China’s CO₂ Emissions: A Thorough Analysis of Spatiotemporal Characteristics and Sustainable Policy from the Agricultural Land-Use Perspective during 1995–2020

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Abstract: Agricultural land use is an important source of CO₂ emissions. Therefore, taking the CO₂ emissions of China’s agricultural land use during 1995–2020 as a case, we firstly calculated its composition and analyzed the spatiotemporal evolution characteristics. Then, the Tapio decoupling model and logarithmic mean Divisia index (LMDI) were, respectively, used to identify the decoupling relationship between the CO₂ emission change and economic growth, and analyze the driving factors for CO₂ emissions. (1) The CO₂ emissions of China’s agricultural land use were composed of two main phases (fluctuating growth phase (1995–2015) and rapid decline phase (2016–2020)). The total CO₂ emissions exhibited a non-equilibrium spatial distribution. The inter-provincial CO₂ emissions differences first expanded and then shrunk, but the inter-provincial differences of CO₂ emissions intensity continuously decreased. (2) The total CO₂ emissions of China’s agricultural land use increased from 50.443 Mt in 1995 to 79.187 Mt in 2020, with an average annual growth rate of 1.82%. Fertilizer, agricultural diesel and agricultural (plastic) film were the main sources of anthropogenic agricultural-land-use CO₂ emissions. Controlling the use of fertilizer and agricultural diesel and improving the utilization efficiency of agricultural (plastic) film could be an effective way to reduce CO₂ emissions. (3) The Tapio decoupling relationship between the CO₂ emission change and economic growth was a weak decoupling state during 1995–2015 and a strong decoupling state during 2016–2020. This result indicates that China’s agricultural land use can be effectively controlled. (4) The agricultural economic level is the decisive factor in promoting CO₂ emissions increase, and its cumulative contribution was 476.09%. Inversely, the CO₂ emission intensity, agricultural structure and agricultural labor force were three key factors, with cumulative contributions of −189.51%, −16.86% and −169.72%, respectively. Collectively, based on the findings obtained from the present research, we have proposed some suggestions to promote the sustainable use of agriculture lands in China.

Keywords: agricultural land use; CO₂ emissions; spatiotemporal evolution; Tapio decoupling; LMDI; China

1. Introduction

The 21st century has seen a world full of catastrophic issues such as natural resource depletion, environmental deterioration and climate change [1]. Economic development leads to larger proportion of resource consumption, which boosts CO₂ emissions in return. During the general debate at the 75th session of the United Nations General Assembly held in 2020, China pledged to achieve carbon peaking by 2030 and carbon neutrality by 2060 [2]. According to the Intergovernmental Panel on Climate Change (IPCC), global temperature is expected to rise by 1.4 to 5.8 °C from 1990 to 2100 [3]. The Earth is undergoing changes brought by global warming, including melting glaciers, food chain disruption, and the spread of physiological disease, just to name a few. As a result, societal activities and
human survival are threatened. To offset the negative impacts of global warming, many countries have taken measures, among which CO$_2$ emission reduction is at the top of the agenda [4,5]. Despite this, global efforts to reduce CO$_2$ emissions have been modest, and CO$_2$ emissions are still increasing [6,7]. As a result, reducing these CO$_2$ emissions has become a hot topic worldwide.

Agricultural land use, a common socio-economic activity, has been a major factor in CO$_2$ emissions. Statistics demonstrate that agricultural CO$_2$ emissions account for 30% of the total emissions by human society, among which China, a major agricultural country, contributes 10–12% of agricultural CO$_2$ emissions alone [8–11]. Given this fact, it is crucial for China to deliver on our commitment of lower or zero CO$_2$ emissions. For our response to climate change, CO$_2$ emission reduction in the agricultural sector is pivotal if we are to boost our economy and sustain agricultural development. Due to such circumstances, the academic community has fixated its attention on agricultural land use, which has given rise to fruitful research. To reduce the amount of CO$_2$ emissions, the IPCC proposed a CO$_2$ emission coefficient method calculated by the consumption amounts of fuel, the oxidation ratio and the corresponding carbon coefficient. Scholars such as Yu et al. [12] used this formula to estimate CO$_2$ emissions and the carbon intensity of agricultural land in China. Wang et al. [13] also applied this CO$_2$ emission coefficient method to calculate the CO$_2$ emissions of agricultural land in the Loess Plateau with the aid of RS (remote sensing) and GIS (geographic information system) technology.

Some scholars have found that China’s agricultural activities emit more CO$_2$ compared with other countries [14,15]. However, arguments on the relationship between the CO$_2$ emissions of agricultural land use and economic growth remain are still lacking [16–18]. In this effort, the EKC (Environmental Kuznets Curve) relationship and Tapio decoupling model had been applied to verify this relationship. Cui et al. [19] found an ‘inverted U-shaped’ relationship between them. Namely, with economic development, the value of the environmental degradation indicator increased first, and then the indicator decreased after the unit of CO$_2$ emissions developed further. Zhang et al. [20] emphasized that economic growth needs to diminish its dependence on agricultural CO$_2$ emissions so as to achieve a comprehensive upgrade. Notwithstanding, the adoption of the Taipo decoupling method does not reflect a sufficient and detailed spatial evolution analysis [21–24].

On the other hand, current methods such as logarithmic mean Divisia index (LMDI) models [25–27], the STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) equation [28,29], the Kaya identity [30] and the EKC model [31] are important research tools to explore the influencing factors of agricultural-land-use CO$_2$ emissions. For example, Bennetzen et al. [32] confirmed that agricultural CO$_2$ emissions can only be limited to a certain level from the perspective of global agricultural production. Wu argues that the population, urbanization rate, agricultural science and technology and other human factors are the driving forces of agricultural CO$_2$ emissions [33]. Rosa suggested that enhancing the STIRPAT model through ecological resilience measures could better represent the pressing importance of environmental impacts [34]. However, we believe that the LMDI model can better identify its influencing factors. The present LMDI model is applied to break down agricultural CO$_2$ emissions into factors including efficiency, structure, economic development and workforce size [35]. For instance, Jiang et al. focus on the driving mechanisms of the agricultural carbon effect and agricultural CO$_2$ emission equality [36]. Moreover, Chen et al. believe that efficiency, structure and workforce size [37] are inhibitors of agricultural CO$_2$ emissions, while agricultural economic development is a promotor [38,39]. Relevant documents are listed in Table 1.
Table 1. Relevant Studies of CO\textsubscript{2} emissions from agricultural land use.

<table>
<thead>
<tr>
<th>Period and Area</th>
<th>Subject</th>
<th>Method</th>
<th>Limitations and Innovation</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995–2017 China and its 31 provinces</td>
<td>Agricultural land CO\textsubscript{2} emissions</td>
<td>Theil index</td>
<td>Spatiotemporal differences in carbon intensity and per capita CO\textsubscript{2} emissions were analyzed, without considering their drivers.</td>
<td>[18]</td>
</tr>
<tr>
<td>2004–2009 Suzhou City</td>
<td>Agricultural CO\textsubscript{2} emissions</td>
<td>Kaya identity</td>
<td>The impact effects of the driving factors were obtained, lacking specific shares.</td>
<td>[40]</td>
</tr>
<tr>
<td>2008–2017 Fujian province</td>
<td>Agricultural CO\textsubscript{2} emissions</td>
<td>The ordered weighted aggregation and geographically and temporally weighted regression</td>
<td>These studies only analyze the changes in CO\textsubscript{2} emissions in individual provinces and cannot make policy recommendations from a national perspective.</td>
<td>[41]</td>
</tr>
<tr>
<td>1995–2014 Hebei province</td>
<td>Agricultural CO\textsubscript{2} emissions</td>
<td>Kaya identity, STIRPAT and ridge regression</td>
<td></td>
<td>[19]</td>
</tr>
<tr>
<td>2000–2010 Zhejiang Province</td>
<td>Regional Land-Use CO\textsubscript{2} emissions</td>
<td>The Grossman decomposition model</td>
<td></td>
<td>[42]</td>
</tr>
<tr>
<td>2008–2017 China and its 30 provinces</td>
<td>Agricultural CO\textsubscript{2} emissions</td>
<td>Tapio decoupling and LMDI</td>
<td>These studies focused on the analysis of driving factors, with little attention to the Spatiotemporal evolution of CO\textsubscript{2} emissions change.</td>
<td>[43]</td>
</tr>
<tr>
<td>1961–2017 Global and regional</td>
<td>Land-use emissions</td>
<td>Kaya identity</td>
<td></td>
<td>[44]</td>
</tr>
<tr>
<td>1988–2019 Turkey</td>
<td>Agricultural land CO\textsubscript{2} emissions</td>
<td>The autoregressive distributed lag empirical approach</td>
<td></td>
<td>[45]</td>
</tr>
<tr>
<td>1980–2015 India</td>
<td>Non-CO\textsubscript{2} emission from cropland based agricultural activities</td>
<td>LMDI</td>
<td></td>
<td>[46]</td>
</tr>
<tr>
<td>1990–2018 Jiangsu Province</td>
<td>Agricultural CO\textsubscript{2} emissions</td>
<td>STIRPAT</td>
<td></td>
<td>[47]</td>
</tr>
<tr>
<td>1995–2020 China and its 31 provinces</td>
<td>Agricultural land CO\textsubscript{2} emissions</td>
<td>Kernel density estimation, Tapio decoupling and LMDI</td>
<td>This paper, firstly, combines Kernel density, Tapio decoupling and LMDI to reveal spatiotemporal dynamics characteristics, Tapio decoupling relationship and drivers of agricultural-land-use CO\textsubscript{2} emissions from a national perspective, then gives policy implications to reduce CO\textsubscript{2} emissions.</td>
<td>This paper</td>
</tr>
</tbody>
</table>

The abovementioned research results are undoubtedly significant for improving the agricultural-land-use CO\textsubscript{2} emission accounting system and enriching research in this field. However, the common feature of studies from the above literature is that they seldom combine the decoupling relationship (the relationship between agricultural-land-use CO\textsubscript{2} emissions and economic development), Kernel density estimates and driver analysis from a national perspective. Therefore, the previous studies only reflect part of the correlation between CO\textsubscript{2} emission change and economic growth. On top of that, in view of space-time changes and their contributors, targeted suggestions are missing. At present, agricultural-land-use CO\textsubscript{2} emissions in China are still at a high level. A systematic analysis of the spatial variation of agricultural-land-use CO\textsubscript{2} emissions (at the provincial level) and its driving factors in China is of great practical importance to promote agricultural-land-use efficiency and sustainable agricultural development. To fill that blank and promote the efficiency of agricultural land use, it is crucial to analyze the spatiotemporal differences in agricultural-land-use CO\textsubscript{2} emissions in China and their influencing factors. So, we are the first to analyze the spatial and temporal characteristics of CO\textsubscript{2} emissions, decoupling relationships and their drivers in combination, and to propose targeted policy implications for reducing CO\textsubscript{2} emissions from agricultural land use. A mathematical model is built to calculate the volume of CO\textsubscript{2} emissions while categorizing the features of spatiotemporal evolution. Aside from adopting the Tapio model to discuss the decoupling relationship between the CO\textsubscript{2} emission changes and economic growth, this paper also uses the LMDI model to analyze the drivers of CO\textsubscript{2} emissions. In addition, a review of agricultural-land-use CO\textsubscript{2} emission levels in China could facilitate the sustainable use of agricultural land resources. China’s expertise on CO\textsubscript{2} reduction will serve as guidance for other developing countries for sustainable agricultural land use within a rapid urbanization process.
2. Materials and Methods

2.1. Data Description

Considering the inconsistency in the statistical figures of Hong Kong, Macau and Taiwan, the research area is composed of 31 provinces and cities, autonomous regions and municipalities directly under the central government excluding Taiwan, Hong Kong and Macau. The time period of this study spans from 1995 to 2020 due to data availability and statistical lag. Data incited includes China’s agricultural output value (output value of planting industry), the total output value of agriculture, forestry, livestock and sideline fishery figures, agricultural fertilizer use, pesticide use, agricultural (plastic) film use, agricultural diesel use, crop sown area, effective irrigated area and agricultural-labor-force population, all of which can be traced back to the China Statistical Yearbook, China Agricultural Statistical Yearbook (1995–2020) and provincial statistical yearbooks. Data concerning CO$_2$ emission factors such as fertilizer, pesticides, film, irrigation, agricultural diesel and land plowing can be found in the United Nations Intergovernmental Panel on Climate Change (IPCC) and the related literature. The detailed CO$_2$ emission coefficients are shown in Appendix A Table A1. As for terminologies, agricultural-land-use CO$_2$ emissions and agricultural output in this paper are specified as anthropogenic CO$_2$ emissions and plantation output, respectively. Moreover, 2015 was designated as the base year to calculate the agricultural output value and the total output value of agriculture, forestry, animal husbandry and fishery due to the incomparability of the overall prices.

2.2. Empirical Methods

2.2.1. Carbon Emission and Carbon Intensity Calculation Methods

Based on previous studies and China’s current situation, the paper calculates the CO$_2$ emissions of China’s agricultural land use by the CO$_2$ emission coefficient method:

\[ ET = \sum ET_i = \sum T_i \times \delta_i \]

where ET represents the total CO$_2$ emissions of agricultural land use (Mt); $i$ represents the type of carbon source; $T_i$ represents the amount of class i carbon source; $\delta_i$ represents the CO$_2$ emissions coefficient of the Class i carbon source.

In addition, the carbon intensity is calculated by the following formula:

\[ E_a = \frac{ET}{F_f} \]

where $E_a$ denotes carbon intensity (t/10$^4$ CNY) and $F_f$ denotes plantation output (10$^{11}$ CNY).

2.2.2. Kernel Density Estimation

Kernel density estimation is a common nonparametric estimation method used to demonstrate the dynamic distribution of data [48]. It emphasizes the use of the kernel density curve to capture the distribution characteristics of the data. It can effectively avoid the subjectivity of function settings in parameter estimation, thereby improving the authenticity of the estimation results [49]. This strength makes the kernel density estimation a typical method to measure regional differences [50]. The formula uses $f(x)$ to represent the density function of variable $x$, and the probability density of $x$ can be explained with

\[ f(x) = \frac{1}{Nh} \sum_{i=1}^{N} K \left[ \frac{x_i - \bar{x}}{h} \right] \]

where $h$ is the bandwidth; $N$ is the number of observations; $K(\cdot)$ is the kernel function; $x_i$ is the independent but homogeneous variable; $\bar{x}$ is the mean value.

The right bandwidth and kernel function is essential to obtain a fit result. If the data feature and kernel function are designated, the result will be a larger bandwidth, smoother density function curve and lower accuracy of estimation or vice versa [51].
The Epanechnikov kernel function was applied in this study. The kernel density distribution of agricultural-land-use CO₂ emissions in major years was visualized through Eviews software (Eviews 10.0, IHS Global Inc., Irvine, CA, USA). Since non-parametric estimation has no definite function expression, graphical comparison is normally used to examine its distribution variation [51]. We can describe the dynamic evolution of regional differences on agricultural-land-use CO₂ emissions by observing the position, shape and extensibility of the density function (Table 2).

Table 2. Correlation between density curve and degree of differences.

<table>
<thead>
<tr>
<th>Degree of Disparity</th>
<th>Peak Height</th>
<th>Peak Width</th>
<th>Peak Point</th>
<th>Peak Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Increase</td>
<td>Flat</td>
<td>Distensible</td>
<td>Move left</td>
<td>Increase</td>
</tr>
<tr>
<td>Decrease</td>
<td>Steep</td>
<td>Narrowed</td>
<td>Move right</td>
<td>Reduce</td>
</tr>
</tbody>
</table>

2.2.3. Tapio Decoupling Model

In 1993, OECD created the concept of “decoupling”, broken down into absolute and relative decoupling, to describe the relationship between economic growth and environmental stress [52]. Absolute decoupling means economic growth but a level or decreasing resource consumption. Relative decoupling means that economic growth outruns resource consumption. However, there are obvious flaws in OECD’s decoupling model, based on which Tapio proposed “decoupling elasticity” in 2005 [53]. Decoupling elasticity relates the ratio of economic growth to the degree of CO₂ emission change, a concept that can better reflect the relationship between the change in CO₂ emissions and economic growth. The formula is shown below:

\[ e = \frac{\Delta ET}{ET} \frac{ET}{ET_0} \]

where \( e \) represents decoupling elasticity (the ratio of economic growth to the degree of CO₂ emission change); \( ET \) represents agricultural-land-use CO₂ emissions (Mt); \( \Delta ET \) represents the variation in agricultural-land-use CO₂ emissions (Mt); \( F_0 \) represents the output value of the planting industry (10¹¹ CNY); \( F f \) represents the increased output value of the planting industry (10¹¹ CNY).

2.2.4. LMDI Decomposition

We used the LMDI method to construct a driver model of agricultural-land-use CO₂ emissions in China. The model, proposed by Ang [54], explores the effect of each factor on the total index. It can produce a unique result featuring full decomposition and without any residuals. In addition, it provides eight effective strategies to deal with the question of the zero-value [32]. Given the advantages, the LMDI method has been deemed as perfect and, therefore, widely used by many researchers [55, 56]. The full formula extends as follows:

\[ ET = \frac{ET}{F f} \times \frac{F f}{G g} \times \frac{G g}{L b} \times L z \]

Let \( E_a = \frac{ET}{F f}, H_e = \frac{F f}{G g}, K_o = \frac{G g}{L b} \), and Equation (8) can be written as:

\[ ET = E_a \times H_e \times K_o \times L z \]

where \( ET, F f, G g, \) and \( L b \) represent the total CO₂ emissions of agricultural land use (Mt), the plantation output (10¹¹ CNY), the total output values of agriculture, forestry, animal husbandry and fishery (10¹¹ CNY) and the agricultural-labor-force population (10⁶ persons), respectively. \( E_a, H_e, K_o \) and \( L z \) denote the carbon intensity factor, agricultural structure factor, agricultural economic level factor and agricultural labor factor, respectively.
Based on the above equation, \( E_{t0} \) and \( E_{t1} \) are set as the baseline and target periods of agricultural-land-use \( \text{CO}_2 \) emissions. Hence, the change in total agricultural-land-use \( \text{CO}_2 \) emissions (\( E_{\text{tot}} \)) can be explained with:

\[
\Delta E_{\text{tot}} = E_{t1} - E_{t0} = \Delta E_a + \Delta H_e + \Delta K_o + \Delta L_z
\]

(7)

where \( E_{t1} \) represents the total \( \text{CO}_2 \) emissions during the \( t \) period (Mt); \( E_{t0} \) represents the initial total \( \text{CO}_2 \) emissions (Mt); \( \Delta E_a \) represents the \( \text{CO}_2 \) emission intensity; \( \Delta H_e \) represents the agricultural structure; \( \Delta K_o \) represents the agricultural economic level; \( \Delta L_z \) represents the agricultural labor force contributing to agricultural-land-use \( \text{CO}_2 \) emissions in China. The full formulae of drivers extend as:

\[
\Delta E_a = \frac{E_{t1} - E_{t0}}{\ln E_{t1} - \ln E_{t0}} \times \ln \frac{E_{a1}}{E_{a0}}
\]

(8)

\[
\Delta H_e = \frac{E_{t1} - E_{t0}}{\ln E_{t1} - \ln E_{t0}} \times \ln \frac{H_{et}}{H_{e0}}
\]

(9)

\[
\Delta K_o = \frac{E_{t1} - E_{t0}}{\ln E_{t1} - \ln E_{t0}} \times \ln \frac{K_{ot}}{K_{o0}}
\]

(10)

\[
\Delta L_z = \frac{E_{t1} - E_{t0}}{\ln E_{t1} - \ln E_{t0}} \times \ln \frac{L_{zt}}{L_{z0}}
\]

(11)

3. Results and Analysis

3.1. Results from Agricultural Land Use

3.1.1. Temporal Characteristics

According to the calculation, China’s agricultural land use changed from 50.443 Mt to 79.187 Mt during 1995–2020 (Figure 1), with an annual growth of 1.82%. The figure demonstrates that the curve rose first and then declined, constituting a fluctuating growth (1995–2015) stage and a rapid decline (2016–2020) stage. At first, China’s agricultural land use grew from 50.443 Mt in 1995 to 91.414 Mt in 2015, with an annual growth of 3.02%. Then, it decreased from 90.413 Mt in 2016 to 79.187 Mt in 2020 instead, with an annual fall of -3.26%. Judging from Figure 1, the total agricultural land use almost doubled, but the growth rate exhibited a downward trend. A large amount of agricultural land use means greater efforts in agricultural-land-use reduction in China. However, the declining growth rate indicates that the philosophy of high-quality and low-carbon development was fully implemented. Additionally, the way agricultural land resource is used has been transforming from high-carbon to low-carbon. Total agricultural land use peaks in 2015 when the establishment of a pilot zone for national ecological civilization was proposed. In this zone, the use of chemical fertilizers and pesticides shrank sharply for low-carbon agriculture, a move that boosted vitality for a green and ecological civilization. Meanwhile, carbon intensity decreased from 0.217 t/10^4 CNY in 1995 to 0.112 t/10^4 CNY in 2020 (Figure 1), showing a downward trend. This change signifies that the concepts of low-carbon development from the 19th CPC National Congress have been put into practice in the agriculture sector.
As shown in Figure 1, the agricultural output increased from $232.150 \times 10^{11}$ CNY in 1995 to $709.548 \times 10^{11}$ CNY in 2020, up by 4.56%, which indicates sound agricultural development and steady growth. The change derives from the effective measures of the Chinese government: modern and intensive agriculture building, better agricultural infrastructure, subsidy policies, and improved yield rate. It can be observed that the growth rate fluctuated between 1995 and 2013, but stayed stable between 2013 and 2020, a sign of high-quality and sustainable agricultural sector. Notably, the growth rate of agricultural output between 2019 and 2020 slowed down, which reflects the negative impact of COVID-19 on the agricultural sector.

### 3.1.2. Spatial Evolution

This research studied 1995, 2005, 2015 and 2020 to highlight the spatial and temporal differences in agricultural-land-use CO$_2$ emissions in China from 1995 to 2020. According to the calculation of agricultural-land-use CO$_2$ emissions, the CO$_2$ emissions values of each province ranged from 0 to 9 (Mt). For comparison, provinces with similar CO$_2$ emissions values were categorized into three groups, namely, low CO$_2$ emission (0–3), medium CO$_2$ emission (3–6) and high CO$_2$ emission (6–9), which is a better method to reveal the temporal and spatial differences of agricultural-land-use CO$_2$ emissions [17]. Figure 2 demonstrates the spatial-temporal evolution trend of agricultural-land-use CO$_2$ emissions in China’s 31 provinces. The agricultural-land-use CO$_2$ emissions changed significantly from 1995 to 2020. Specifically, a number of low-carbon provinces demonstrated an inverted V-shaped trend, but that of medium-carbon provinces and high-carbon provinces demonstrated a V-shaped trend. In 1995, there was no province with high CO$_2$ emissions. However, Henan, Shandong and Hebei joined the high-CO$_2$-emission rank in 2015 while Hebei was removed in 2020. The number of medium-carbon provinces increased from 5 in 1995 to 11 in 2020. The number of low-carbon provinces first reduced from 26 in 1995 to 16 in 2015 but then increased to 18 in 2020.
In terms of spatial evolution, the inter-provincial differences in China’s agricultural-land-use CO₂ emissions widened from 1995 to 2015 and narrowed from 2015 to 2020 (Figure 3), manifested by non-equilibrium spatial distribution (i.e., there are spatial differences in carbon emission levels), a finding consistent with that of previous studies [35]. From 1995 to 2015, the middle- and high-carbon areas were mainly in the eastern and central part of China, while the low-carbon areas mainly in Inner Mongolia, Qinghai and Tibet. Fundamentally, the eastern and central regions are suitable for crop cultivation, which demonstrates the close relationship between the climate and the natural condition.

Figure 2. Spatial distribution of CO₂ emissions from agricultural land use in China. (a) 1995; (b) 2005; (c) 2015; (d) 2020.

Figure 3. (a) The kernel density of the CO₂ emissions from agricultural land use; and (b) the kernel density of the carbon intensity from agricultural land use.
The pronounced spatial-temporal variation in CO₂ emissions in Henan, Xinjiang and Inner Mongolia was represented by large increments in CO₂ emissions, measuring 3.877 Mt in Henan, 3.112 Mt in Xinjiang and 2.226 Mt in Inner Mongolia. The high CO₂ emissions of the Henan, Shandong and Hebei provinces suggest that major agricultural provinces are the main source of CO₂ emissions. In these provinces, agricultural development is dominated by traditional methods such as high-input and high-emission development models. From 1995 to 2020, spatial and temporal differences in CO₂ emissions in Xinjiang were prominent. Agricultural-land-use CO₂ emissions in Xinjiang grew by 5.22% on average, an increase that can be accounted for by the Western Development Strategy between 2001 and 2012. During this period, Xinjiang had seen land reclaimed for crop growing, new crop varieties, the introduction of high-quality fertilizers and pesticides and agricultural mechanization enhancements. As the result, the regional economy developed significantly.

To reveal the dynamic evolution characteristics of regional differences in agricultural-land-use CO₂ emissions in China, we formed a kernel density curve based on each province’s agricultural-land-use CO₂ emissions from 1995 to 2020. Judging from Figure 3, the distribution of agricultural-land-use CO₂ emissions in 31 provinces had three characteristics. First, values increased first and then decreased at a certain point. The direction change in the curve demonstrates this feature fairly. This result is consistent with the finding of Li et al. [57]. Second, there were expanding provincial differences in agricultural-land-use CO₂ emissions. From 1995 to 2015, the peak became lower and two sides of the curve were flattened. Third, there were narrowing inter-provincial differences. The peak was higher from 2015 to 2020.

According to the calculation, each province’s carbon intensity varied between 0 and 0.31 (t/10⁴ CNY). The paper classifies them into low-intensity [0–0.10], medium-intensity [0.10–0.20] and high-intensity [0.20–0.31] so as to clearly reflect the spatial-temporal differences (Figure 4). From 1995 to 2020, the carbon intensity of China’s agricultural land use changed markedly. The number of high-intensity provinces shrank from 19 in 1995 to 0 in 2020. The ten medium-intensity provinces increased to 25 from 1995 to 2015, then reduced to 22 in 2020. The number of low-intensity provinces rose from 2 in 1995 to 9 in 2020. Specifically, the high-intensity areas were mainly distributed in coastal, central and developed areas. However, these inter-provincial differences narrowed between 2005 and 2020. This change resulted from the decreasing carbon intensity due to improved agricultural science and technology. Among all provinces, Inner Mongolia witnessed a noticeable change in carbon intensity. The reason can be traced back to China’s Western Development Strategy between 2001 and 2012, which energized the local economy. Overall, the carbon intensity of agricultural land use in 31 provinces has decreased, and in inter-provincial differences has narrowed.

In this paper, the dynamic evolution characteristics of inter-regional agricultural-land-use carbon intensity from 1995 to 2020 were revealed using the kernel-density curve. Judging from Figure 3, the distribution of agricultural-land-use carbon intensity in 31 provinces had three characteristics. First, a decreasing carbon intensity, which can be testified by the leftward curve. Second, narrowing inter-provincial differences, as the peak of agricultural-land-use CO₂ emissions got higher and the two ends of the curve shrank.
Figure 4. Spatial distribution of carbon intensity of agricultural land use in China. (a) 1995; (b) 2005; (c) 2015; and (d) 2020.

3.1.3. Characteristics of Carbon Sources

In Figure 1, chemical fertilizer stands out as the largest carbon source of agricultural-land-use CO$_2$ emissions, accounting for 60.23% of the total, a finding the same as that of Yang et al. [58]. From 1995 to 2015, fertilizer-generated CO$_2$ emissions rose from 32.187 Mt to 53.938 Mt, up by 2.61% year on year. However, from 2015 to 2020, it reduced from 53.938 Mt to 47.027 Mt, down by 2.70% year on year. Obviously, fertilizers are a major factor in agricultural-land-use CO$_2$ emissions and carbon intensity.

Agricultural diesel represented the second-largest source of agricultural-land-use CO$_2$ emissions, taking up 14.10% of the total (Figure 1). Agricultural diesel-generated CO$_2$ emissions first rose, then declined and then peaked in 2015 with 3.026 Mt. Specifically, from 1995 to 2015, they increased from 6.450 Mt to 13.026 Mt, up by 3.58% year on year. However, from 2015 to 2020, they decreased from 13.026 Mt to 10.957 Mt, down by 3.40% year on year. This result indicates a gradual slowdown in the rate of growth of CO$_2$ emissions, which have tended to decline steadily in recent years. This is due to the development of agricultural technology, the increased mechanization of China’s agriculture and the increase in the multiple-cropping index of agricultural land. The steady decline in recent years can be accounted for by refined agricultural technology, agricultural mechanization and the multi-cropping index.

Agricultural (plastic) film was the third largest source, accounting for 13.01% of the total (Figure 1). Additionally, pesticides and irrigation were other sources, accounting for 9.94% and 2%. CO$_2$ emissions generated by agricultural (plastic) film and pesticides peaked in 2015. This phenomenon demonstrates that the National Ecological Civilization Pilot Area effectively curbed the use of high-carbon agricultural materials such as fertilizer, diesel, agricultural (plastic) film and pesticides.

The percentages of the others were so small that they can be almost ignored. However, it should be noted that land-plowing accounts for 0.68% of the total CO$_2$ emissions, showing
an upward trend. The gradual increase in CO\textsubscript{2} emissions indicates a growing multiple-cropping index. From 2015 to 2020, the total CO\textsubscript{2} emissions decreased year on year as the result of low-carbon development policy in the agricultural sector. Therefore, it is feasible to apply clean technologies in agricultural production nationwide without the use of pesticide and fertilizer.

3.2. Decoupling Elasticity

A decoupling model of agricultural-land-use CO\textsubscript{2} emissions and economic development can be drawn up based on the decoupling elasticity values. In the decoupling index system, 0, 0.8 and 1.2 are the critical values to divide decoupling intervals between the CO\textsubscript{2} emission change and economic growth. Decoupling status includes decoupling, coupling, and negative decoupling. Additionally, the detailed categorization is demonstrated in Appendix A Table A2. Among all the statuses, strong decoupling is the optimal, because it represents a sustained agricultural output increase with minimal CO\textsubscript{2} emissions. By contrast, strong negative decoupling is the worst, for it represents an agricultural output decrease with a high amount of CO\textsubscript{2} emissions. Weak decoupling indicates that agricultural production is increasing and carbon emissions are also increasing. Table 3 demonstrates the decoupling elasticity of China’s agricultural-land-use CO\textsubscript{2} emissions from 1995–2020 calculated with Equation (7).

Table 3. Decoupling elasticity between economic growth and agricultural-land-use CO\textsubscript{2} emissions from 1995 to 2020.

<table>
<thead>
<tr>
<th>Periods</th>
<th>(\Delta C/C)</th>
<th>(\Delta F/F_f)</th>
<th>(e)</th>
<th>Decoupling status</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995–1996</td>
<td>0.068</td>
<td>0.140</td>
<td>0.483</td>
<td>WD</td>
</tr>
<tr>
<td>1996–1997</td>
<td>0.046</td>
<td>0.157</td>
<td>0.296</td>
<td>WD</td>
</tr>
<tr>
<td>1997–1998</td>
<td>0.030</td>
<td>0.092</td>
<td>0.331</td>
<td>WD</td>
</tr>
<tr>
<td>1998–1999</td>
<td>0.022</td>
<td>0.106</td>
<td>0.208</td>
<td>WD</td>
</tr>
<tr>
<td>1999–2000</td>
<td>0.012</td>
<td>0.093</td>
<td>0.126</td>
<td>WD</td>
</tr>
<tr>
<td>2000–2001</td>
<td>0.032</td>
<td>0.034</td>
<td>0.940</td>
<td>EC</td>
</tr>
<tr>
<td>2001–2002</td>
<td>0.024</td>
<td>0.080</td>
<td>0.301</td>
<td>WD</td>
</tr>
<tr>
<td>2002–2003</td>
<td>0.021</td>
<td>0.082</td>
<td>0.255</td>
<td>WD</td>
</tr>
<tr>
<td>2003–2004</td>
<td>0.061</td>
<td>0.009</td>
<td>6.965</td>
<td>END</td>
</tr>
<tr>
<td>2004–2005</td>
<td>0.034</td>
<td>0.048</td>
<td>0.230</td>
<td>WD</td>
</tr>
<tr>
<td>2005–2006</td>
<td>0.032</td>
<td>0.072</td>
<td>0.449</td>
<td>WD</td>
</tr>
<tr>
<td>2006–2007</td>
<td>0.040</td>
<td>0.084</td>
<td>0.476</td>
<td>WD</td>
</tr>
<tr>
<td>2007–2008</td>
<td>0.013</td>
<td>0.056</td>
<td>0.238</td>
<td>WD</td>
</tr>
<tr>
<td>2008–2009</td>
<td>0.031</td>
<td>0.065</td>
<td>0.475</td>
<td>WD</td>
</tr>
<tr>
<td>2009–2010</td>
<td>0.030</td>
<td>0.041</td>
<td>0.740</td>
<td>WD</td>
</tr>
<tr>
<td>2010–2011</td>
<td>0.027</td>
<td>0.045</td>
<td>0.594</td>
<td>WD</td>
</tr>
<tr>
<td>2011–2012</td>
<td>0.024</td>
<td>0.074</td>
<td>0.323</td>
<td>WD</td>
</tr>
<tr>
<td>2012–2013</td>
<td>0.017</td>
<td>0.044</td>
<td>0.376</td>
<td>WD</td>
</tr>
<tr>
<td>2013–2014</td>
<td>0.015</td>
<td>0.042</td>
<td>0.362</td>
<td>WD</td>
</tr>
<tr>
<td>2014–2015</td>
<td>0.004</td>
<td>0.046</td>
<td>0.093</td>
<td>WD</td>
</tr>
<tr>
<td>2015–2016</td>
<td>-0.011</td>
<td>0.041</td>
<td>-0.273</td>
<td>SD</td>
</tr>
<tr>
<td>2016–2017</td>
<td>-0.023</td>
<td>0.045</td>
<td>-0.515</td>
<td>SD</td>
</tr>
<tr>
<td>2017–2018</td>
<td>-0.041</td>
<td>0.039</td>
<td>-1.040</td>
<td>SD</td>
</tr>
<tr>
<td>2018–2019</td>
<td>-0.043</td>
<td>0.046</td>
<td>-0.942</td>
<td>SD</td>
</tr>
<tr>
<td>2019–2020</td>
<td>-0.028</td>
<td>0.040</td>
<td>-0.712</td>
<td>SD</td>
</tr>
</tbody>
</table>

Note: WD represents weak decoupling, END represents strong negative decoupling and SD represents strong decoupling.

From 1995 to 2020, the decoupling relationship between CO\textsubscript{2} emissions change and economic growth covers weak decoupling, growth connection, negative decoupling of expansion and strong decoupling. However, weak decoupling and strong decoupling are the main features (Table 3). It means that China’s agricultural land use has come a long way in the context of low-carbon and sustainable development. The two-stage
decoupling relationship also carried great weight. The weak decoupling stage (1995–2015), the ideal state, had a mean decoupling elasticity of 0.713. Specifically, the relatively high elasticity values between 2003 and 2004 were the result of the SARS outbreak in 2002 when agriculture suffered great losses. The strong decoupling stage (2016–2020) was the optimal because of the reduced environmental pressure with less agricultural-land-use CO₂ emissions. This change was facilitated by the national ecological protection pilot zone in 2015 when the use of agricultural products was controlled and a low-carbon development philosophy was carried out. The finding demonstrates that China’s agricultural land use can be controlled.

3.3. Analysis based on LMDI Model

The LMDI model breaks down the drivers of agricultural-land-use CO₂ emissions into factors including carbon intensity, agricultural structure, the agricultural economic development level and agricultural labor. Using Equations (8) to (14), each factor’s contribution to China’s agricultural-land-use CO₂ emissions from 1995 to 2020 were measured. The results are presented in Figure 5.

![Figure 5](image-url)  
**Figure 5.** (a) Results of the cumulative effects of agricultural-land-use CO₂-emission drivers in China from 1995 to 2020 ($\Delta E_a$, $\Delta H_e$, $\Delta K_e$, $\Delta L_z$, $\Delta E_{tot}$ represent the carbon intensity effect, agricultural structure effect, agricultural economic level effect, agricultural labor effect and total effect, respectively.) (b) The cumulative total effects during 1995–2020.

There was a 28.744 Mt change in China’s agricultural-land-use CO₂ emissions over the past 25 years. Specifically, carbon intensity, agricultural structure, agricultural economic level and agricultural labor factors contributed to −54.472 Mt, −4.848 Mt, 136.846Mt and −48.782 Mt of emissions, respectively. Additionally, their contribution percentages were −189.51%, −16.86%, 476.09%, and −169.72% (Figure 6). The carbon intensity, the agricultural structure and the agricultural labor altogether cut down 108.102 Mt of carbon emissions, with carbon intensity being the major constraint. By contrast, agricultural economic level served as a main driver of pollution with 136.846 Mt CO₂ emissions. This fact demonstrates that agricultural mechanization, especially the extensive use of machines such as tractors, etc., the multiple-crop index and the land use rate lead to a significant increase in agricultural-land-use CO₂ emissions.
From 1995 to 2020, the cumulative contribution of the agricultural economic development level led to agricultural-land-use CO₂ emissions 3.3.3. Agricultural Economic Level (Figure 6). This is mainly due to the downturn in the secondary and tertiary industries (Figure 6). This represents the agricultural structure; 

The agricultural economic level contributes the largest increase in agricultural-land-use CO₂ emissions due to carbon intensity, agricultural structure, agricultural economic level and agricultural labor. (b) The total contribution rates of each driver during the entire period.

To analyze the contribution value and rate of the four CO₂-emission drivers, this research explored their statuses in three stages: the first stage (1995–2005), the second stage (2005–2015) and the third stage (2015–2020). Consequently, the detailed results are demonstrated in Figure 7.

3.3.1. Carbon Intensity (Eₐ)

Carbon intensity refers to the CO₂ emissions per unit of GDP, an index used to assess the relationship between a country’s economic development and CO₂ emissions [59]. From 1995 to 2020, the additive effect of emission intensity in agricultural land use was
−54.472 Mt (Figure 5), and its contribution rate was −189.51% (Figure 6), representing an inhibitory effect on agricultural-land-use CO₂ emissions, a result consistent with a previous study in China [38]. Judging from the data, the inhibitory effect of agricultural-land-use efficiency was relatively stable. Despite a promoting effect in 2000–2001 and 2003–2004, the other years were characterized by a constantly reinforced inhibiting effect (Figure 5). It can be seen that the inhibitory effect of carbon intensity on CO₂ emissions of agricultural land use was continuously strengthened. In the third stage (2015–2020) especially, 29.755 Mt of CO₂ emissions were reduced, making up 11% of the total. This reduction can be accounted for by agricultural subsidies in 2016, a move that improved efficiency by encouraging the use of agricultural machines. Investment in agricultural technology has led to higher yield and productivity, which has greatly reduced CO₂ emissions. Therefore, enhancing agricultural use efficiency will be essential for agricultural-land-use CO₂ emission reduction in the long run.

3.3.2. Agricultural Structure (Hₑ)

Agricultural structure is the ratio of the total output value of planting to that of agriculture, forestry, animal husbandry and fishery. A larger ratio means a greater proportion of planting being accounted for in the agricultural sector. According to Figures 5 and 6, agricultural structure helped to reduce 4.848 Mt of CO₂ emissions, representing a total contribution of −16.86%, a finding consistent with previous studies in China [42,60]. It indicates that adjusting agricultural structure has a limited and unsteady inhibitory effect on agricultural-land-use CO₂ emissions. In the third stage (2015–2020), agricultural structure factors led to a 3.135 Mt increase in CO₂ emissions (Figure 7), representing an annual contribution rate of −13% (Table 4). In addition, this inhibiting effect was not obvious in other stages. The results indicate that agricultural structure factors have limited effects on agricultural CO₂ emission reduction. This finding reveals a stable agricultural structure. The reasons for this are China’s expansive territory, large latitude span and abundant climate diversity. In particular, the eastern and central regions have excellent natural conditions, including light, water, temperature, heat, and location, all of which have boosted agricultural development.

<table>
<thead>
<tr>
<th>Effects</th>
<th>Annual Average Contribution Rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Carbon intensity</td>
<td>1</td>
</tr>
<tr>
<td>Agricultural structure</td>
<td>15</td>
</tr>
<tr>
<td>Economic level of agriculture</td>
<td>3</td>
</tr>
<tr>
<td>Agricultural labor</td>
<td>1</td>
</tr>
</tbody>
</table>

3.3.3. Agricultural Economic Level (Kₒ)

The agricultural economic level contributes the largest increase in agricultural-land-use CO₂ emissions in China, making it a decisive factor in CO₂ emission growth, a finding consistent with previous studies [38,59]. From 1995 to 2020, the cumulative contribution of the agricultural economic development level led to agricultural-land-use CO₂ emissions reaching 136.846 Mt, with a cumulative contribution rate of 476.09%. During the second phase (2005–2015), it contributed the most emissions, generating 58.211 Mt CO₂ (Figure 7), which indicates a rapid economic development. In addition, in 2019–2020 this factor contributed 10.632 Mt CO₂ emissions (Figure 5), and the contribution rate was −473.536% (Figure 6). This is mainly due to the downturn in the secondary and tertiary industries caused by the COVID-19 outbreak, which forced labor-flowing into the primary sector, leading to the expansion of production and the significant increase in agricultural GDP. For instance, the area sown with crops expanded, inputs in agricultural supplies increased, and agricultural machines became widely used. The development of the agricultural economy
is necessary to satisfy people’s basic needs, which leads to CO₂ emission increase because of greater inputs. At the same time, the decoupled development of agricultural economy and CO₂ emission reduction in agricultural land use is a long-term task. Therefore, it will continue to be the leading factor in the foreseeable future.

3.3.4. Agricultural Labor (Lₐ)

The size of the agricultural labor force constitutes an inhibitor of agricultural-land-use CO₂ emissions, a finding consistent with a previous study [38]. As demonstrated in Figures 5 and 6, the cumulative additive effect of agricultural labor between 1995 and 2020 was −48.782 Mt and the total contribution rate was −169.72%. Apart from its promoting effect in periods such as 1996–1997, 1998–1999 and 2015–2020, agricultural labor served as an inhibitor in other years. In the first stage (1995–2005), emissions from the agricultural labor force reduced by a limited amount of 5.825 Mt CO₂. In the third stage (2015–2020), however, it reduced by 23.871 Mt CO₂ (Figure 7), making up 10% of the total (Table 4). This phenomenon was closely related with changes in agricultural labor. Economic development, industrialization and urbanization forced the labor force to leave the agricultural sector. As a result, few farmers formed a comparative advantage by owning large acres of agricultural land. Their efforts to use methods including agricultural (plastic) film, water-saving irrigation and precision farming have significantly reduced CO₂ emissions. Unfortunately, the sudden outbreak of COVID-19 disrupted the secondary and tertiary industries, leading to a surplus of labor, which greatly restricted the inhibitory effect of agricultural labor.

4. Conclusions and Policy Implications

4.1. Discussion

The findings of this study accurately reveal the spatiotemporal evolution of agricultural-land-use CO₂ emissions in China over the past 25 years, the decoupling relationship between CO₂ emission change and economic growth, and the driving factors of agricultural land use. The conclusions drawn can serve as a solid scientific foundation for the agricultural sector to formulate ecological development plans, CO₂-emission-reduction strategies and green-development plans.

This paper conducted research based on the accounting results of agricultural-land-use CO₂ emissions from 1995 to 2020. It analyzed the spatiotemporal evolution characteristics and the decoupling relationship, while identifying the contributors toward CO₂ emissions through the LMDI model. The findings in this paper were basically consistent with those of the previous studies. As demonstrated in the previous studies, the spatial variation of CO₂ emissions is polarized [61]. According to this paper, however, there is only weak polarization (concentration trend) in the spatial distribution of CO₂ emissions and carbon intensity because the regional disparity is narrowing.

There are some limitations that exist in this paper. On the one hand, in terms of the accounting method, the IPCC inventory adopted is based on a fixed formula while taking the CO₂ emission coefficient into account. Therefore, the accuracy of CO₂ emission accounting is sacrificed to some extent. At the same time, the same formula and conversion factor throughout the research may also result in certain errors between the accounting results and actual CO₂ emissions. On the other hand, the LMDI model cannot exhaust all the possible driving factors. Therefore, only the major drivers of CO₂ emissions are elaborated on in this paper.

4.2. Conclusions

Given the importance of agricultural activities, the paper calculated and analyzed agricultural-land-use CO₂ emission components and temporal and spatial evolution characteristics in China’s 31 provinces between 1995 and 2020. In addition, the Tapio decoupling model was used to explore the decoupling relationship between agricultural-land-use CO₂ emission changes and economic growth. At the same time, the LMDI model was
introduced to identify the main factors affecting agricultural-land-use CO$_2$ emissions. The research results are demonstrated below. From 1995 to 2020, China’s agricultural-land-use CO$_2$ emissions register an inverted-U-shape increase from 50.443 Mt to 79.187 Mt, and are characterized by a fluctuating growth phase (1995–2015) and rapid decline phase (2016–2020). In terms of spatial evolution, agricultural-land-use CO$_2$ emissions in China were distributed in an unbalanced manner and inter-provincial differences expanded first and then narrowed. Specifically, Henan, Shandong and Hebei provinces produced the largest volumes of CO$_2$ emissions, but Inner Mongolia, Qinghai and Tibet emitted the minimum amount of CO$_2$. In general, carbon intensity decreased, and inter-provincial differences narrowed.

In terms of the source, chemical fertilizer accounted for 60.23% of the total agricultural-land-use CO$_2$ emissions, being the largest emitter, followed by agriculture diesel, agricultural (plastic) film, pesticides, irrigation and land plowing with a share of 14.10%, 13.01%, 9.94%, 2%, 0.68%, respectively. The extensive use of high-carbon materials in agriculture sector has generated a large amount of CO$_2$, thus hindering the process of low-carbon agriculture. Nevertheless, since the national ecological civilization pilot zone was established in 2015, the use of high-carbon agricultural materials has been brought under control.

In terms of the decoupling relationship, there are two stages which exist between CO$_2$ emissions change and economic growth: the weak decoupling stage (1995–2015) and the strong decoupling stage (2016–2020). CO$_2$ emission change and economic growth were in the optimal conditions. The decreased growth rate of agricultural output from 2019 to 2020 demonstrates that the COVID-19 outbreak has negatively impacted on the agricultural sector.

The carbon intensity effect, agricultural structure effect and agricultural labor force effect played an important role in reducing the agricultural-land-use CO$_2$ emissions in China. Above all, the agricultural economic level plays a decisive role in promoting agricultural-land-use CO$_2$ emissions. As for absolute coefficients, the four drivers’ influences on agricultural-land-use CO$_2$ emissions were $E_a$ ($-189.51\%$), $H_e$ ($-16.86\%$), $K_o$ ($476.09\%$), $L_x$ ($-169.72\%$).

4.3. Policy Implications

According to the conclusions of this paper, the following suggestions can be proposed to promote the low-carbon and high-quality development for China.

First, agricultural-land-use strategy should be adjusted based on regional differences. The reason for this is that the total CO$_2$ emissions exhibited a non-equilibrium spatial distribution, and the total carbon emissions of each region were different. For instance, in areas with high CO$_2$ emissions and carbon intensity (Henan, Shandong and Hebei provinces), local agricultural departments need to effectively allocate production elements such as capital, labor and technology. The agricultural sector should focus on improving agricultural production techniques, and increasing the use of energy-efficient agricultural machinery. Furthermore, the government should strengthen regular agricultural land surveys and formulate more precise agricultural development strategies to reduce resource waste, and obtain maximum economic benefits.

Second, since fertilizers, pesticides and agricultural (plastic) film are the main carbon sources, local governments need to accurately implement fertilizer supply quota policies. In addition, subsidy policies for agricultural products should be raised to encourage the use of organic fertilizers and low-carbon pesticides and machines. Agricultural materials (agricultural (plastic) film) should be recycled as much as possible to improve the efficiency of resource utilization to reduce carbon emissions. In the provinces with a high-carbon intensity, including Inner Mongolia, Shanghai, Jilin, Xinjiang and Anhui, enterprises specializing in agricultural science and technology should facilitate innovations in emission reduction and pollution control.

Finally, the structure of agricultural production should be adjusted. The reason is that the agricultural structure factor has a small inhibitory effect on CO$_2$ emissions, and even
had a diving effect in some years. Particularly, the planting structure should be properly planned. People should appropriately allocate the ratio between crops such as grain, oilseeds, vegetables and fruits in the planting industry according to local conditions. For example, in the provinces with a great increase in CO$_2$ emissions such as Henan, Xinjiang and Inner Mongolia, people should optimize the variety mix, e.g., to grow more high-yield crops (sweet potatoes, corn and potatoes) and fewer resource-extensive varieties (oilseed and sugar crops).

**Author Contributions:** Conceptualization, J.J. and S.L.; methodology, S.L. and Y.Z. (Yangming Zhou); validation, Y.Z. (Yexi Zhong), H.H. and D.C.; formal analysis, S.L.; investigation, S.L.; resources, S.L. and Y.Z. (Yangming Zhou); data curation, H.H. and D.C.; writing—original draft preparation, J.J. and S.L.; writing—review and editing, J.J. and Y.Z. (Yexi Zhong); visualization, S.L.; supervision, J.J. and Y.Z. (Yangming Zhou); project administration, Y.Z. (Yexi Zhong) and Y.Z. (Yangming Zhou); funding acquisition, J.J. and Y.Z. (Yexi Zhong). All authors have read and agreed to the published version of the manuscript.

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**Appendix A**

**Table A1.** CO$_2$ emission coefficient of agricultural land and reference sources.

<table>
<thead>
<tr>
<th>Type of Carbon Source</th>
<th>Carbon Emission Coefficient</th>
<th>Reference Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chemical fertilizer</td>
<td>0.896 kg·kg$^{-1}$</td>
<td>West and Marland [62]</td>
</tr>
<tr>
<td>Pesticide</td>
<td>4.934 kg·kg$^{-1}$</td>
<td>Post and Kwon [63]</td>
</tr>
<tr>
<td>Agricultural film</td>
<td>5.180 kg·kg$^{-1}$</td>
<td>Institute of Resource, Ecosystem and Environment of Agriculture</td>
</tr>
<tr>
<td>Irrigation</td>
<td>25 kg·hm$^{-2}$</td>
<td>Dubey [64]</td>
</tr>
<tr>
<td>Agricultural diesel</td>
<td>0.593 kg·kg$^{-1}$</td>
<td>The Intergovernmental Panel on Climate Change</td>
</tr>
<tr>
<td>Land plowing</td>
<td>3.126 kg·hm$^{-2}$</td>
<td>College of Biological Sciences [65]</td>
</tr>
</tbody>
</table>

**Table A2.** Schematic diagram of decoupling states.

<table>
<thead>
<tr>
<th>Decoupling State</th>
<th>$\Delta ET/ET$</th>
<th>$\Delta F_{f}/F_{t}$</th>
<th>$e$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Negative Decoupling</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expansion negative</td>
<td>$&gt;0$</td>
<td>$&gt;0$</td>
<td>$(1.2, +\infty)$</td>
</tr>
<tr>
<td>Strong negative</td>
<td>$&gt;0$</td>
<td>$&lt;0$</td>
<td>$(-\infty, 0)$</td>
</tr>
<tr>
<td>Weak negative</td>
<td>$&lt;0$</td>
<td>$&lt;0$</td>
<td>$[0, 0.8)$</td>
</tr>
<tr>
<td><strong>Decoupling</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weak decoupling</td>
<td>$&gt;0$</td>
<td>$&gt;0$</td>
<td>$[0, 0.8)$</td>
</tr>
<tr>
<td>Strong decoupling</td>
<td>$&lt;0$</td>
<td>$&gt;0$</td>
<td>$(-\infty, 0)$</td>
</tr>
<tr>
<td>Recession decoupling</td>
<td>$&lt;0$</td>
<td>$&lt;0$</td>
<td>$(1.2, +\infty)$</td>
</tr>
<tr>
<td><strong>Coupling</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Expansive coupling</td>
<td>$&gt;0$</td>
<td>$&gt;0$</td>
<td>$[0.8, 1.2]$</td>
</tr>
<tr>
<td>Recessive coupling</td>
<td>$&lt;0$</td>
<td>$&lt;0$</td>
<td>$[0.8, 1.2]$</td>
</tr>
</tbody>
</table>
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