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Original Research

Estimation and Prediction of Carbon Emissions in the Farmland Ecosystem of Kaifeng City, China

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Abstract

The burning of fossil fuels and unsustainable use of resources and land have resulted in a gradual increase in global temperatures. Climate change in 2023 indicates that the average global temperature is already 1.1 °C higher than before the Industrial Revolution. Regional measurement of carbon emissions is crucial for effectively mitigating climate warming. This study estimates the carbon emissions of the farmland ecosystem in Kaifeng city from 2010 to 2021 based on seven key factors. The findings indicate that overall carbon emissions have fluctuated and increased over time while the carbon emission intensity has decreased annually. Through the calculation of the Tapio decoupling model, it is observed that the decoupling status of the farmland ecosystem in Kaifeng city from 2010 to 2021 has transitioned from weak decoupling to strong decoupling, demonstrating the progress made towards green and low-carbon agriculture in Kaifeng city. Using the grey prediction model GM (1, 1), carbon emissions are estimated to reach 1.39×10^6 t by 2030. This research provides carbon emission data and trends for the farmland ecosystem in Kaifeng city from 2010 to 2021, explores the decoupling relationship between farmland ecosystem carbon emissions and the economy, and predicts carbon emissions until 2030 under current policies. Based on these findings, recommendations for emission reduction were proposed.

Keywords: Farmland ecosystem, agricultural carbon emission, tapio decoupling model, grey prediction model

Introduction

The farmland ecosystem plays a crucial role in agriculture, both as a protective barrier for the natural ecological environment and as a vital component of national food security and economic stability. However, as rapid economic development continues, agriculture faces significant challenges, such as environmental deterioration and degradation of cultivated land quality, posing serious obstacles to the sustainable development of the planting industry [1]. On a global scale, although China's agriculture sector

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has the largest total greenhouse gas emissions, its per capita and unit output emissions are relatively low compared to other countries. Additionally, China has produced more food while significantly reducing greenhouse gas emissions, making emission reduction in agriculture more challenging [2]. China has taken aggressive measures to combat climate change and aims to reach peak carbon dioxide emissions by 2030, achieving carbon neutrality by 2060. Progress has already been made, as evident from the 2020 progress report on China's implementation of its nationally determined contributions, which indicates a 12.8% decrease in fertilizer consumption compared to 2015.

Furthermore, the utilization rate of the three major grain crops has increased by 5 percentage points to reach 40.2% [3]. These efforts underscore the significance of addressing carbon emissions from China's agricultural sector. Agriculture constitutes China's second-largest carbon emissions source, with agricultural activities contributing 10%-12% of the total global greenhouse gas emissions [4]. In this context, it is imperative to study the carbon emission characteristics, decoupling effects, and trend predictions related to regional farmland ecosystems to facilitate the low-carbon development of agriculture. The Ministry of Agriculture and Rural Affairs (MARA) issued an implementation plan for emission reduction and nitrogen fixation in agriculture and rural areas, recognizing the importance of emission reduction and nitrogen fixation in agriculture and rural areas. This plan outlines six tasks, including energy conservation and emission reduction in the planting industry and animal husbandry, which guide establishing an agricultural carbon emission measurement system [5].

Numerous studies have been conducted on agricultural carbon emissions from various perspectives. Wang utilized the LMDI (logarithmic mean Divisia index) additive decomposition model and concluded that the agricultural production structure and economic level are key factors contributing to the increase in carbon emissions from farmland ecosystems in Henan Province [6]. He et al., employing the LMDI decomposition model, found that the development of the agricultural economy had the largest impact on total agricultural carbon emissions in Lanzhou, followed by demographic and agricultural structural factors [7]. Using the LMDI method, Fang et al. decomposed carbon emissions into structure, activity, and intensity effects [8]. They applied the grey prediction model to estimate the carbon peak year under different transition strategies. They compared it with the US energy transition to determine the optimal path for China's carbon peak. Qiu et al., through constructing a VAR (vector autoregression) model, identified environmental regulation and technological progress as reasons for reducing agricultural carbon emissions [9]. Ali et al., using the autoregressive distributed lag model, investigated the impact of agricultural technology on agricultural carbon emissions in Pakistan, finding a positive correlation between pesticides, economic growth, and agricultural carbon emissions [10].

Additionally, Zhu et al., Li et al., and Li et al. studied agricultural carbon emissions in Jiangxi province, Hunan province, and Anhui province, respectively, employing the LMDI decomposition model and Tapio decoupling effect mode [3, 11, 12]. Effective carbon emission prediction plays a crucial role in policy formulation and implementation. However, there is no fixed and stable prediction model for agroecosystem emissions. Zhao et al. used the grey prediction model GM (1,1) to forecast a slow decline in agricultural carbon emissions in Jiangsu province from 2016 to 2030 [13]. Shaheen et al. calculated Pakistan's agricultural carbon emissions in 2030 using the grey prediction model, indicating a 69% growth rate compared to 2010 and emphasizing the acceleration of nitrous oxide emissions due to urbanization and agriculture [14]. Fang et al. improved the Gaussian process regression method (GPR) by incorporating the particle swarm optimization algorithm (PSO) [15]. They applied the improved PSO-GPR method to predict the total carbon emissions of China, the United States, and Japan from 2013 to 2020, concluding that China's total carbon emissions would initially increase but eventually exhibit a downward trend. Wang et al. predicted agricultural carbon emissions for the period 2021-2030 based on the STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model, observing a downward trend, indicating that Shanxi province's agriculture had achieved its carbon peak goal [16].

In summary, most previous studies have primarily focused on the national or provincial level when investigating agricultural carbon emissions. It becomes evident that most research outcomes concentrate on agricultural carbon emissions at the national level or in economically developed provinces and cities [16, 17]. Conversely, studies addressing urban agricultural carbon emissions in Henan province are scarce. Thus, this study aims to fill this research gap by selecting Kaifeng City in Henan province as the research subject. Drawing from previous research methodologies, this study will utilize the carbon emission factor method, the Tapio decoupling model, and the grey prediction model to calculate and analyze the farmland ecosystem of Kaifeng City. These findings will contribute to future research endeavors and policy formulation related to agricultural carbon reduction in Kaifeng City.

The Study Region and Methodology

The Study Region

Kaifeng, situated in the central region of Henan province, China, is located on the middle and lower plains of the Yellow River. It shares borders with Zhengzhou, the capital of Henan province, to the north; Anyang city to the east; Luoyang city to the west; and Xinxiang city to the south. The topography of Kaifeng city is predominantly flat, characterized by vast plains. In terms of climate, Kaifeng falls within the temperate monsoon zone and experiences four distinct seasons throughout the year. It serves as one of China's significant regions for rice cultivation due to its favorable agricultural conditions. As of 2021, the city boasts a growing area of 5.27×10^8 m^2, yielding a total grain output of 3.06×10^6 t.

Data Sources and Processing

The data utilized in this study, including fertilizer usage, film usage, pesticide usage, effective irrigated area, agricultural diesel usage, plowed area, and agricultural output value (current price), were obtained from the Kaifeng city Statistical Yearbook from 2010 to 2021. In cases where the effective irrigated area data were incomplete in the yearbook, information from previous years in the Henan Provincial Statistical Yearbook was selected to fill the gaps. The cultivated area was calculated based on the sown area of the crops in the current year. It should be noted that the data in the Kaifeng Statistical Yearbook for 2020 were adjusted using the results from the agricultural census. Therefore, the most recent data available should take precedence. Data processing involved using Excel 2021, while data visualization and graph drawing were performed using Origin 2021.

Calculation of Carbon Emissions in Farmland Ecosystems

Currently, no direct method is available for detecting domestic and international carbon emissions. The United Nations Intergovernmental Panel on Climate Change (IPCC) has proposed using carbon emission factor methods to measure carbon emissions [4]. Based on relevant studies [5,18-23], carbon emissions from farmland ecosystems can be categorized into seven aspects: (1) Fertilizer usage during production and application leads to direct or indirect carbon emissions from agriculture. (2) Pesticide usage during production and application leads to direct or indirect carbon emissions from agriculture. (3) Agricultural film usage during production and application leads to direct or indirect carbon emissions. (4) Carbon emissions from diesel fuel consumption in agricultural activities. (5) Soil plowing disrupts organic carbon pools, causing carbon to be released into the atmosphere. (6) Carbon emissions arise from the utilization of electrical energy during land irrigation, indirectly consuming fossil energy sources. (7) The methane produced by rice cultivation

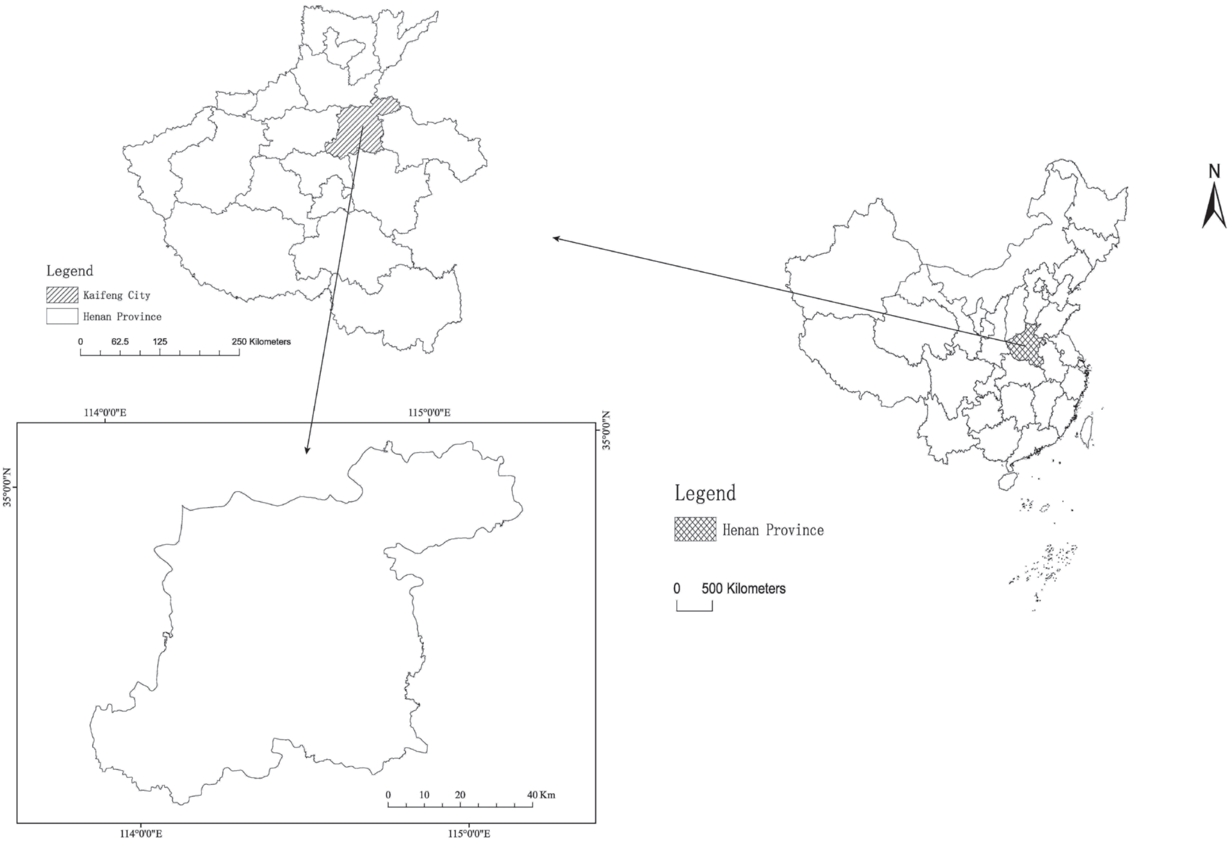

Fig. 1. Location of Kaifeng city in Henan province. Note: Based on the standard map No. GS (2020) 4619 of the standard map service website of the Ministry of Natural Resources, the boundary of the base map is not modified.

Table 1. Carbon Emission Coefficients of Sources in Agricultural Production Activities.

Emission sources	Carbon emission coefficient	References
Fertilizer	0.8596 kg/kg	He et al. 2018
Pesticide	4.93 kg/kg	Oak Ridge National Laboratory, USA
Mulch	5.18 kg/kg	Li et al. 2011
Diesel	0.5927 kg/kg	IPCC
Irrigate	20.476 kg/hm^2	Li et al. 2011
Plow	3.126 kg/hm^2	Duan et al. 2011

contributes significantly to methane emissions in China and globally, where rice cultivation accounts for a major portion of total global methane emissions [24]. Table 1 presents the reference carbon emission factors used in this study (since different references are based on different scenarios, this article harmonizes the units of carbon emission factors based on the scenarios of this study and facilitates the subsequent application).

Referring to the calculation formula proposed by [6], this study formulated the equation for estimating carbon emissions from agricultural production activities as follows:

$$E = \sum E_i = \sum G_i * \delta_i * \frac{44}{12}$$

Where E is the total carbon emissions from agricultural production activities, E_i refers to the carbon emissions from various sources of agricultural production activities, G_i denotes the amount of carbon input from each agricultural production activity, and ε_i signifies the carbon emission coefficient of each source of carbon emissions. The conversion coefficient of 44/12 was used to convert the carbon equivalent to CO_2. The formula estimates the carbon emissions specifically for growing rice:

$$E_{rice} = S_{rice} * \gamma * 25$$

Where E_{rice} represents the carbon emissions generated by rice cultivation (10^4t), is the planting area of paddy fields (hm^2) in Kaifeng city, and γ is the CH_4 emission coefficient of rice cultivation, which has a value of 0.2367 t/hm^2. A conversion coefficient of 25 was used to convert the CH_4 emissions to CO_2 equivalents (Wang et al. 2022).

Economic Decoupling Model

The economic decoupling model is an approach to economic development that seeks to separate economic growth from resource consumption and environmental impacts. Its goal is to achieve a decoupling between economic growth on one hand and resource utilization efficiency and environmental pressure on the other. Traditional economic growth has typically been accompanied by increased resource consumption and environmental burdens. However, as sustainable development and environmental protection have become increasingly important, the decoupling model presents a new path to economic prosperity that simultaneously reduces resource consumption and minimizes environmental damage.

For the analysis of decoupling effects, the OECD (Organization for Economic Co-operation and Development) in their report "Indicators to measure decoupling of environmental pressures for economic growth," categorized it into absolute decoupling and relative decoupling. They define decoupling as a state when the growth rate of environmental pressures is lower than the economic growth rate during a specific period. Absolute decoupling occurs when environmental pressures remain stable or decline while the economy grows. On the other hand, relative decoupling refers to a positive growth rate in environmental pressures, but at a smaller rate compared to the economic growth rate. In contrast to the two-division method proposed by OECD, which distinguishes between absolute and relative decoupling, Tapio proposed an eight-division decoupling index that provides a more precise reflection of the decoupling relationship between economic development and carbon dioxide emissions under different circumstances [25].

Building upon Tapio's decoupling theory, this study aims to establish a relationship between carbon emissions from farmland ecosystems and agricultural GDP in Kaifeng city [26]. By examining the interplay between these factors, we can gain insights into the decoupling potential and explore strategies for achieving sustainable agricultural development while minimizing carbon emissions.

$$\varepsilon_{C,GDP} = \frac{\Delta C/C}{\Delta GDP/GDP}$$

In the formula, $\varepsilon_{C,GDP}$ represent the elasticity between agricultural economic growth and carbon emissions, corresponding to the decoupling index. This index reflects the specific state of decoupling, as illustrated in Fig. 1. Here, C denotes the total amount of carbon emissions from agriculture, while GDP represents the gross domestic product of the agricultural sector.

Prediction of Agricultural Carbon Emissions

The Gray prediction model GM (1, 1) is a data processing method that uses time series data as samples. It gradually accumulates and generates the original series based on the pattern of the original series increasing or decreasing. This model is particularly useful for scenarios with limited data and unclear patterns, offering high prediction accuracy. It has found wide applications in various fields, such as population forecasting, sales volume forecasting, and tourism forecasting. In this study, we employ the GM (1, 1) model to determine the trend of agricultural carbon emissions in Kaifeng city. By utilizing the measured agricultural carbon emissions data from 2010 to 2021 in Kaifeng city, we construct the raw data and simulate the agricultural carbon emissions for 2022-2030. The main steps in building the mathematical model include obtaining the cumulatively generated sequence from the original sequence.

$$x^{(1)}(t) = \sum_{i=1}^{t} x^{(0)}(i)$$

Next, we establish the differential equation.

$$\frac{\Delta x^{(1)}}{\Delta t} + a x^{(1)}(t) = \mu$$

To improve the accuracy of the final data, we incorporate a mean generating sequence for revision.

$$z^{(1)}(t) = \frac{x^{(1)}(t) + x^{(1)}(t-1)}{2}$$

Since the time difference, Δt is set to 1 in the calculations, the final equation is modified as follows:

$$x^{(0)}(t) = \mu - a z^{(1)}(t)$$

The matrix form of the equation is Y = BU;

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(N) \end{bmatrix}; \quad B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(N) & 1 \end{bmatrix}; \quad U = \begin{bmatrix} a \\ \mu \end{bmatrix};$$

The grey parameters μ and a are solved by the least square method.

$$U = (B^T \times B)^{-1} \times B^T Y$$

Substituting the grey parameter into the time function, we can obtain:

$$x^{(1)}(t) = \left[x^{(0)}(1) - \frac{\mu}{a}\right] e^{-a(t-1)} + \frac{\mu}{a}$$

The predicted value of carbon emissions in the planting industry in Kaifeng city in corresponding years can be obtained.

$$x^{(0)}(t+1) = x^{(1)}(t+1) - x^{(1)}(t) \quad t = 1,2,\cdots,n$$

Lastly, we conducted residual, posterior difference, and correlation tests to assess the model's accuracy. These tests were employed to validate the predictions of carbon emissions in the agricultural sector of Kaifeng city from 2022 to 2030.

Results and Discussion

Characterization of the Time Series of Carbon Emission

Total Carbon Emissions and Influencing Factors

In 2021, the carbon emissions from Kaifeng's farmland ecosystem amounted to 1.39×10^6 t, indicating an increase of 3.78×10^4 t compared to the 2010 Figure of 1.35×10^6 t. This translates to an average annual increase of 3.1×10^3 t, as illustrated in Fig. 2. Overall, the trend of carbon emissions from 2010 to 2021 exhibits fluctuations with an upward trajectory. Between 2010 and 2013, the carbon emissions from Kaifeng city's farmland ecosystem showed an overall upward trend. In comparison to 2010, the carbon emissions in 2013 increased by 5.52×10^4 t, with an average annual growth rate of 1.34%. However, in 2014, there was a decrease of 3.52×10^4 t compared to 2013. From 2014 to 2016, the trend shifted to a more moderate upward stage, with an average annual growth rate of 1.32%. The period from 2016 to 2018 marked a downward stage, demonstrating a noticeable decline in carbon emissions. The average annual reduction rate during this period was 2.41%, reaching its lowest value of 1.34×10^6 t in 2018. This reduction can be attributed to implementing measures such as the reduced use of chemical fertilizers, pesticides, and agricultural diesel, resulting in a significant decrease in carbon emissions. In 2019, carbon emissions experienced a surge, reaching the highest value of 1.42×10^6 tons within the study range, reflecting an annual growth rate of 5.95%. Subsequently, from 2019 to 2021, a steady decrease brought the carbon emissions down to 1.39×10^6 t in 2021, with an average annual reduction rate of 1.12%. Fig. 3. demonstrates that fertilizers contribute the most to the total carbon emissions, ranging from 0.941-1.0147 million tons. The trend of fertilizer usage aligns closely with the overall carbon emissions during the study period. Other significant carbon sources, in descending order, include mulch film, agricultural diesel, pesticides, rice, irrigation, and tilling, accounting for percentages ranging from 9.8% to 11.4%, 6.1% to 8.8%, 5.0% to 8.5%, 2.2% to 2.9%, 1.8% to 1.9%, and 0.68% to 0.71%, respectively.

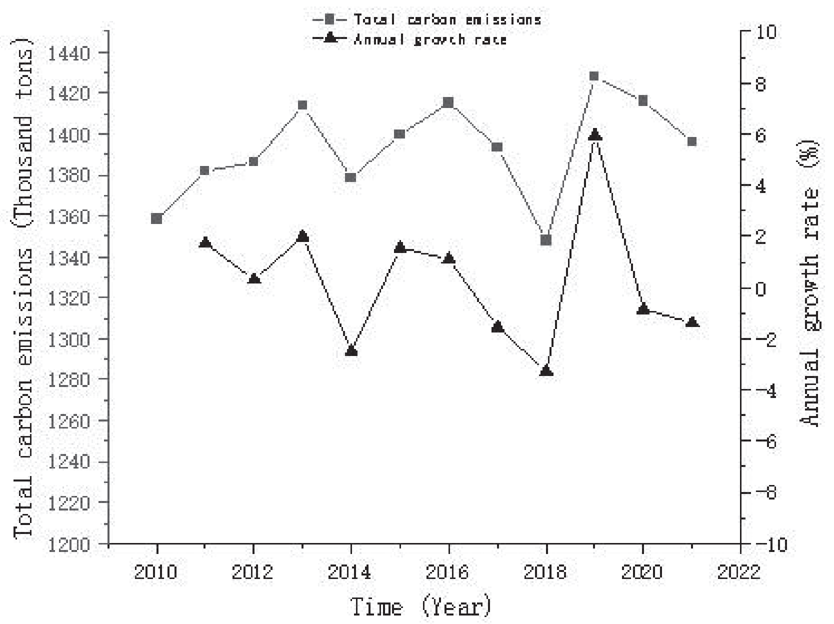

Fig. 2. Total carbon emissions and annual growth rate of farmland ecosystem in Kaifeng city (2010-2021).

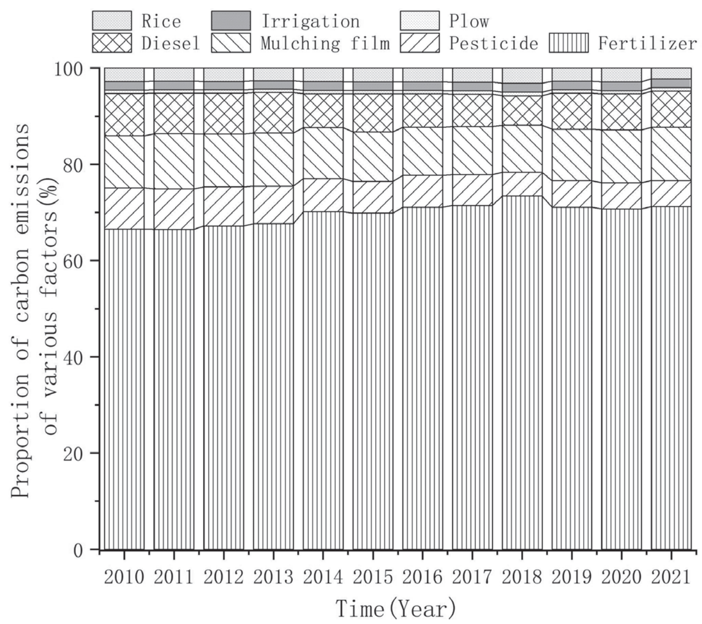

Fig. 3. Proportion of carbon emissions in farmland ecosystems in Kaifeng city.

Time-Series Characteristics of Carbon Emission Intensity

This study defines carbon emission intensity as the amount of carbon dioxide released per ten thousand yuan of gross plantation output value (t/10,000 yuan) [6]. By analyzing the measured carbon emissions from farmland ecosystems in conjunction with the total value of agricultural output, we calculated the changes in carbon emission intensity for Kaifeng city's farmland ecosystems from 2010 to 2021, as depicted in Fig. 4. The overall trend of carbon emission intensity for farmland ecosystems in Kaifeng city exhibits fluctuations and a decreasing pattern. It decreased from 0.533 in 2010 to 0.295 in 2021, representing an average annual decline rate of 4.68%. These findings indicate that adjusting the structure of Kaifeng city's farmland ecosystems has led to improved production and utilization efficiency.

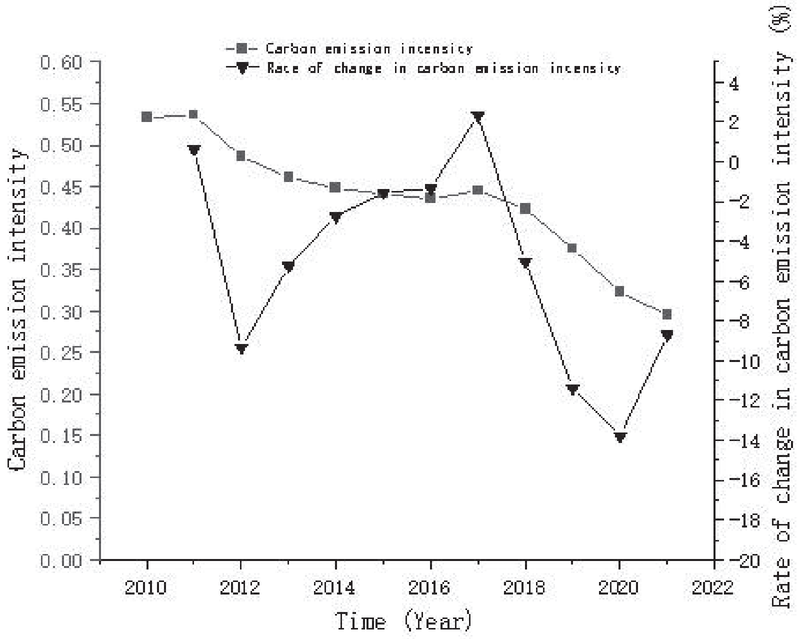

Fig. 4. Carbon emission intensity and its rate of change.

Structural Changes in Carbon Emissions

Table 2 provides an overview of the carbon emission structure, highlighting the proportions and trends of different sources. It is evident that fertilizer application contributes significantly to carbon emissions, with the highest proportion observed. In 2021 alone, carbon emissions resulting from fertilizer application amounted to 9.94×10^5 tons. When examining specific sources, it is clear that carbon emissions attributed to fertilizer usage, mulch film, tilling, and irrigation have shown an overall fluctuating upward trend. The emissions rose from 9.04×10^5 t, 1.46×10^5 t, 9.5×10^5 t, and 2.4×10^5 t to 9.94×10^5 t, 1.54×10^5 t, 9.9×10^5 t, and 2.63×10^4 t in 2021. In contrast, carbon emissions stemming from pesticides, agricultural diesel, and rice exhibited a decline over the study period. The emissions decreased from 1.16×10^5 tons, 1.19×10^5 t, and 3.8×10^4 t, respectively, to 7.56×10^4 t, 1.04×10^5 t, and 3.12×10^4 t.

These findings underscore the importance of addressing the high carbon emissions associated with fertilizer application, mulch film, tilling, and irrigation. Implementing measures to improve efficiency, optimize resource utilization, and promote sustainable farming practices can significantly reduce carbon emissions from these sources. Moreover, reducing carbon emissions from pesticides, agricultural diesel, and rice highlights the potential for implementing more environmentally friendly alternatives and practices within the agricultural sector. By understanding the changing carbon emission structure and targeting key sources, policymakers and stakeholders can develop effective strategies to mitigate carbon emissions and promote sustainable development in Kaifeng city's farmland ecosystems.

Decoupling Analysis of Carbon Emissions

Table 3 presents the decoupling elasticity between Kaifeng farmland ecosystems and economic growth, based on the Tapio decoupling model, from 2011 to 2021. The relationship between farmland ecosystems and economic growth in Kaifeng city during this period is primarily characterized by weak decoupling. This implies that as economic growth increases, carbon emissions also rise, and when economic growth accelerates, carbon emissions increase faster, which is less desirable [1]. Overall, there has been an evolution from weak to strong decoupling, aligning with the changing trend of carbon emissions. In 2010-2011, negative decoupling was observed, indicating that both economic growth and carbon emissions are increasing, with carbon emission growth outpacing economic growth. This situation is less desirable.

From 2012 to 2019, we observed a fluctuation stage characterized by three decoupling states: weak decoupling, strong decoupling, and weak negative decoupling. The Kaifeng city government has made efforts to strengthen the control of carbon emissions from farmland ecosystems without hindering economic development. Within this stage, improvements can be made in the agricultural sector, particularly in components such as fertilizers and pesticides, to reduce their carbon emissions while promoting sustainable growth. From 2020 to 2021, Kaifeng city enters the stage of strong decoupling, where economic growth continues to rise while carbon emissions decline. This stage represents the most desirable scenario, indicating that environmental protection and adopting green low-carbon concepts in agricultural production have proven effective. Implementing measures to reduce pesticide

Table 2. Carbon emissions from farmland ecosystem in Kaifeng city, 2010-2021 (10^4 t).

Year	Fertilizer	Pesticide	Mulch	Diesel	Plow	Irrigation	Rice	Gross	Annual growth
2010	90.41	11.61	14.66	11.98	0.95	2.42	3.80	135.84	
2011	91.90	11.58	15.81	11.70	0.96	2.43	3.81	138.19	2.35
2012	93.13	11.21	15.23	11.77	0.96	2.44	3.88	138.62	0.42
2013	95.62	11.08	15.55	11.92	0.97	2.50	3.74	141.37	2.75
2014	96.67	9.50	14.62	9.71	0.95	2.47	3.94	137.85	-3.52
2015	97.74	9.24	14.39	11.11	0.95	2.52	4.02	139.97	2.12
2016	100.59	9.36	14.14	9.83	0.96	2.52	4.12	141.53	1.56
2017	99.54	8.94	13.89	9.40	0.95	2.52	4.09	139.33	-2.19
2018	98.90	6.70	13.15	8.25	0.98	2.52	4.28	134.78	-4.55
2019	101.47	7.83	15.38	10.65	0.99	2.52	3.95	142.79	8.01
2020	100.13	7.70	15.52	10.57	1.00	2.58	4.09	141.59	-1.20
2021	99.42	7.56	15.44	10.47	0.99	2.63	3.12	139.62	-1.97

Table 3. Decoupling elasticity of carbon emissions and economic growth of farmland ecosystem in Kaifeng city.

Year	$\Delta C/C$	$\Delta GDP/GDP$	Decoupling elasticity	Decoupling state
2011	0.0175	0.0109	1.6076	Expansion negative decoupling
2012	0.0027	0.0963	0.0275	Weak decoupling
2013	0.0210	0.0709	0.2961	Weak decoupling
2014	-0.0278	0.0025	-11.0527	Strong decoupling
2015	0.0150	0.0305	0.4916	Weak decoupling
2016	0.0106	0.0243	0.4368	Weak decoupling
2017	-0.0160	-0.0392	0.4072	Weak negative decoupling
2018	-0.0363	0.0182	-1.9951	Weak decoupling
2019	0.0601	0.1638	0.3667	Weak decoupling
2020	-0.0097	0.1306	-0.0744	Strong decoupling
2021	-0.0073	0.0741	-0.0991	Strong decoupling

and fertilizer usage, coupled with enhanced efficiency in carbon emissions, demonstrates a commitment to a green and low-carbon agricultural development path.

Forecasting and Peak Analysis of Agricultural Carbon Emissions

This study employed the Gray Prediction Model GM (1,1) to predict agricultural carbon emissions in Kaifeng city from 2010 to 2030. The predicted values were compared with the actual data available from 2010 to 2021, and the results were analyzed using the Ratio of grade and residual test, as presented in Table 4. The Ratio of grade was calculated to assess the goodness-of-fit between the predicted and actual data. Our findings indicate that the value of the Ratio of grade falls within the interval $(e^{-\frac{2}{n+1}}, e^{\frac{2}{n+2}})$, suggesting that the GM (1,1) model is suitable for this study and provides a reliable prediction.

Furthermore, the residual test was conducted to evaluate the accuracy of the model. The $\varepsilon(k)$ values obtained from the residual test were found to be less than 0.1. This indicates that the model fits the data well and has the potential to make more precise predictions. Overall, the application of the GM (1,1) model demonstrates its effectiveness in predicting agricultural carbon emissions for Kaifeng city. The satisfactory Ratio of grade falling within interval A and the small $\varepsilon(k)$ values validate the model's accuracy and reliability.

Table 5 presents the results of using the gray prediction model GM (1,1) to calculate carbon emissions from Kaifeng farmland ecosystems from 2022 to 2030.

Table 4. Measurement and testing of carbon emissions from farmland ecosystem in Kaifeng city.

Year	Original value /10^4 t	Predicted value /10^4 t	Residual examination
2010	135.84	135.84	0.0000
2011	138.19	138.74	-0.0039
2012	138.62	138.80	-0.0013
2013	141.37	138.87	0.0177
2014	137.85	138.93	-0.0078
2015	139.97	139.00	0.0069
2016	141.53	139.06	0.0174
2017	139.33	139.19	0.0015
2018	134.78	139.26	-0.0327
2019	142.79	139.32	0.0248
2020	141.59	139.39	0.0160
2021	139.62	139.46	0.0017

The data shows a gradual increase in carbon emissions during this period, ranging from 1,394,600 t in 2022 to 1,398,800 t in 2030. Compared to the previous year, a rise of 0.26% in carbon emissions was observed in 2030. Although the measurement indicates an upward trend, it is important to note that the rate of increase has been decreasing year by year. This is in contrast to the period from 2011 to 2020, when carbon emissions experienced a rise of 2.46%. The slowing upward trend suggests the need for focused efforts to reduce carbon emissions while safeguarding agricultural production in Kaifeng city.

As a significant agricultural area in Henan province, Kaifeng city's approach to carbon reduction will be centered on agricultural development. In pursuit of this objective, the city has implemented various programs. For instance, the Kaifeng city 2021 Agricultural and Rural Pollution Control War Implementation Plan proposes several measures. These include reducing the use of fertilizers and pesticides, promoting research and development of new fertilizer products, and increasing the utilization of new nitrogen fertilizers like slow-release fertilizers. These initiatives aim to achieve the objective of reducing carbon emissions while ensuring sustainable agricultural practices.

It is important to recognize that carbon emissions in the agricultural sector are influenced by various factors, including local policies and other contextual aspects [5]. These factors can cause significant variations in emissions levels during different periods.

The forecast indicated a gradual increase in carbon emissions within the farmland ecosystem of Kaifeng city in the foreseeable future. Nevertheless, it should be noted that numerous factors influence carbon emissions in the farmland ecosystem, and policy changes often significantly impact emission levels. Therefore, recent years' data provides more accurate results due to its proximity to the current environmental landscape and policy frameworks. Considering the data obtained from 2019 to 2021, the projected carbon emissions for the years 2022 to 2030 demonstrate a downward trend. By 2030, the carbon emissions in the farmland ecosystem of Kaifeng city are expected to decrease to 1.229 million tons, representing a reduction of 129,200 t compared to the emissions recorded in 2010. These findings suggest positive progress in mitigating carbon emissions within the farmland ecosystem of Kaifeng city.

Conclusions

Farmland ecosystems play a crucial role in shaping global ecological dynamics. They contribute to greenhouse gas emissions and possess a remarkable capacity for carbon sequestration. Hence, it is imperative to prioritize the control of carbon emissions within farmland ecosystems while striving for low-carbon and environmentally sustainable agricultural practices. Based on the research of this article, the following key conclusions and suggestions were drawn.

(1) During the period from 2010 to 2021, the carbon emissions of the farmland ecosystem in Kaifeng city exhibited a fluctuating upward trend, with an overall increase of 9.0×10^4 t and an average annual growth rate of 0.28%. Simultaneously, the carbon emission intensity demonstrated a year-on-year decrease, declining from 0.53 in 2010 to 0.30 in 2021. Among various contributing factors, fertilizers accounted for the largest proportion, ranging from 66.5% to 71.4%. The changing trend in fertilizer usage mirrored the overall carbon emissions, indicating that the primary cause of carbon emissions in Kaifeng city's farmland ecosystem was the application of fertilizers. Consequently, reducing fertilizer usage, enhancing efficiency, and promoting the adoption of new fertilizers and pesticides have emerged as effective strategies for carbon emissions reduction. Furthermore, efforts should be made to enhance the efficacy of fertilizer application, maximizing its benefits while minimizing environmental implications. Encouraging

Table 5. Prediction of carbon emission value of farmland ecosystem in Kaifeng city (2022-2030).

Year	2022	2023	2024	2025	2026	2027	2028	2029	2030
Predicted carbon emissions (10^4t)	139.46	139.52	139.59	139.65	139.72	139.78	139.85	139.92	139.98

the adoption of environmentally friendly alternatives, such as slow-release fertilizers, can contribute to lowering carbon emissions while ensuring sustainable agricultural practices.

(2) The period from 2010 to 2021 witnessed a notable shift in the decoupling state between the farmland ecosystem and economic growth

in Kaifeng city. Initially, weak decoupling was observed during the years 2010-2017. However, this has transitioned into strong decoupling during the subsequent period of 2018-2021. This transformation signifies that green and low-carbon agricultural development in Kaifeng city has yielded phased results, successfully containing agricultural carbon emissions. The transition from weak to strong decoupling highlights the positive progress in aligning economic growth with environmental sustainability objectives. The implementation of effective policies, technological advancements, and sustainable farming practices have contributed to reducing the carbon footprint associated with agricultural activities in Kaifeng city. The attainment of strong decoupling indicates that agricultural practices and economic growth in Kaifeng city have become less reliant on carbon-intensive processes, leading to reduced carbon emissions within the farmland ecosystem, and it demonstrates the successful integration of economic prosperity and environmental protection.

In conclusion, utilizing the grey prediction model GM (1,1), the projected carbon emissions of the farmland ecosystem in Kaifeng city from 2022 to 2030 indicated a slow growth trend. Nonetheless, recent data suggest a decline in carbon emissions by 2030 compared to the levels recorded in 2010. These findings underscore the significance of persistent efforts and policy interventions to reach sustainable targets for reducing carbon emissions within Kaifeng city's farmland ecosystem. Looking ahead, continuous commitment and consistent actions are essential to uphold this decreasing trend and accomplish long-term sustainability objectives. To further mitigate carbon emissions in the upcoming years, it is imperative to concentrate on enhancing agricultural practices, embracing advanced technologies, advocating precision farming techniques, and implementing environmentally friendly fertilizers and pesticides.

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Conflict of Interest

The authors declare no conflicts of interest.

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