricultural development at the provincial level, and the findings are of great practical significance for promoting the coordinated and high-quality development of regional green agriculture in China. Therefore, the research significance of this paper was demonstrated through the following points. First, we recalculated China's agricultural carbon sinks using the latest carbon equivalent factors from the UN Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report to provide a new perspective for developing a more effective CO_2 reduction strategy. Second, we estimated the net carbon emissions of China's agriculture, which can more accurately indicate the actual growth of China's agriculture and provide a reference for decision making to precisely reduce the regional disparity of China's AGTFP. Third, we analyzed the dynamic convergence of AGTFP in the spatial dimension to clarify the dynamic evolutionary characteristics of AGTFP convergence and to reveal the sources of regional disparities in AGTFP growth in China.

2. Materials and Methods

2.1. Measurement of Agriculture Carbon Sinks and Carbon Emissions and Non-Point Source Pollution

At present, there are no relevant statistics on the environmental indicators of agricultural carbon source emissions of CO_2, carbon sinks and agricultural non-point source pollution of CO_2. Therefore, it was necessary to measure the above three indicators and calculate them. Then, the net carbon emissions in the agricultural production process were obtained by subtracting the carbon sequestration by carbon sinks from the agricultural carbon source emissions, which was a good quantitative basis for measuring China's AGTFP from the perspective of carbon sinks in the following context.

2.1.1. Measurement of Agriculture Carbon Sinks

The United Nations Framework Convention on Climate Change (UNFCCC) referred to the concept of carbon sinks as "processes or activities that reduce greenhouse gases in the atmosphere". Crop carbon sequestration referred to the process by which crops convert CO_2 in the air into carbohydrates through photosynthesis, releasing oxygen while fixing the carbon in the crop for its own growth and development. This section draws on the calculations used by Chen et al. (2021) [35] to calculate the carbon sink by crop production systems, including: carbon absorption by trees (CS_{TA}) and soil organic carbon (SOC) increases due to straw, litter, pruning and root residue return (CS_{SR}); manure application (CS_{MA}); and no-tillage management (CS_{NT}).

$$TCS_i = CS_{TA} + CS_{SR} + CS_{MA} + CS_{NT} \quad (1)$$

where TCS_i represents the total carbon sequestration. CS_{TA} represents the carbon absorbed by tea and fruit trees aside from that removed by harvesting, pruning and litter, which was 527.5 (Li, 2012) [39] and 930 (Lv, 2019) [40] kg C ha^{-1} yr^{-1}, respectively. The detailed calculation process and explanation of CS_{SR}, CS_{MA} and CS_{NT} are shown in Appendix A.

2.1.2. Measurement of Agriculture Carbon Emissions

The United Nations Framework Convention on Climate Change (UNFCCC) referred to the concept of carbon sources as "processes or activities that emit greenhouse gases into the atmosphere". Based on the carbon accounting approach of the United Nations Intergovernmental Panel on Climate Change (IPCC), the formula for agricultural carbon emissions was constructed as follows.

$$E_c = \sum E_i = \sum T_i \times \delta_i \quad (2)$$

where E_c represents the total agricultural carbon emission, E_i represents the emission of the i-th category of agricultural carbon source, T_i represents the specific value of the i-th category of agricultural carbon source, and δ_i represents the carbon emission coefficient of each agricultural carbon source. Based on previous studies [3,41], the paper determined the corresponding carbon sources and carbon emission coefficients from agricultural land use, rice and livestock breeding, and the indirect N_2O emissions from in-field nitrogen fertilizer application and straw burning based on the characteristics of agricultural production activities and consideration of data availability. Carbon emissions from agricultural land use covered carbon emissions from fertilizers, pesticides, agricultural films, diesel, tillage, irrigation, etc., in the agricultural production process. In addition, the conversion of carbon dioxide (CO_2), nitrous oxide (N_2O), methane (CH_4), etc., into standard C equivalents and the unification of measurement units facilitated the calculation and subsequent comparison of content. The UN Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report stipulated that the conversion C-equivalent standard was that the greenhouse effect caused by 1 t N_2O is equivalent to that caused by 273 t CO_2, and the greenhouse effect caused by 1 t CH_4 is equivalent to the greenhouse effect caused by 27 t CO_2. Because 1 t CO_2 contains 0.272 7 t C, the C contained in 1 t N_2O and 1 t CH_4 is approximately 74.256 t and 7.344 t. The detailed calculation process and explanation of carbon emission are shown in Appendix A.

2.1.3. Measurement of Agriculture Carbon Non-Point Source Pollution

The paper used the idea of the inventory analysis method to account for agricultural non-point source pollution. The method assumed that a certain agricultural activity corresponds to a certain amount of agricultural pollution emissions and integrated a variety of analytical methods to establish the agricultural activity and pollution emissions response relationship, with the unit as the core. The pollutants were mainly COD, TN and TP, and the formula for accounting for agricultural non-point source pollution emissions are as follows [2].

$$E_n = \sum_i EU_i \rho_i (1-\eta_i) C_i(EU_i, S) = \sum_i PE_i (1-\eta_i) C_i(EU_i, S) \quad (3)$$

where E_n represents the emission of agricultural non-point source pollution (i.e., CODCR, TN and TP). EU_i represents the indicator statistic of unit i; ρ_i represents the pollution production coefficient of pollutant of unit i; η_i represents the coefficient characterizing the efficiency of relevant resource utilization; PE_i represents the pollution production of pollutant of unit i. This indicator does not take into account the maximum potential pollution caused by comprehensive resource utilization and management factors. C_i represents the emission coefficient of pollutant of unit i, which is determined by the unit characteristics (EU_i) and spatial characteristics (S) and characterizes the combined effects of regional environment, rainfall and various management measures on agricultural non-point source pollution.

The indicators of agricultural non-point source pollutant discharges evaluated in the paper mainly included COD_{CR}, TN and TP remitted to water bodies through surface runoff and farmland drainage, etc. Therefore, based on the characteristics of agricultural production activities, the identified pollution-producing units were pollution discharges from farmland fertilizers, livestock and poultry breeding and farmland solid waste. According to the Class III standard on surface water environmental quality standard (GB3838-2002), the individual pollutant indicators were converted into equivalent emissions. The formula is: Pollutant equivalent emissions = pollutant emissions/pollutant discharge evaluation standard.

2.2. SBM-DEA Model

DEA has become a mainstream technique for efficiency evaluation, since it has many advantages, such as not assuming functional relationships, non-subjective weights and the ability to analyze decision unit invalid factors [2]. The DEA method is usually used to evaluate the efficiency of production containing non-desired outputs. Although the traditional directional distance function can better solve the problem of evaluating the efficiency of production containing non-desired outputs, it cannot eliminate the non-efficiency components caused by the input–output slack. To solve the problem of relaxation of variables and the measurement error caused by radial direction, Tone (2001) [42] proposed a non-radial, non-oriented SBM data envelopment analysis model based on relaxation variables, but that model still cannot distinguish and rank multiple equally valid cells. Therefore, Tone (2002) [43] proposed a super-efficient SBM model to solve that problem. Since SBM-DEA takes the input–output slack variables into account, making the efficiency evaluation results more accurate and solving the problem of further comparing and ranking many effective units, it has thus been widely used by scholars [23–28]. In this paper, we applied the method of Tone (2002) [43] to measure the AGTFP of China from the perspective of carbon sink.

We supposed there existed M decision-making units (DMUs). $P(x)$ represents the set of production possibilities; x represents the production input; y represents the economic output; and b represents the undesired output—all of which can be freely disposed of for input factor x and economic output y. Therefore, if $(y, b) \in P(x)$ and $y' \leq y, x' \geq x$, then $(y', b) \in P(x)$ or $P(x') \in P(x)$. Similarly, when the environmental output also satisfies free disposability, the environmental output indicator will also satisfy the above axioms. When agriculture does not have to pay the corresponding economic cost for the environmental pollution generated during the production process, the production possibility set will take the following form.

$$P(x) = \begin{cases} (x, y, b) : \sum_{m=1}^{M} z_m x_m \leq x; \sum_{m=1}^{M} z_m y_m \geq y; \\ \sum_{m=1}^{M} z_m b_m \leq b, z_m \geq 0, m = 1, .., M \end{cases} \tag{4}$$

When the environmental output is weakly disposable, the environmental output b will satisfy the following axiom: if $(y, b) \in P(x)$ and $0 < \theta < 1$, then $(\theta y, \theta b) \in P(x)$. This axiom states that each unit of emission reduction will cause an equally proportional reduction in economic output. That is, it is the economic cost of the agricultural production process due to emissions, just as the non-point source pollution emission rights and carbon emission rights gradually established in China are the economic costs due to emissions. In this case, the production may take the form of:

$$P(x) = \begin{cases} (x, y, b) : \sum_{m=1}^{M} z_m x_m \leq x; \sum_{m=1}^{M} z_m y_m \leq y; \\ \sum_{m=1}^{M} z_m b_m = b, z_m \geq 0, m = 1, .., M \end{cases} \tag{5}$$

The specific expression of the super-efficiency model constructed by Tone (2002) [43] is as follows.

$$\rho = min \frac{\frac{1}{m} \sum_{i=1}^{M} \frac{\overline{x}}{x_{ik}}}{\frac{1}{s_1 + s_2} \left(\sum_{i=1}^{s_1} \frac{\overline{y_l^d}}{y_{l_0}^d} + \sum_{k=1}^{s_2} \frac{\overline{y_k^d}}{y_{k_0}^d} \right)}$$
$$s.t. \begin{cases} \overline{x} \geq \sum_{j=1, j \neq j_0}^{n} x_{ij} \lambda_j; \overline{y^d} \leq \sum_{j=1, j \neq j_0}^{n} y_{lj}^d \lambda_j; \overline{y^u} \leq \sum_{j=1, j \neq j_0}^{n} y_{kj}^d \lambda_j \\ \overline{y^d} \leq y_{lj}^d; \overline{y^u} \leq y_{kj}^d \\ \lambda_j \geq 0, i = 1, \ldots, m; j = 1, \ldots, n; l = 1, \ldots, s_1; k = 1, \ldots, s_2 \end{cases} \tag{6}$$

where n denotes the number of decision units, which is the number of provinces in this study. Each DMU consists of input m, desired output s_1 and non-desired output s_2. x denotes the elements in the input matrix; y^d denotes the elements in the desired output matrix; y^u denotes the data in the non-desired output matrix; and ρ denotes the efficiency value of the DMU.

The green production efficiency values measured by the SBM model are static, and the Malmquist model complements the SBM model well by analyzing dynamically the changes in efficiency values between the two preceding and following years. Therefore, the global reference Malmquist model (GML model), which uses the sum of the periods as a possible reference set, is used to calculate the production efficiency values.

$$s^g = s^1 \cup s^2 \cup \ldots \cup s^p = \left\{ \left(x_j^1, y_j^1 \right) \cup \left(x_j^2, y_j^2 \right) \cup \ldots \cup \left(x_j^p, y_j^p \right) \right\} \tag{7}$$

The index formula for GML is as follows:

$$M_g \left(x^{t+1}, y^{t+1}, x^t, y^t \right) = \frac{E^g \left(x^{t+1}, y^{t+1} \right)}{E^g \left(x^t, y^t \right)} \tag{8}$$

The same global frontier is referenced in the calculation of the Malmquist index for the two adjacent periods, but the calculation of the efficiency change still uses the respective frontier, so that the efficiency change (EC) is expressed as

$$EC = \frac{E^{t+1} \left(x^{t+1}, y^{t+1} \right)}{E^t \left(x^t, y^t \right)} \tag{9}$$

where the degree to which frontier t + 1 is close to the global frontier is represented by $\frac{E^g\left(x^{t+1},y^{t+1}\right)}{E^{t+1}\left(x^{t+1},y^{t+1}\right)}$, and a larger ratio indicates that frontier t + 1 is closer to the global frontier, and the degree to which frontier t is close to the global frontier is represented by $\frac{E^g\left(x^t,y^t\right)}{E^t\left(x^t,y^t\right)}$, with a larger ratio indicating that the frontier t is closer to the global frontier. The variation of efficiency can be obtained by dividing the above two values.

$$TC_g = \frac{E^g\left(x^{t+1}, y^{t+1}\right)/E^{t+1}\left(x^{t+1}, y^{t+1}\right)}{E^g\left(x^t, y^t\right)/E^t\left(x^t, y^t\right)} = \frac{E^g\left(x^{t+1}, y^{t+1}\right)}{E^{t+1}\left(x^{t+1}, y^{t+1}\right)} \times \frac{E^t\left(x^t, y^t\right)}{E^g\left(x^t, y^t\right)} \tag{10}$$

Thus, the Malmquist index can be decomposed into efficiency changes and technological changes.

$$M_g\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = \frac{E^g\left(x^{t+1}, y^{t+1}\right)}{E^g\left(x^t, y^t\right)} = \frac{E^{t+1}\left(x^{t+1}, y^{t+1}\right)}{E^t\left(x^t, y^t\right)}\left(\frac{E^g\left(x^{t+1}, y^{t+1}\right)}{E^{t+1}\left(x^{t+1}, y^{t+1}\right)} \times \frac{E^t\left(x^t, y^t\right)}{E^g\left(x^t, y^t\right)}\right) = EC \times TC \tag{11}$$

If ML > 1, it means that AGTFP is increasing; conversely, if ML < 1, it means that AGTFP is decreasing. EC > 1 indicates that the DMU moved to the best practice frontier; TC measures the movement of the best practice frontier caused by technological progress.

2.3. Spatial Effect Model

2.3.1. Method of Spatial Autocorrelation

The study of spatial autocorrelation is a crucial concept to reveal the distribution of spatial data, and the calculation of the degree of correlation in spatial autocorrelation is the primary method to study spatial autocorrelation [34]. The autocorrelation test of AGTFP is the first step in constructing the spatial econometric model. We applied RSDA to test the spatial correlation and selected the global spatial correlation as well as the local spatial correlation in ESDA analysis tool to test the spatial correlation of AGTFP.

The global spatial correlation can be used to analyze the spatial agglomeration state of AGTFP, and the Greary'C coefficient and Moran'I index are used in most cases. Since the global Moran'I index can more closely reflect the degree of similarity between neighboring regions, we chose the global Moran'I index to test the spatial correlation of AGTFP. The formula for constructing the global Moran'I index is as follows.

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{N} w_{ij}\left(y_i - \overline{y}\right)\left(y_j - \overline{y}\right)}{S_0\sum_{i=1}^{N}\left(y_i - \overline{y}\right)^2} \tag{12}$$

where y_i and y_j represent the AGTFP of the *i*-th and *j*-th provinces, respectively; n = 1, 2,..., 30 represents the number of provinces that we studied; $\overline{y}$ represents the mean value of AGTFP of the 30 provinces; w_{ij} is the spatial adjacency weight matrix; $S_0 = \sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}$ represents the spatial weight aggregation; and the Moran'I ∈ [−1,1]. The larger the value of Moran'I index, the higher the degree of spatial correlation between regions. If the Moran'I index is significantly greater than 0, it means that there is a positive spatial correlation between regions, which is expressed as "high-high" or "low-low" spatial clustering. If the Moran'I index is significantly less than 0, it means that there is a negative spatial correlation between regions, which is expressed as "high-low" or "low-high" spatial clustering. If the Moran'I index is 0, it means that there is no spatial correlation between regions, and the AGTFP of each province is independently distributed. After the Moran'I index is obtained, its significance needs to be tested. In this section, we will use the Z statistic test, which is calculated by the following formula.

$$Z(I) = \frac{I - R(I)}{\sqrt{VAR(I)}} \tag{13}$$

where $R(I) = \frac{-1}{n-1}$, $VAR(I) = \left[\frac{1}{w_0^2(n^2-1)}\left(n^2 w_1 + n w_2 + 3w_0^2\right)\right] - R^2(I)$, $w_0 = \sum_{i=1}^{N}\sum_{j-1}^{N} w_{ij}$, $w_1 = \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\left(w_{ij} + w_{ji}\right)^2$, $w_2 = \sum_{i=1}^{N}\left(w_{i\cdot} + w_{\cdot j}\right)^2$. $w_{i\cdot}$ and $w_{\cdot j}$ are the sum of the *i*-th row and *j*-th column in the spatial weight matrix. If the value of Z(*I*) is greater than zero, it means that there is a spatially positive correlation of AGTFP between provinces; if the value of Z(I) is less than zero, it means that there is a spatially negative correlation of AGTFP between provinces; if the value of Z(I) is equal to zero, it means that there is a spatially independent distribution of AGTFP between provinces.

2.3.2. Method of Spatial Convergence Analysis

Since the convergence analysis can visualize the performance of an algorithm and evaluate an algorithm scientifically from a theoretical point of view, convergence analysis is widely applied by scholars [44]. The methods for studying spatial convergence are absolute α convergence, absolute β convergence and conditional β convergence. Absolute α convergence refers to the fact that the gap between different regions will gradually decrease and eventually converge with time. Absolute β convergence assumes that the marginal factor rewards are decreasing. Under this premise, the regions will eventually reach the same steady-state level as time elapses. Conditional β convergence indicates that the resource endowment conditions of different regions are different and closely related to economic growth, making it difficult to achieve a consistent steady-state level among regions. Previous econometric models have led to biased convergence conclusions due to often ignoring the correlation with geographic location [45]. Therefore, we incorporated spatial factors into previous econometric models to examine the regional convergence differences of AGTFP in China from a spatial perspective.

(1) Absolute α convergence analysis

When absolute α convergence is tested for the dispersion of AGTFP in China, if α shows a decreasing trend, there is a convergence trend among provinces. Different tests have different sensitivities to the data, so the α coefficient and the coefficient of variation will be used to jointly test the convergence characteristics of AGTFP among provinces to ensure the robustness of the test results. The equations of each test method are as follows.

$$\alpha = \sqrt{\frac{\sum_{i=1}^{N}\left(lny_{it} - \overline{lny_t}\right)^2}{n}} \tag{14}$$

$$CV = \frac{S}{\overline{y_t}} \tag{15}$$

where y_{it} is the AGTFP of the *i*-th province in *t*-th year, and $\overline{y_t}$ is the mean value of the AGTFP of the provinces in *t*-th year.

(2) Absolute β convergence analysis

Absolute β convergence can test whether provinces that started with lower AGTFP can catch up with provinces that started with higher AGTFP through higher growth rates. Based on the method of Barro et al. (1995) [45], we used an absolute β convergence model. for the test, and the model equation is as follows.

$$\frac{ln(y_{it}/y_{i0})}{T} = \alpha + \beta y_{i0} + \mu_{it} \tag{16}$$

where y_{it} and y_{i0} are the AGTFP of the *i*-th province in *t*-th year. T represents the average annual growth rate of AGTFP of province *i* from 2000 to 2019; α and β are parameters to be estimated; μ_{it} is the random error term. If the parameter β is significantly negative, it means that the AGTFP among Chinese provinces has an absolute β-convergence trend.

(3) Conditional β convergence analysis

Conditional β convergence refers to the fact that the steady-state level of AGTFP in each province is associated with some resource endowment conditions. It is difficult to reach the same steady-state level in all provinces. In order to consider the influence of external environment on the steady-state level of AGTFP in each province, we added control variables to the model when conducting the conditional β convergence test. If the estimation result of β remains significantly negative, it indicates the existence of conditional β convergence among provinces. Based on previous studies, we selected the level of economic development (GDP), agricultural industrial restructuring (AIR), agricultural infrastructure (AID), energy consumption (EC), effective irrigation rate (EI) and disaster incidence rate (DOR) as the control variables for each province. GDP was expressed as gross output per capita. AIR was expressed as the ratio of total plantation output to total agricultural output. AID was expressed as the ratio of road mileage to provincial and district administrative area. EC was expressed as rural electricity consumption. EI was expressed as the ratio of irrigated area to total sown area of crops. DOR was expressed as the ratio of disaster area to total sown area of crops. The conditional β convergence test model for AGTFP in China is as follows.

$$d(lny_{it}) = lny_{it} - lny_{i(t-1)} = \alpha + \beta lny_{i(t-1)} + \gamma x_{it} + \mu_{it} \tag{17}$$

where lny_{it} represents the AGTFP of the i-th province in t-th year. x_{it} is the control variable mentioned above. α, β and γ are the parameters to be estimated. Additionally, μ_{it} is the random error term.

(4) Spatial Econometric Model

Traditional econometric models largely ignore the geographical correlation between regions, thus yielding biased spatial convergence results [45]. The inclusion of spatial factors can not only avoid the endogeneity of spatial spillover effects but also study the direction of spatial spillover effects. Therefore, spatial econometric models are mostly used by scholars to study spatial characteristics [41,46]. Currently, scholars often apply SEM, SDM and SLM [47,48] to introduce geographic features to construct models, and the spatial lag model (SAR) and spatial error model (SEM) can reflect the correlation between different regions. Based on the studies of scholars such as Yu et al. (2012) [46] and Elhorst (2012) [41], we combined spatial factors to construct a convergence model and consider a spatial perspective to study the convergence of regional differences in AGTFP. The y_t with one period lag is set as the explanatory variable in the β convergence model to construct the dynamic space (SDM) conditional β convergence model, dynamic space (SAR) conditional β convergence model and dynamic space (SEM) conditional β convergence model of AGTFP in each province of China. The specific models are as follows.

$$\begin{gathered} ln\frac{y_{it}}{y_{it-p}} = \alpha + \beta lny_{it-p} + \rho wln\frac{y_{it}}{y_{it-p}} + \gamma x_{it} + \varepsilon_{it}, \\ \varepsilon_{it} = \lambda w\varepsilon_{it} + \mu_{it}, \mu_{it} \sim N\left(0, \sigma^2\right) \end{gathered} \tag{18}$$

SAR conditional β convergence model

$$ln\frac{y_{it}}{y_{it-p}} = \alpha + \beta lny_{it-p} + \rho wln\frac{y_{it}}{y_{it-p}} + \gamma x_{it} + \varepsilon_{it}, \varepsilon_{it} \sim N\left(0, \sigma^2\right) \tag{19}$$

SEM conditional β convergence model

$$ln\frac{y_{it}}{y_{it-p}} = \alpha + \beta lny_{it-p} + \gamma x_{it} + \varepsilon_{it}, \varepsilon_{it} = \lambda w\varepsilon_{it} + \mu_{it}, \mu_{it} \sim N\left(0, \sigma^2\right) \tag{20}$$

where y_{it} and y_{it-p} are the values of AGTFP for each Chinese province in t-th year and $(t-p)$-th year; w is the spatial weight matrix; α, β and γ are the parameters to be estimated; λ and ρ represent the spatial correlation coefficients, which are a reflection of the relationship between AGTFP interactions among provinces; ε_{it} and μ_{it} are both random error terms obeying independent identical distribution; x_{it} represents the control variables. If β is significantly negative, it indicates that the AGTFP in each province showed dynamic spatial convergence. We selected the number of lags as one period.

2.4. Variable Selection and Data Source

Based on the production characteristics of agriculture, the paper selected the input–output data of 30 provinces (excluding Tibet) in mainland China from 2000 to 2019 to calculate the AGTFP. The input indicators included land, labor, machinery and fertilizer. The output indicators included the desired output and non-desired output, and non-desired output included agricultural non-point pollution (NP) and agricultural net carbon emissions (NCE). According to the class III surface water environmental quality standard (GB3838-2002), the calculation of agricultural non-point source pollution was converted to the three types of agricultural non-point source pollution emissions in agricultural pollution loads. In addition, when calculating the net agricultural carbon emissions, greenhouse gases, such as CO_2, N_2O and CH_4, emitted into the atmosphere during the production process were uniformly converted into standard carbon (C) equivalents, thus unifying the measurement units and subtracting them from agricultural carbon sequestration to obtain the net agricultural carbon emissions. Additionally, when calculating the spatial econometric model, we selected the level of economic development (GDP), agricultural industrial restructuring (AIR), agricultural infrastructure (AID), energy consumption (EC), effective irrigation rate (EI), disaster occurrence rate (DOR), financial support for agriculture (FS) and major grain producing areas (MGP) of each province as the control variables. The specific index selection and data sources are shown in Table 1.

Table 1. AGTFP assessment indicators and data sources.

	Assessment Indicators	Indicators' Explanation	Unit	Source	Reference
Input	Land	the total sown area of crops	10^4 hectares	"China Agricultural Statistics" and "China Rural Statistical Yearbook"	Gong (2020) [17] Chen et al. (2021) [19]
	Labor	employees in the primary industry	10^4 People	"China Statistical Yearbook"	Gong (2020) [17] Chen et al. (2021) [19]
	Machinery	the total power of agricultural machinery	10^4 Tons	"China Agricultural Statistics" and "China Rural Statistical Yearbook"	Gong (2020) [17] Chen et al. (2021) [19]
	Fertilizer	the amount of chemical fertilizer actually used in agricultural production calculated by the pure method	10^4 kilowatts	"China Agricultural Statistics" and "China Rural Statistical Yearbook"	Gong (2020) [17] Chen et al. (2021) [19]
Output	GVAO (Expected output)	the total output value of agriculture, forestry, animal husbandry and fishery at constant prices in 2000	10^8 CNY	"China Agricultural Statis-tics" and "China Rural Statistical Yearbook"	Gong (2020) [17] Chen et al. (2021) [19]
	NP (Non-expected output)	the pollution of chemical oxygen demand, total nitrogen and total phosphorus caused by pollutants entering the water body through surface runoff and farmland drainage	10^4 Tons	Calculated results	Yu et al. (2022) [11] Shen et al. (2018) [20]
	NCE (Non-expected output)	the value that uses agricultural carbon emissions minus agricultural carbon sinks	10^4 Tons	Calculated results	Yu et al. (2022) [11]

Table 1. *Cont.*

	Assessment Indicators	Indicators' Explanation	Unit	Source	Reference
control variables	GDP	GDP per capita	10^4 CNY	China Statistical Yearbook	Liu et al. (2021) [5]
	AIR	the total output value of planting industry/total agricultural output value	-	"China Agricultural Statistics" and "China Rural Statistical Yearbook"	Yu et al. (2022) [11] Liu et al. (2021) [5]
	AID	number of road miles/administrative area	-	China Regional Economic Statistics Yearbook	Wang et al. (2021) [22]
	EC	rural electricity consumption	10^8 kW/h	China Agricultural Statistics	Reza et al. (2016) [49]
	EI	the effective irrigated area/total sown area of crops	-	"China Agricultural Statistics" and "China Rural Statistical Yearbook"	Kumar et al. (2008) [50]
	DOR	agricultural disaster area/total sown area of crops	-	"China Agricultural Statistics" and "China Rural Statistical Yearbook"	Nwaiwu et al. (2015) [51]
	FS	local financial expenditure on agriculture, forestry and water affairs	10^8 CNY	National Bureau of Statistics	Gong (2020) [17]
	MGP	MGP is a dummy variable, if a province belongs to the major grain producing area, MGP = 1, otherwise MGP = 0	-	Ministry of Agriculture and Rural Affairs of the People's Republic of China	Li et al. (2022) [28]

Note: GVAO represents gross value of agriculture, NP represents agricultural non-point pollution, NCP represents agricultural net carbon emissions, GDP represents GDP per capita, AIR represents agricultural industrial restructuring, AID represents agricultural infrastructure, EC represents energy consumption, EI represents effective irrigation rate, DOR represents disaster occurrence rate, FS represents financial support for agriculture, and MGP represents major grain producing areas.

3. Results and Analysis

3.1. Calculation Results of Agricultural Net Carbon Emissions

Based on the measurement methods introduced in Section 2.1, we calculated the agricultural carbon source emissions, carbon sinks and net carbon emissions for each province in China. The following Table 2 lists the mean values of carbon emissions, carbon sinks and net carbon emissions for 2000–2019. Beijing had the smallest agricultural carbon emission, with a mean value of 92.563×10^4 tons. Henan had the largest agricultural carbon emission, with a mean value of 2414.393×10^4 tons. Guangdong had the largest agricultural carbon sink, with a mean value of 1034.076×10^4 tons. Henan had the highest mean value of agricultural net carbon emissions, while Beijing had the lowest. Agricultural land use carbon emissions were highest in Henan, Shandong and Hebei. Rice fields carbon emissions were highest in Jiangxi, Jiangsu and Hunan. Shandong, Henan and Chongqing had the highest livestock and poultry farming carbon emissions. The highest carbon sinks by crop production systems and soil organic carbon occurred in Guangdong, Guangxi and Shanxi.

Table 2. Total agricultural net carbon emissions in China's provinces in 2000–2019. Unit: 10,000 t.

Area	CE_{LU}	CE_{RF}	CE_{LP}	INE	TCE	CS_{TA}	CS_{SR}	CS_{MA}	CS_{NT}	TCS	NCE
Beijing	29.737	0.150	56.694	5.983	92.563	62.515	3.599	0.006	4.723×10^{-5}	66.120	28.168
Tianjin	49.472	1.539	64.482	22.896	138.389	32.452	1.872	0.005	1.821×10^{-5}	34.329	104.060
Hebei	829.965	9.111	738.539	43.523	1621.138	898.696	51.783	0.061	2.701×10^{-5}	950.540	670.598
Shanxi	263.153	0.084	190.409	28.587	482.233	291.346	16.791	0.014	5.127×10^{-6}	308.150	174.083
Inner Mongolia	447.113	5.962	750.333	29.127	1232.535	58.209	3.382	0.046	1.271×10^{-5}	61.636	1170.898
Liaoning	368.994	34.822	484.129	44.610	932.554	327.118	18.826	0.046	3.960×10^{-6}	345.990	586.564
Jilin	407.043	26.695	405.600	35.111	874.449	59.334	3.449	0.031	6.423×10^{-6}	62.814	811.634
Heilongjiang	688.669	159.465	462.716	16.086	1326.936	34.033	2.079	0.029	3.008×10^{-6}	36.141	1290.794
Shanghai	45.449	43.035	35.679	5.859	130.021	17.327	1.000	0.004	1.545×10^{-6}	18.330	111.691
Jiangsu	686.999	794.893	375.799	32.792	1890.483	195.794	11.862	0.043	8.459×10^{-6}	207.700	1682.784
Zhejiang	332.842	291.746	165.505	26.156	816.249	377.078	24.871	0.018	2.616×10^{-7}	401.967	414.282
Anhui	691.652	696.298	444.793	34.173	1866.916	179.744	12.967	0.045	7.065×10^{-6}	192.756	1674.160
Fujian	280.960	215.281	218.843	29.939	745.022	563.643	35.886	0.024	3.186×10^{-9}	599.553	145.469
Jiangxi	368.187	834.582	378.977	50.660	1632.405	359.088	21.829	0.035	5.401×10^{-7}	380.952	1251.453
Shandong	1095.156	18.440	1054.839	92.867	2261.302	621.067	36.179	0.100	2.606×10^{-5}	657.347	1603.955
Henan	1177.588	69.285	1096.862	70.658	2414.393	433.098	26.304	0.088	1.539×10^{-5}	459.490	1954.902
Hubei	643.983	726.931	459.902	55.751	1886.568	421.412	28.265	0.045	7.556×10^{-7}	449.722	1436.845
Hunan	573.306	915.444	665.073	62.096	2215.920	497.848	30.605	0.061	2.155×10^{-7}	528.514	1687.405
Guangdong	463.018	463.049	496.962	58.187	1481.216	976.971	57.046	0.058	1.100×10^{-8}	1034.076	447.140
Guangxi	475.255	459.621	510.989	36.565	1482.430	937.841	54.912	0.050	1.725×10^{-6}	992.803	496.453
Hainan	97.717	68.554	97.052	11.756	275.080	155.198	8.960	0.009	4.078×10^{-8}	164.167	110.913
Sichuan	224.263	121.680	238.992	55.059	639.993	230.944	13.879	0.022	1.147×10^{-8}	244.846	395.147
Chongqing	622.403	350.763	1081.456	86.247	2140.868	623.061	39.998	0.088	2.333×10^{-7}	663.147	1477.722
Guizhou	265.837	105.476	384.729	45.753	801.795	316.310	22.073	0.026	4.982×10^{-8}	338.410	488.322
Yunnan	466.099	48.739	651.605	51.209	1217.651	505.417	35.133	0.046	4.325×10^{-8}	540.596	677.054
Shanxi	14.300	10.571	272.830	26.585	662.767	953.935	56.480	0.016	1.201×10^{-5}	101.043	561.724
Gansu	363.115	0.237	222.148	26.094	554.953	347.576	20.155	0.022	1.779×10^{-6}	36.775	518.178
Qinghai	306.711	0.000	359.654	14.022	414.105	5.399	0.311	0.014	3.715×10^{-6}	5.724	408.381
Ningxia	36.622	3.808	306.409	17.780	422.686	80.036	4.608	0.005	2.265×10^{-6}	84.649	338.037
Xinjiang	93.364	5.134	98.497	1.756	527.076	657.896	37.864	0.031	1.765×10^{-6}	69.579	457.497

Note: CE_{LU} represents the agricultural land use carbon emissions; CE_{RF} represents the rice fields carbon emissions; CE_{LP} represents the livestock and poultry farming carbon emissions; INE represents the indirect N_2O emissions; TCE represents the total carbon emissions; CS_{TA} represents the carbon sinks by crop production systems, including carbon absorption by trees; CS_{SR} represents the soil organic carbon increases due to straw, litter, pruning and root residue return; CS_{MA} represents carbon sink by manure application; CS_{NT} represents the carbon sink by no-tillage management; TCS represents the total carbon sinks; NCE represents the net carbon emission.

3.2. Empirical Results and Analysis of China's AGTFP

Based on MAXDEA software, we separated technical progress and technical efficiency to obtain the average annual growth rates for the MI index, EC index and TC index in each province from the carbon sink perspective (Table 3). Except for Heilongjiang and Ningxia, whose AGTFP was decreasing, the AGTFPs of all the other 28 provinces were increasing. Among them, Beijing, Tianjin and Chongqing had an average annual growth rate of MI over 1. Beijing had the highest AGTFP growth rate of 2.068%, and Heilongjiang had the lowest AGTFP growth rate of −0.094%. The EC growth rates in Shanxi, Inner Mongolia, Jilin, Heilongjiang, Jiangsu, Zhejiang, Fujian, Shandong, Guangxi, Guizhou, Ningxia and Xinjiang were negative, while Fujian had the lowest EC growth rate of −0.162%. The remaining provinces had a positive average annual growth rate of EC. The average annual growth rate of EC in Beijing and Shanghai exceeded 1. Beijing had the highest TC growth rates. The average annual growth rate of TC in Beijing was 3.030%. The negative average annual growth rate of TC in Tianjin, Shanghai and Qinghai indicated that the technological progress showed a decreasing trend.

Table 3. Average annual growth rates of MI, EC and TC from 2000 to 2019 from the carbon sink perspective (%).

Province	MI	EC	TC	Province	MI	EC	TC
Beijing	2.068	3.517	3.030	Henan	0.183	0.010	0.173
Tianjin	0.613	0.341	−0.271	Hubei	0.147	0.129	0.276
Hebei	0.045	0.538	0.586	Hunan	0.347	0.102	0.245
Shanxi	0.201	−0.119	0.082	Guangdong	1.066	0.125	0.941
Inner Mongolia	0.183	−0.046	0.229	Guangxi	0.188	−0.195	0.384
Liaoning	0.168	0.003	0.171	Hainan	0.397	0.866	0.466
Jilin	0.368	−0.110	0.258	Sichuan	0.380	0.068	0.311
Heilongjiang	−0.094	−0.143	0.049	Chongqing	1.844	0.977	0.858
Shanghai	0.006	5.363	−0.085	Guizhou	0.157	−0.273	0.431
Jiangsu	0.500	−0.045	0.545	Yunnan	0.366	0.215	0.150
Zhejiang	0.639	−0.060	0.699	Shanxi	0.214	0.102	0.316
Anhui	0.127	0.043	0.170	Gansu	0.456	0.109	0.347
Fujian	0.723	−0.162	0.561	Qinghai	0.578	0.683	−0.104
Jiangxi	0.275	0.046	0.229	Ningxia	−0.035	−0.233	0.269
Shandong	0.390	−0.060	0.450	Xinjiang	0.149	−0.027	0.176

Note: MI represents total factor productivity, EC represents efficiency changes, TC represents technological progress.

3.3. Spatial Effect Analysis

On the basis of measuring China's AGTFP, we further analyzed its distribution pattern, the spatial effects, the power source, spatial and temporal divergence and convergence of China's AGTFP growth. We explained the spatial and temporal convergence of China's AGTFP in a panoramic manner from the perspective of spatial and temporal dynamics.

3.3.1. Empirical Results and Analysis of Spatial Autocorrelation

According to the calculation methods of spatial autocorrelation, we conducted a test on the mean value of China's AGTFP, and the test results are shown in Table 4. Table 4 shows the results of the global autocorrelation test of AGTFP in China, where the Moran'I index of AGTFP was greater than 0 and passed the 1% significance level test in 2000 and 2018, while it passed the 10% significance level test in 2007, 2010, 2016, and in the remaining years, it passed the 5% significance level test. Overall, there was a significantly positive spatial correlation between the AGTFP of each province in China. In addition, a larger Moran'I value indicates a stronger spatial correlation; a maximum value of 0.243 in 2016 indicates the strongest spatial correlation. The Moran'I index had fluctuated during 2000–2019, but the overall trend was upward, rising from 0.103 in 2000 to 0.153 in 2019. This indicates that there was a presence of agricultural green technology diffusion and technology exchange among neighboring provinces, with an overall increasing trend of diffusion and exchange, as indicated by the spatial spillover effects. Resource endowment and natural location conditions were inextricably linked to agricultural green production, and the convergence of agricultural green technology conditions was higher in neighboring or closer provinces. With the diffusion and exchange of knowledge and green technology, the AGTFP in neighboring or closer provinces was spatially correlated.

Table 4. Global correlation test results of AGTFP in China.

Year	AGTFP		
	Moran'I	**Z Value**	***p* Value**
2000	0.103	0.305	0.000 ***
2001	0.024	0.576	0.038 **
2002	0.126	0.888	0.028 **
2003	0.215	2.223	0.018 **
2004	0.057	0.828	0.013 **
2005	0.123	0.809	0.020 **
2006	0.064	0.879	0.021 **
2007	0.114	1.358	0.019 **
2008	0.182	2.287	0.087 *
2009	0.118	1.382	0.011 **
2010	0.143	0.967	0.084 *
2011	0.094	1.139	0.016 **
2012	0.085	0.383	0.012 **
2013	0.033	0.020	0.035 **
2014	0.216	2.042	0.049 **
2015	0.091	1.208	0.021 **
2016	0.234	1.842	0.083 *
2017	0.181	2.453	0.033 **
2018	0.150	0.154	0.001 ***
2019	0.153	0.305	0.044 **

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.3.2. Empirical Results and Analysis of Spatial Convergence

Based on previous studies [31,52], we used convergence methods such as absolute α convergence, absolute β convergence and conditional β convergence to analyze the convergence of AGTFP in China.

(1) Empirical Results and Analysis of Absolute α Convergence

According to the calculation methods of the α coefficient and coefficient of variation, we performed a test on the mean value of China's AGTFP, and the test results are shown in Figure 1. Figure 1 shows that the test results of each method had different values, but the trend was relatively smooth and had a small upward trend, which indicated that China's AGTFP will not have an absolute alpha convergence trend in a certain period of time. The reason for such a situation may be that the paper involved green technologies, such as environmental pollution and resource saving. However, the current lack of motivation to promote related technologies makes it difficult for Chinese agricultural green technologies to diffuse. Additionally, the provinces with higher AGTFP in the initial year maintained higher efficiency levels, while the provinces with lower AGTFP in the initial year had difficulty in imitating and learning quickly. This made it difficult for absolute α convergence trends to occur within a certain period of time.

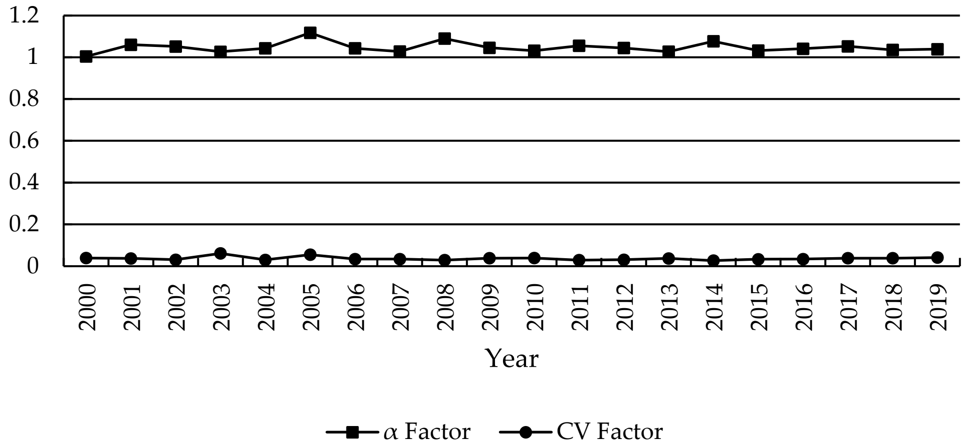

Figure 1. Trend of α convergence of AGTFP in China. Note: CV represents coefficient of variation.

(2) Empirical Results and Analysis of Absolute β Convergence

Based on the calculation methods of absolute β convergence, we performed a test on the mean value of China's AGTFP, and the test results are shown in Table 5. Table 5 shows that the results for absolute β convergence of AGTFP and the β coefficients of the eastern, central, western regions and the national average were significantly negative at the 1% level. This indicates that the AGTFP of the national region, the eastern region, the central region, the western region were characterized by absolute β convergence. In addition, the β coefficients were significantly positive at the 1% level for all three time periods within the period 2000–2019, except for 2000–2004, where all β coefficients were significantly negative at the 1% level, indicating that China's AGTFP was characterized by non-absolute β convergence.

Table 5. Absolute β convergence results for AGTFP.

Factor		Sub-Region			Sub-Time			
	Nationwide	East	Central	West	2000–2004	2005–2009	2010–2014	2014–2019
β	−0.941 *** (0.043)	−0.904 *** (0.069)	−0.989 *** (0.084)	−0.911 *** (0.075)	−1.313 *** (0.097)	1.100 *** (0.124)	1.126 *** (0.098)	1.171 *** (0.083)
α	0.958 *** (0.044)	0.922 *** (0.071)	1.008 *** (0.083)	0.927 *** (0.077)	1.331 *** (0.099)	1.127 *** (0.127)	1.142 *** (0.099)	1.093 *** (0.085)
R^2	0.471	0.487	0.478	0.450	0.646	0.469	0.467	0.576

Note: Robust standard errors in parentheses *** $p < 0.01$.

(3) Empirical Results and Analysis of Conditional β Convergence Analysis

Based on the calculation methods of conditional β convergence, we performed a test on the mean value of China's AGTFP, and the test results are shown in Table 6. Table 6 shows the results of the conditional β convergence of AGTFP in China. First, from the time perspective, the β coefficients of the national, eastern, central and western regions were significantly negative, and the national, eastern and western regions all pass the test at the 1% significance level. This indicates that the AGTFP of each region in China had a conditional β convergence posture. Second, from the time perspective, the β coefficients of China's AGTFP are significantly negative for the period 2000–2019, and all four periods in Table 5 pass the 1% significance level test. This indicates that the AGTFP of China had a conditional beta convergence posture. Overall, the AGTFP of China in the national, eastern, central and western regions had significant conditional β convergence characteristics. Because of the differences in resource endowment of different provinces, the AGTFP in different provinces converges to its own steady-state level at different rates.

Table 6. Conditional β convergence results for AGTFP.

Factor	Nationwide	Sub-Region East	Central	West	Sub-Time 2000–2004	2005–2009	2010–2014	2014–2019
β	−0.911 ***	−0.887 ***	−0.961 ***	−0.905 **	−1.093 ***	−0.882 ***	−0.891 ***	−0.984 ***
	(0.042)	(0.068)	(0.081)	(0.076)	(0.091)	(0.108)	(0.086)	(0.072)
α	0.930 ***	0.895 ***	0.917 ***	0.916 ***	1.028 ***	0.956 ***	0.896 ***	1.081 ***
	(0.044)	(0.078)	(0.107)	(0.089)	(0.099)	(0.130)	(0.088)	(0.087)
GDP	0.001 ***	0.002 ***	0.003 ***	0.004 ***	0.007 ***	0.005 ***	0.001 ***	0.001 ***
	(0.001)	(0.002)	(0.006)	(0.004)	(0.007)	(0.006)	(0.002)	(0.00)
AIR	0.001	0.007	0.100	−0.009	0.068	−0.029	0.013	−0.053
	(0.032)	(0.066)	(0.118)	(0.68)	(0.078)	(0.101)	(0.049)	(0.055)
AID	0.002	0.001	0.032	−0.001	0.005	−0.003	−0.004 **	0.003 *
	(0.001)	(0.002)	(0.022)	(0.002)	(0.004)	(0.006)	(0.001)	(0.02)
EC	−0.001	−0.001	−0.022	0.003	0.00	0.004	−0.002	0.001
	(0.001)	(0.001)	(0.015)	(0.014)	(0.004)	(0.003)	(0.001)	(0.001)
EI	−0.005	0.002	0.042	−0.007	0.009	0.006	0.008	−0.022 **
	(0.007)	(0.038)	(0.101)	(0.012)	(0.018)	(0.026)	(0.011)	(0.01)
DOR	0.001	0.051	−0.049	−0.012	0.035	−0.017	0.002	0.018 *
	(0.0019)	(0.031)	(0.044)	(0.036)	(0.045)	(0.049)	(0.034)	(0.034)
FS	−0.001	−0.00	−0.003	−0.004	00.046	−0.024	0.001	−0.006 ***
	(0.001)	(0.002)	(0.005)	(0.003)	(0.044)	(0.015)	(0.003)	(0.002)
MGP	−0.004	−0.015	−0.011	0.014	−0.001	−0.009	0.010	−0.013
	(0.005)	(0.011)	(0.023)	(0.014)	(0.012)	(0.016)	(0.008)	(0.009)
R^2	0.474	0.503	0.492	0.460	0.661	0.469	0.510	0.634

Note: Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. GDP represents GDP per capita, AIR represents agricultural industrial restructuring, AID represents agricultural infrastructure, EC represents energy consumption, EI represents effective irrigation rate, DOR represents disaster occurrence rate, FS represents financial support for agriculture, and MGP represents major grain producing areas.

3.3.3. Empirical Results and Analysis of SDM Model

Before the spatial analysis, we proceeded with some preliminary statistical tests (Table 7). The results of the LM test showed significant spatial error and spatial lag; therefore, a spatial model should be used instead of a mixed regression model. The fixed effects model was determined by the Hausman test. The likelihood ratio (LR) and the Wald test showed that SDM cannot be degraded to SAR and SEM models; therefore, we used the dynamic spatial model (SDM) to study the dynamic spatial change dynamics of AGTFP in China.

Table 7. Statistical tests of the spatial econometric model.

		Statistic	*p* Value
LM	Spatial error	14.236	0.000 ***
	Spatial lag	33.587	0.000 ***
Hausman	-	20.040	0.000 ***
LR	SDM-SAR	43.254	0.000 ***
	SDM-SEM	13.187	0.001 ***
Wald	SDM-SAR	12.041	0.004 ***
	SDM-SEM	14.012	0.001 ***

Note: *** $p < 0.01$.

Table 8 shows the results of the conditional β convergence test for the dynamic spatial SDM of AGTFP. Table 6 illustrated that after incorporating the spatial factors and lagged variables of China's AGTFP, the β coefficient was still significantly negative at the 1% statistical level. This indicates that the regional convergence characteristics of China's AGTFP were still evident after considering the endowment conditions of each province's GDP, AIR, AID, EC, EI and DOR. Therefore, the potential factors, such as inter-regional agricultural production factor flows and institutional environment, also played a non-negligible role in regional disparities. In addition, the spatial correlation coefficient ρ passed the 1% significance level test and was positive, indicating that the spatial spillover effect of AGTFP in China was increasing, and it was necessary to further promote the exchange of agricultural-related green production activities among provinces, and the regions with higher AGTFP played a demonstrative role in driving other Chinese provinces with lower AGTFP to improve continuously.

Table 8. Results of the conditional β convergence test for the dynamic spatial SDM of AGTFP.

Variable	SDM	Variable	SDM
β	−0.942 *** (0.042)	DOR	0.002 *** (0.021)
α	0.604 (0.109)	FS	0.002 ** (0.00)
GDP	0.003 *** (0.002)	MGP	0.002 (0.049)
AID	−0.001 (0.003)	ρ	15.009 ** (1.015)
AIR	0.018 (0.081)	σ^2	0.003 *** (0.001)
EC	0.001 (0.002)	R^2	0.466
EI	0.0139 *** (0.044)	Log-likelihood	816.547

Note: Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$. GDP represents GDP per capita, AIR represents agricultural industrial restructuring, AID represents agricultural infrastructure, EC represents energy consumption, EI represents effective irrigation rate, DOR represents disaster occurrence rate, FS represents financial support for agriculture, and MGP represents major grain producing areas.

4. Discussion

Over the period of 2000–2019, the AGTFP in most Chinese provinces showed an upward trend, which is similar to the growth trend of AGTFP measured by scholars such as Chen et al. (2021) [2], Huang et al. (2022) [53] and Yang et al. (2022) [54]. However, the AGTFP of each province differed from these studies. The reason is that we put carbon sinks into the measurement framework of AGTFP, which can effectively reduce CO_2 emissions. Additionally, Lin (2018) [31] and Chen et al. (2021) [35] came to the same conclusion. Chen et al. (2021) [35] studied the carbon sequestration and carbon footprint of 16 crop production systems in China from 2001 to 2018, and they found that the crop system can effectively alleviate its own carbon emission. Additionally, other scholars [36,55–58] have also calculated the agricultural carbon sink by crop production systems, including carbon absorption by trees and soil organic carbon, manure application and no-tillage management, and they came to similar conclusions. Therefore, there is a minor difference from the results of AGTFP measurement without considering carbon sinks. The significant increase in China's AGTFP indicates that after China's economy entered a medium- to high-speed development stage, China has focused great attention on the transformation of the economy to a high-quality development model over the past decades. A series of material input reduction and various comprehensive management measures have gradually taken effect and successfully put the economy and the environment on a harmonious development track. However, the decomposition indicators of AGTFP in each province were not promising, with 11 provinces showing a decreasing trend in technical efficiency to varying degrees, similar to the findings of Sun et al. (2020) [59], who found a significant increase in AGTFP in China, and 25 provinces showed a decreasing trend in the decomposition indicators of the AGTFP trend. Although all provinces are trying to innovate their economic development models and have accomplished great achievements in stabilizing the economy, adjusting the structure and promoting development, the gap between the advanced and backward provinces still exists. Guo et al. (2021) [60] had similar findings on this point. The main reason for the occurrence of the above situation may be the obvious difference in economic development between different regions, with different resource endowments and industrial advantages, and distinct degrees of green and low-carbon development in agriculture.

In response to the forms of agricultural development in different regions, applying local policies will become one of the effective paths to promote green agricultural development.

In addition, spatial factors had a positive contribution to AGTFP growth. Spatial proximity can promote the dissemination of agricultural green technology and knowledge. The neighboring regions can share high-quality agricultural resource elements. The results of the study through the spatial econometric model indicated that the Moran'I index of AGTFP in each province was significantly positive, showing that the green development between different provinces was spatially interconnected, and cross-regional cooperation and agriculture promotion were of great practical importance. Chen et al. (2022) [61] also argued that the exhibition of cross-regional cooperation targeted the policies. On the other hand, the convergence test showed that the Chinese AGTFP did not have an absolute σ and β convergence trend, and the gap between the regions will not be reduced, which is also consistent with the findings of Guo et al. (2021) [60]. The possible reasons for this result are that the relevant green technologies are currently not accessible, technology promotion is more sluggish, and green technologies are difficult to diffuse. Higher AGTFP efficiency zones maintain higher levels of efficiency, and lower efficiency zones find it difficult to imitate them. The spatial econometric model in this paper showed that the AGTFP had a conditional β convergence posture and had a dynamic spatial conditional β convergence state, while Xu et al. (2022) [62] concluded that the AGTFP did not have a dynamic spatial conditional β convergence state, which is inconsistent with the findings of this paper. The reason for the occurrence of the above may be the inconsistency of the conditional resource endowment of the selected provinces, which can lead to different study results.

5. Conclusions and Recommendations

5.1. Conclusions

From the perspective of agricultural carbon sink, the paper took the agricultural net carbon emissions and agricultural non-point source pollution as unexpected outputs and incorporated them into the calculation framework of AGTFP. We used the super-efficiency productivity index model SBM-DEA to calculate and evaluate the AGTFP in 30 provinces of China from 2000 to 2019. Then, we used the global Moran'I index to analyze the spatial concentration of AGTFP in various provinces of China and studied the convergence trend of China's AGTFP through the absolute α convergence, absolute β convergence and conditional β convergence. Finally, we used the dynamic spatial SDM model to explore the spatiotemporal differentiation and dynamic spatial convergence characteristics of China's AGTFP growth. Our findings can provide a reference for proposing an optimal pathway to improve the AGTFP from the perspective of agricultural carbon sinks, and they are useful for identifying the sources of regional differences in China's green agricultural development, narrowing the regional differences and providing the theoretical support and decision-making basis for regional green agricultural development. Our research also contributes to a well-balanced institutional mechanism for coordinated regional development at the level of green agricultural development. The main research conclusions are as follows:

(1) From the perspective of agricultural carbon sink, the AGTFPs of 28 out of 30 provinces in China were growing, while that of Heilongjiang and Ningxia was decreasing. Among them, the average annual growth rate of MI in Beijing, Guangdong and Chongqing exceeded 1. The average annual growth rate of AGTFP in Beijing was the highest, reaching 2.068%, while that in Heilongjiang was the lowest, reaching −0.094%. In addition, the growth of AGTFP in most provinces was attributed to the improvement of technological progress.

(2) Overall, there was a significantly positive spatial correlation between the AGTFPs in various provinces of China. The Moran'I index of the AGTFP showed an upward trend of fluctuation during the study period, rising from 0.103 in 2000 to 0.153 in 2019, among which the maximum value was 0.243 in 2016. This indicated the presence of diffusion and technology exchange between neighboring provinces regarding agricultural green

technology. With the diffusion and exchange of knowledge and green technology, the AGTFP in neighboring provinces or closer provinces had spatial relevance.

(3) The AGTFP in China did not have absolute α convergence and absolute β convergence characteristics; provinces with higher AGTFP in the initial year maintained higher efficiency levels, while low-AGTFP regions found it difficult to quickly imitate and learn. However, after controlling for the control variable of resource endowment of each province, the conditional β convergence characteristics showed that the convergence characteristics of different provinces were closely related to different resource endowments. Additionally, there were still obvious conditional β convergence characteristics after the spatial factors were considered. The spatial correlation coefficient ρ was positive at the significance level of 1%, which indicated that the spatial spillover effect of AGTFP in China was constantly increasing.

5.2. Recommendations

Based on the above research conclusions, we proposed corresponding countermeasures and suggestions:

(1) According to the development of agriculture in different provinces, local policies will become one of the effective ways to promote sustainable agricultural development. First, for provinces with high agricultural land use carbon emissions, such as Henan, Shandong and Hebei, local governments should increase efforts to return farmland to forests, reduce the use of chemical fertilizers and pesticides, pay attention to conservation tillage systems, reasonably carry out tillage and crop rotation to enhance the carbon sink function of the region, offset the higher carbon emissions and improve the ecological environment of farmland. Second, in provinces where rice fields emit a high amount of carbon dioxide, such as Jiangxi, Jiangsu and Hunan, the government should strengthen the management of rice fields, promote over-belly return, develop biogas and strictly prohibit burning in situ to inhibit the spread of greenhouse gases and cultivate soil fertility. Third, for Shandong, Henan, Chongqing and other provinces with high carbon emissions from livestock and poultry breeding, it is essential to reasonably plan the livestock industry, reasonably treat livestock and poultry manure using modern composting processes, vigorously promote biogas projects and implement carbon reduction policies, i.e., using clean energy instead of traditional energy.

(2) The government should focus on developing a series of policies to enhance the carbon sink capacity of agricultural land in order to reduce the concentration of greenhouse gases in the atmosphere, mainly from the following three aspects. The government should adopt a protective farming system, reduce the use of chemical fertilizers and pesticides, decrease straw burning and promote straw return to the fields according to the resource endowment conditions of different regions through government subsidies in order to enhance the carbon sink capacity of farmland, increase the carbon sink capacity of grasslands through rational planning of livestock farming, implementation of grazing pause or even grazing ban and returning grazing to grass. Afforestation and reforestation in eligible areas can significantly improve the vegetation cover of land, and the carbon sink capacity of agricultural land can be increased.

(3) Policy makers should develop AGTFP growth strategies for different provinces according to the spatial characteristics of China's AGTFP and local conditions. The endowment conditions, such as geographic and natural conditions, vary significantly among the regions in China, but the AGTFPs among different provinces have obvious spatial correlation. Therefore, policy makers should consider each province's factor endowment advantages, as well as resource and environmental carrying capacity, tapping the potential of the carbon sink market and formulating relevant measures to reduce emissions and increase sinks, as well as prevent and treat pollution to improve the ecological environment. With rich carbon sinks, Guangdong, Guangxi and Shanxi should further maximize the spatial spillover effect, improve the radiation demonstration role and realize the docking of green technology and green growth through management experience and technology

exchange. To further enhance the AGTFP, agricultural carbon sinks should be increased, and the agricultural ecological environment should be optimized.

(4) Local governments should combine their own agricultural development to promote a coordinated development of AGTFP in each province at multiple levels, so as to achieve high-quality development of agriculture. First, the government should increase financial support for green agricultural development and enhance the conservation of agricultural resources while improving the efficiency of agricultural resource utilization. Second, the eastern and central provinces should further improve the efficiency of effective irrigation, actively develop water-saving agriculture, promote dry-farming and water-saving agricultural technologies and improve the efficiency of water resources utilization. Gansu, Xinjiang and other western provinces should further strengthen environmental management, optimize the agricultural industrial structure, formulate policies to reduce energy consumption and improve energy use efficiency, and develop effective strategies to deal with major disasters to reduce the negative impact of disasters on ecological and agricultural production activities.

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Appendix A

The detailed calculation methods for CS_{SR}, CS_{MA} and CS_{NT} are as follows:

$$CS_{SR} = \frac{SR_i + RB_i}{1000} \times 29.025 + 272.33 \tag{A1}$$

where the tree body does not consider the root residue, and the litter and pruning are equivalent to straw return. The biomasses of litter and pruning for tea and fruit trees (take citrus, for example) are 1682 (You, 2008) [55] and 1843 (Wu et al., 2010) [56] kg ha^{-1}, respectively.

$$CS_{MA} = M_{i,c} \times 19.1\% \tag{A2}$$

where Mc refers to the carbon input due to manure application. This value can be calculated by Equation (5). The 19.1% refers to the percentage of input carbon converted into soil organic carbon (Wang et al., 2015) [57].

$$CS_{NT} = 120 \times NTR \tag{A3}$$

where 120 refers to no-tillage management, which can increase SOC by 120 kg ha^{-1} (Luo et al., 2010) [58]; NTR refers to the proportion of no-tillage area to total area.

According to the existing research literature, the emission coefficients and reference sources of various carbon sources are summarized as follows (Table A1).

Table A1. Agricultural land use carbon emission sources, carbon emission coefficients and reference sources.

Carbon Source	Carbon Emission Coefficient	Reference Source
Fertilizer	0.8965 kgC·kg^{-1}	West and Marland (2002) [63]
Pesticide	4.9341 kgC·kg^{-1}	West and Marland (2002) [63]
Agricultural Film	5.18 kgC·kg^{-1}	Wang and Zhang (2016) [64]
Diesel Fuel	0.5927 kgC·kg^{-1}	IPCC (2007) [65]
Plowing	312.6 kgC·hm^{-2}	Wu and Li (2007) [66]
Agricultural Irrigation	25 kgC·ha^{-1}	Dubey and Lal (2009) [67]

The CH_4 emissions produced by rice planting not only account for most of the CH_4 emissions in China but also have a heavy impact on the global atmospheric CH_4 emissions. Therefore, when considering the carbon emission coefficient of rice production, it needs to be considered by varieties and regions. On the basis of Min and Hu (2012) [68], the obtained C emission coefficients of rice by variety and region were transformed into the C emission coefficients, and the C emission coefficients of rice varieties (early rice, mid-season rice and late rice) were obtained by province (Table A2).

Table A2. Rice carbon emission coefficients in each province. Unit: kg·hm^{-1}.

Area	Early Rice (Single Cropping Rice)	Mid-Season Rice (Single Cropping Late Rice, Winter Paddy Field and Wheat Stubble Rice)	Double-Cropping Late Rice
Beijing	0	901.96	0
Tianjin	0	773.11	0
Hebei	0	1045.12	0
Shanxi	0	451.32	0
Inner Mongolia	0	608.80	0
Liaoning	0	629.94	0
Jilin	0	379.74	0
Heilongjiang	0	566.54	0
Shanghai	846.05	3672.59	1874.81
Jiangsu	1095.57	3650.70	1881.63
Zhejiang	979.68	3951.42	2352.04
Anhui	1141.93	3493.29	1881.63
Fujian	527.68	2963.57	3586.01
Jiangxi	1054.67	4460.01	3122.42
Shandong	0	1431.68	0
Henan	0	1216.92	0
Hubei	1193.74	3065.74	2658.83
Hunan	1002.85	3836.89	2324.77
Guangdong	1026.03	3887.34	3517.83
Guangxi	846.05	3257.40	3347.39
Hainan	915.59	3564.87	3367.85
Sichuan	446.54	1754.14	1261.24
Chongqing	446.54	1754.14	1261.24
Guizhou	347.70	1503.26	1431.68
Yunnan	162.26	494.27	518.13
Shanxi	0	852.87	0
Gansu	0	465.6	0
Qinghai	0	0	0
Ningxia	0	501.08	0
Xinjiang	0	715.83	0

Livestock and poultry farming is an important emission source of CH_4 and N_2O emissions. The CH_4 emission coefficient comprises the CH_4 emission coefficient of gastrointestinal fermentation of livestock and poultry and the CH_4 emission coefficient of livestock and poultry excrement. The N_2O emission coefficient is the N_2O emission coefficient of livestock and poultry excrement. According to the development of animal husbandry in China, the research objects are mainly CH_4 emissions and excrement caused by gastrointestinal fermentation of cattle (dairy cows, cattle, buffalo), sheep, pigs, horses, donkeys, mules, camels, rabbits and other poultry during the breeding process. Emissions of CH_4 and N_2O are generated during processing. Based on the research of Min and Hu (2012) [68], the emission coefficients of various carbon sources were summarized and converted into C exclusion coefficients (Table A3).

Table A3. Carbon emission coefficients of various livestock and poultry breeds. Unit: kg·$head^{-1}$·a^{-1}.

Livestock and Poultry Breeds	CH_4 Emission Coefficient		N_2O Emission Coefficient	C Emission Coefficient
	Gastrointestinal Fermentation	Fecal Discharge	Fecal Discharge	
Cows	68	16	1	653.9346
Cattle	47.8	1	1.39	445.9218
Buffalo	55	2	1.34	497.4921
Sheep	5	0.16	0.33	61.9956
Pig	1	3.5	0.53	43.4790
Horse	18	1.64	1.39	246.8535
Donkey	10	0.9	1.39	187.2686
Mule	10	0.9	1.39	187.2686
Camel	46	1.92	1.39	439.6524
Rabbit	0.254	0.08	0.02	3.9023
Birds	-	0.02	0.02	1.7616

Note: Since the amount of CH_4 produced by the gastrointestinal fermentation of poultry is small, the emission of CH_4 caused by the gastrointestinal fermentation of poultry is not considered.

The indirect N_2O emissions from in-field nitrogen fertilizer application and straw burning should also be taken into account in carbon emissions. The indirect N_2O emissions are estimated using the following equations.

$$INE_i = (N_2O_{i,ATD-N} + N_2O_{i,L-N} + N_2O_{i,SB}) \times \frac{44}{28} \times 265 \quad \text{(A4)}$$

where INE_i represents the total indirect N_2O emissions; $N_2O_{i,ATD-N}$ represents the N_2O emissions from the atmospheric deposition of volatility; $N_2O_{i,L-N}$ represents the N_2O emissions from leaching and runoff; $N_2O_{i,SB}$ represents the total N_2O emissions from crop straw burning; 44/28 is the molecular conversion factor of N_2 to N_2O; and 265 is the global warming potential of N_2O for a 100-year period.

$$N_2O_{i,ATD-N} = (F_{i,SN} \times EF_{SN-ATD} + F_{i,ON} \times EF_{ON-ATD}) \times 1\% \quad \text{(A5)}$$

$N_2O_{i,ATD-N}$ represents the N_2O emission from atmospheric deposition of N volatility; $F_{i,SN}$ represents the annual amount of synthetic fertilizer N applied to soils; $F_{i,ON}$ represents the amount of manure, compost and other organic N applied to soils; $F\ EF_{SN-ATD}$ represents the fraction of synthetic fertilizer N that volatilizes as NH_3 and NO_x, equal to 11% (IPCC, 2019) [69]; EF_{ON-ATD} represents the fraction of applied organic N fertilizer material that volatilizes as NH_3 and NO_x, equal to 21% (IPCC, 2019) [69]; 1% represents the emission factor for N_2O emissions from atmospheric deposition of N on soils and water surfaces (IPCC, 2019) [69].

$$N_2O_{i,l-N} = (F_{i,SN} + F_{i,ON} + F_{i,CRN}) \times EF_{L-N} \times 1.1\% \quad \text{(A6)}$$

$N_2O_{i,l-N}$ represents the N_2O emission from leaching and runoff; $F_{i,SN}$ represents the annual amount of crop residues' return to soils; EF_{L-N} represents the fraction of all N added to/mineralized in soils in regions where leaching/runoff occurs, equal to 24% (IPCC,

2019) [52]; 1.1% represents the emission factor for N_2O emissions from N leaching and runoff (IPCC, 2019) [52].

$$N_2O_{i,SB} = (SB_i \times EF_{SB-D} + SB_i \times EF_{SB-ATD}) \times 1\% \\ SB_i = Y_i \times RSY_i \times PSB_i \quad (A7)$$

$N_2O_{i,SB}$ represents the total N_2O emission from crop straw burning; RSY_i represents the ratio of straw to yield (Table 4); SB_i represents the dry matter quality (moisture content is 22%) of straw burned; EF_{SB-D} represents direct N_2O released from straw burning (See Table A4); EF_{SB-ATD} represents the fraction of NH_3 and NO_x released from straw burning (See Table A4); PSB_i represents the proportion of straw burned as part of the total straw biomass (Table A5).

Table A4. Greenhouse gas emissions from straw burning by crops per unit weight. Unit: kg kg^{-1}.

Crop	$EF_{SB\text{-}D}$	$EF_{SB\text{-}ATD}$	CH_4
Rice	0.0008	0.0023	0.0025
Wheat	0.0003	0.0021	0.0025
Maize	0.0004	0.0022	0.0025
Beans	0.0007	0.0027	0.0025
Potato	0.0007	0.0027	0.0025
Rape seed	0.0007	0.0027	0.0025
Vegetables	0.0007	0.0027	0.0025
Fruits	-	-	-

Note: $EF_{SB\text{-}D}$ represents direct N_2O released from straw burning; $EF_{SB\text{-}ATD}$ represents the fraction of NH_3 and NO_x released from straw burning. All the data in this table are summarized from Chen et al. 2021 [35].

Table A5. Ratio of straw biomass to yield, the nitrogen concentration in crop straw (root) and return part to the total straw biomass.

Crop	RSY	Straw and Root N Concentration	PSB (%)	
		(%)	2001–2005	2012–2018
Rice	1.1	0.91	41.9	11.9
Wheat	0.9	0.65	30.6	12.0
Maize	0.8	0.92	44.1	30.2
Beans	1.0	1.81	33.9	16.3
Potato	2.0	2.37	15.7	19.7
Rape seed	0.4	0.87	41.3	42.3
Vegetables	5.9	2.98	28.9	18.2
Fruits	-	2.6	-	-

Note: RSY_i represents the ratio of straw to yield; RAR refers to the ratio of above-ground biomass to root biomass; PSB_i represents the proportion of straw burned as part of the total straw biomass. All the data in this table are summarized from Chen et al. 2021 [35].

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