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Have Agricultural Land-Use Carbon Emissions in China Peaked? An Analysis Based on Decoupling Theory and Spatial EKC Model

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Abstract: Assessing the emission-peaking process of agricultural land use provides valuable insights for mitigating global warming. This study calculated agricultural land-use carbon emissions (ALUCEs) in China from 2000 to 2020 and explored the peaking process based on quantitative criteria. Further, we applied the Tapio decoupling index and environmental Kuznets curve (EKC) model to discuss the robustness of the peaking process. The main conclusions are as follows: (1) From 2000 to 2020, China's average ALUCEs were 368.1 Mt C-eq (1349.7 CO_2-eq), peaking at 396.9 Mt C-eq (1455.3 Mt CO_2-eq) in 2015 before plateauing. Emissions from agricultural materials and soil management had entered the declining period, while those from rice cultivation were in the peaking period, those from straw burning were still rising, and those from livestock breeding remained at the plateauing phase. (2) The provinces of Beijing, Tianjin, and nine others saw a decline in ALUCEs, while Hainan, Guizhou, and another nine provinces observed plateauing, and Ningxia, Qinghai, and six other provinces experienced peaking. (3) Decoupling analysis confirmed that emission-peaking states remained stable even with agricultural growth. Instead of an inverted U-shaped relationship, we found an N-shaped relationship between ALUCEs and agricultural GDP. The spatial EKC model indicated that the peaking process had spillover effects between provinces. It is recommended that China accelerate ALUCE mitigation based on the source and phase of emissions, considering the peaking process and magnitude.

Keywords: agricultural land-use carbon emissions; greenhouse gas emissions; emission peak; Tapio decoupling index; environmental Kuznets curve; spatial Durbin model

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1. Introduction

Global warming, an environmental impact of rising carbon emissions, is one of the greatest threats to human survival. While industry and thermal power generation are major contributors to carbon emissions, agriculture also plays a crucial role in emission mitigation [1], which contributes about 20 to 25 percent of global greenhouse gas (GHG) emissions [2,3]. On the one hand, the use of high-carbon materials such as fertilizers, pesticides, and diesel fuel can lead to significant emissions [4]. On the other hand, activities like rice cultivation, straw burning, and livestock breeding release GHGs, such as methane (CH_4) and nitrous oxide (N_2O), which have high global warming potential (GWP) [5]. As the world's largest economy responsible for 28% of global carbon emissions, China has set ambitious emission peak and carbon neutrality targets for all sectors [6]. Although China's emission-peaking target focuses on carbon dioxide (CO_2) emissions, the carbon neutrality target concerns all greenhouse gases. Agricultural land use, as an important source of non-CO_2 GHGs, should take the lead in exerting carbon-mitigation pressure on itself. Given these considerations, it is necessary to discuss the peaking process of China's ALUCEs, which will provide insights into achieving the overall emission peak [7].

Accurate ALUCE accounting is the premise for assessing the process of emission peaking. In practice, field trials, simulation models, and inventory-based accounting have been commonly applied [8,9]. Inventory-based accounting was widely used in macro-level studies for its technical simplicity and convenience for regional cross-sectional comparison [10]. Relevant studies can be summarized into two perspectives. One is to focus on certain carbon sources, such as rice fields [11], soil [12,13], agricultural waste treatment [14,15], and livestock breeding [16–18]. This approach is conducive to an in-depth examination of the carbon emissions of specific activities but cannot reveal the overall emissions of entire chains [19]. The second perspective quantifies carbon emissions from agricultural land use based on life cycle analysis [20], which is both comprehensive and comparable. However, disparities remain in the accounting boundaries by different institutions and researchers. For example, national-level carbon accounting by IPCC [21] covers eleven carbon sources, such as crop residues, rice cultivation, and drained organic soils, which provides an understanding of overall emission levels but is not suitable for estimating the emissions of subdivided areas due to data limitations. Most literature takes the provincial level as the basic study unit [22], the earliest ALUCE-accounting inventory mainly involved agricultural materials, including diesel fuel, chemical fertilizers, pesticides, and electricity [23,24]. With deeper research, three carbon sources commonly constituted the accounting inventory: agricultural materials, rice cultivation, and livestock breeding [25,26]. Aside from these sources, Han et al. [3] further considered N_2O emissions from crop production, and Sun et al. [27] included straw burning in their accounting inventory. Ministry of Ecology and Environment of the People's Republic of China [28] also recommended an inventory for estimating carbon emissions of agriculture, concerning four carbon sources including enteric fermentation, manure management, rice cultivation, agricultural soils, and straw burning.

Although there are differences in accounting boundaries and specific results, it is recognized that a historic maximum in China's ALUCEs appeared around 2015 [27,29,30]. While some studies have concluded that emissions have already peaked [31,32], others have suggested that energy consumption will continue to grow with the increase in agricultural mechanization, and it has not yet been proven whether ALUCEs have steadily crossed the peak [33]. Emission peaking denotes a process in which emissions reach a historical maximum, go through a plateauing period, and eventually decline [34], and the inflection point does not indicate the emission peak. As such, verifying the interaction between carbon emissions and economic development using decoupling theory and the environmental Kuznets curve (EKC) is necessary to avoid misjudging the peak states. Although the EKC has been widely used in the fields of industrial and energy emission peaks [35,36], it is less commonly applied to agricultural emission peaks [37,38]. Zhang and Yan [34] found that the carbon emissions of beef breeding in China had not yet reached their peak, while Chen et al. [39] concluded that Chinese ALUCEs would peak in 2026.

Previous research on ALUCEs has yielded meaningful findings; however, there are still limitations. First, the process of reaching a peak remains largely unexplored. While some studies suggest that Chinese ALUCEs reached a maximum in 2015, it is unreliable to judge whether they have peaked without clarifying the peaking process. Are emissions declining, plateauing, or peaking? Will they continue to increase with agricultural growth or have they decoupled from it? Further evaluation of the emission-peaking process is necessary. Additionally, as agricultural production in China continues to expand, it is crucial to test the interaction between emissions and the economy before reliable judgments can be made about reaching a peak. Second, the provincial-level carbon-accounting inventory needs improvement. Though the national-level carbon-accounting inventory has evolved from being unilateral to comprehensive, the provincial-level one merely covers agricultural materials, rice cultivation, and livestock breeding, lacking detailed discussions of emissions resulting from soil management and straw burning. This leads to an underestimation in carbon accounting that can harm the reliability of subsequent analyses. Third, many studies have applied the ordinary EKC model to test the relationship between carbon emissions and economic development. Nevertheless, considering the geographical environment and resource endowment similarities of neighboring provinces, there is a certain degree of spatial agglomeration in ALUCEs. In addition, there may be policy emulation, technological spillovers, and factor flows during the agricultural land-use process. Ignoring spatial interactions may lead to biased research conclusions.

To overcome these limitations, this research aims to figure out if ALUCEs in China have peaked, which has three primary contributions. First, the emission-peaking process of agricultural land use in China was demonstrated. In addition to investigating the peaking states by using quantitative criteria, the interaction between carbon emissions and agricultural growth was further explored by using the Tapio decoupling theory and the EKC model, as decoupling carbon emissions from economic development is necessary for emission peaking. This analytical framework has the potential to be extended to other sectors, making a marginal contribution to the field of emission-peaking analysis. Second, the provincial-level ALUCE-accounting inventory was expanded, enhancing the accuracy of accounting. In addition to the three categories of emission sources typically selected by existing studies (agricultural materials, rice cultivation, and livestock breeding), our carbon-accounting inventory also included commonly omitted carbon sources such as soil management and straw burning. Third, considering the possible spatial interaction in the peaking process of ALUCEs, we fit the EKC using a spatial econometric model instead of the ordinary panel model, ensuring the robustness of the results. This study expands the existing judgment of the ALUCE-peaking process and provides a basis for provinces to make spatial-coordinating efforts to achieve emission peaking.

2. Approach and Data

2.1. Research Framework

As one of the world's largest agricultural countries, China increased grain production from 462.17 Mt. in 2000 to 695.41 Mt. in 2023. Nevertheless, the increase resulted from the intensification of agricultural material use, characterized by wider mechanization and chemicalization. Therefore, it is of great significance to study the peaking process of ALUCEs in China. This study focuses on the issue of whether ALUCEs in China have peaked and decomposes it into two aspects: the judgment of the peaking process and the robustness of the peaking state. The research framework is shown in Figure 1.

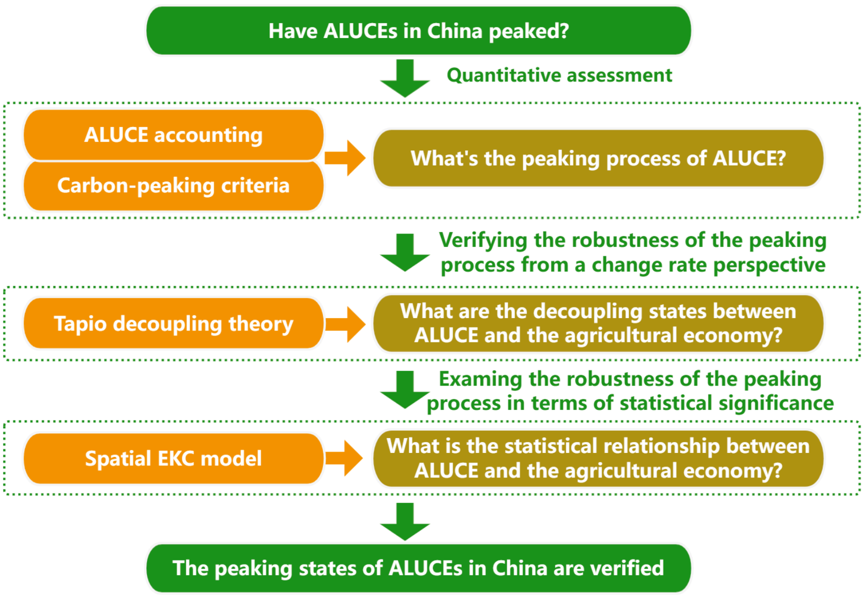

Figure 1. Research framework.

This study calculated the ALUCEs in China between 2000 and 2020 based on life cycle analysis, with five aspects of carbon sources considered: agricultural materials, rice cultivation, soil management, straw burning, and livestock breeding. By using the emission-peaking criteria, we explored the peaking states of ALUCEs for both the entire country and each province. According to the EKC theory and related literature [5], in the early stages of agricultural development, as the scale of agriculture in a region continues to expand, it will inevitably lead to more carbon emissions from agricultural practices, and decoupling carbon emissions from the economy is crucial to achieving peak emissions. Therefore, stricter constraints were applied in addition to quantitative assessments. Specifically, we used the Tapio decoupling index and spatial EKC model to discuss the robustness of peaking states and avoid falsely identifying a peak.

2.2. Accounting Boundary of ALUCEs

Agricultural land use releases three main greenhouse gases, namely, CO_2, CH_4, and N_2O. As greenhouse gas emissions can be expressed in carbon equivalents based on GWP, they are collectively called carbon emissions. Figure 2 displays the boundary for calculating ALUCEs.

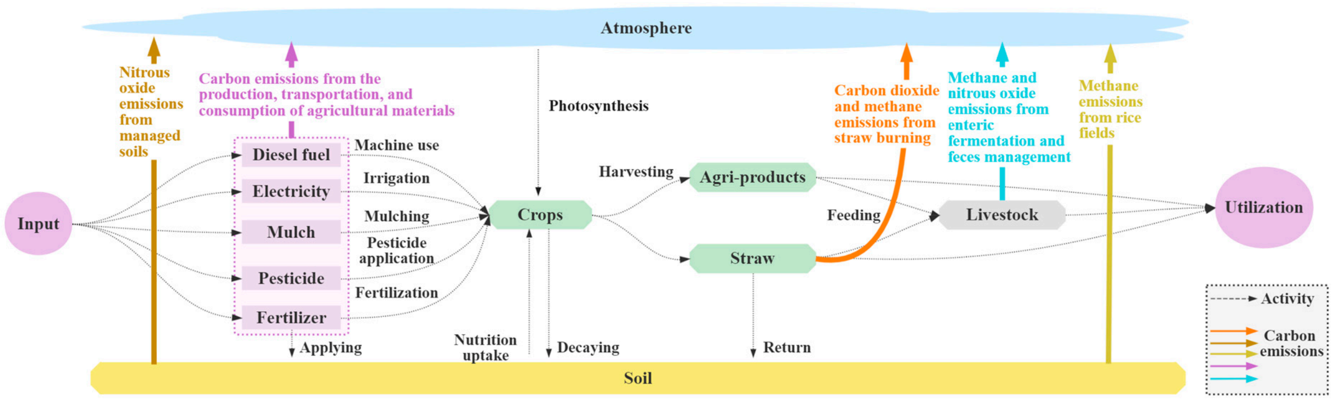

Figure 2. System boundary for ALUCE accounting.

Agricultural land use has twofold opposed carbon effects (that is, emissions and sequestration); however, CO_2 sequestered by crops will subsequently return to the atmosphere through human consumption, and crops act as carbon sinks only in the short term, while the long-term impact on the carbon cycle is negligible. Additionally, as this study aimed to determine solutions to mitigate the anthropogenic emissions in agricultural land use, carbon uptake of crops was not included in the accounting. Based on the system boundary, we considered five sources of ALUCEs: agricultural materials, rice cultivation, soil management, straw burning, and livestock breeding. The corresponding formulas and coefficients (presented in Supplementary Materials) were determined by referencing the accounting inventory of the Chinese government, IPCC, FAO, and other research institutions, as well as widely cited literature in the field. CH_4 and N_2O were converted into standard carbon equivalents (C-eq) using factors of 9.2727 and 81.2727 [40], respectively.

2.3. Criteria for Assessing Emission-Peaking Process

The Carbon Neutral Research Center of China developed quantitative criteria for judging peaking states by combining the Bootstrap method, historical emissions, and statistical tests [41]. Table 1 shows the proposed criteria consisting of three stages: peaking, plateauing, and declining. If carbon emissions have not reached a historical maximum, they are in the rising phase.

Table 1. Criteria for assessing emission-peaking process.

Criteria	Peaking Process
Carbon emissions fluctuate within ±1% of the peak emissions	Peaking
Annual change rate compared to the peak emissions is between −1% and −2%.	Plateauing
Annual change rate compared to the peak emissions is lower than −2%	Declining

2.4. Robustness Analysis for Peaking Process of ALUCEs

2.4.1. Tapio Decoupling Theory

Decoupling refers to the reducing interrelation between multiple variables, which can reveal the interaction between environmental hazards and economic performance. This study applied the Tapio decoupling theory to primarily investigate the potential for peaking states of ALUCEs to maintain stability while experiencing agricultural growth, specifically to examine whether a strong decoupling relationship exists between emissions and the economy. The Tapio decoupling index expresses this relationship using Equation (1).

$$\varepsilon = \frac{\Delta E/E}{\Delta A/A} = \frac{(E_i - E_0)/E_0}{(A_i - A_0)/A_0} \quad (1)$$

The decoupling index (ε) represents the elasticity of ALUCEs in relation to the agricultural economy. It is calculated based on the variation in ALUCEs (ΔE), with E_i and E_0 representing the ALUCEs of the current and base periods, respectively. Similarly, the variation in agricultural GDP (ΔA) reflects changes in the agricultural economy, with A_i and A_0 representing agricultural GDP in the current and base periods, respectively. The decoupling index categorizes how sensitive ALUCEs are to economic changes in eight states, as illustrated in Figure 3.

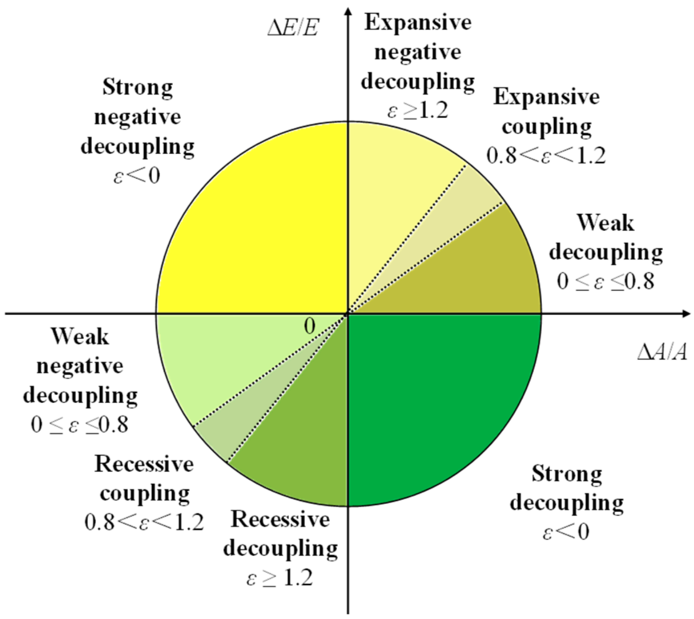

Figure 3. Classification of decoupling states based on change rate and elasticity.

If ALUCEs can maintain a strong decoupling from the agricultural economy, it denotes a decreasing trend with economic growth, indicating a robust state of the peaking process; otherwise, it indicates that the peaking state is unstable. In addition to analyzing the long-term index on a fixed benchmark, we segmented the study period and calculated the short-term Tapio decoupling index for each segment. The combination of long- and short-term analysis can reflect decoupling characteristics during each stage and different short periods of the study.

2.4.2. Spatial EKC Model

The Tapio decoupling theory examines whether carbon emissions decrease steadily with agricultural growth; however, it does not provide a relationship curve between the two. Instead, the EKC model examines the shape of the curve and supports the judgment of the peaking process in terms of statistical significance. An N-shaped relationship between carbon emissions and agricultural GDP indicates that ALUCEs have not yet peaked and are trending upward. If there is no N-shaped relationship but a significant inverted U-shaped one, then ALUCEs have reached their peak. To verify the possibility of an N-shaped relationship, we set the model as a cubic curve in addition to the classical squared function. In addition, the possible spatial correlation of ALUCEs does not meet the assumption of conventional econometrics. To ensure the correctness of the model set, the Lagrange multiplier (LM) test is applied to determine the spatial correlation of the residuals based on the ordinary least squares (OLS). If a spatial correlation exists, spatial econometric models, such as the spatial lag model (SAR), spatial error model (SEM), and spatial Durbin model (SDM), are appropriate to use in the conditional β-convergence test. Because the SDM is the general form of the SAR and SEM, it is used as the benchmark, and the corresponding equation of the convergence test is shown in Equations (2)–(4).

$$ALUCE_{it} = \beta_0 + \beta_1 AGDP_{it} + \beta_2 (AGDP_{it})^2 + \rho \boldsymbol{W} ACLE_{jt} + \varphi_1 \boldsymbol{W} AGDP_{jt} + \varphi_2 \boldsymbol{W} (AGDP_{jt})^2 + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

$$ALUCE_{it} = \beta_0 + \beta_1 AGDP_{it} + \beta_2 (AGDP_{it})^2 + \beta_3 (AGDP_{it})^3 + \rho \boldsymbol{W} ALUCE_{jt} + \varphi_1 \boldsymbol{W} AGDP_{jt} + \varphi_2 \boldsymbol{W} (AGDP_{jt})^2 + \varphi_3 \boldsymbol{W} (AGDP_{jt})^3 + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

$$ALUCE_{it} = \beta_0 + \beta_1 AGDP_{it} + \beta_2 (AGDP_{it})^2 + \beta_3 (AGDP_{it})^3 + \theta X_{it} + \rho \boldsymbol{W} ALUCE_{jt} + \varphi_1 \boldsymbol{W} AGDP_{jt} + \varphi_2 \boldsymbol{W} (AGDP_{jt})^2 + \varphi_3 \boldsymbol{W} (AGDP_{jt})^3 + \eta \boldsymbol{W} X_{jt} + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

where $ALUCE_{it}$ is ALUCEs per person, $AGDP_{\ it}$ is agricultural GDP per person, X_{it} denotes control variables, t denotes time, i represents the local province, β_0 is the constant, θ is the coefficient of control variables, and ε_{it} denotes the error term assumed to meet ε_{it}~iid $(0, \sigma^2)$. μ_i and λ_t are spatial and temporal fixed effects, respectively. β_1, β_2, and β_3 are the parameters that determine the shape of the EKC. j reflects other provinces close to province i; W is the spatial weight matrix; ρ is the spatial autoregressive coefficient, showing the interaction of ALUCEs among provinces; φ_1, φ_2, and φ_3 reflect the spillover effects of agricultural GDP in province j, and η denotes the spillover effect of control variables. The SDM is suitable to be estimated by the method of maximum likelihood. Moreover, Wald and likelihood ratio (LR) tests can determine whether the SDM should be simplified to the SAR or SEM.

Three models will be set for analysis: Equation (2) is a classical EKC model, in which explanatory variables include only the logarithm of the agricultural GDP and its squared term to verify whether there is an inverted U-shaped relationship; Equation (3) adds the cube term of the logarithm of the agricultural GDP into a classical EKC model to explore whether there is an N-shaped relationship; Equation (4) adds control variables based on Model 1, as shown in Table 2.

Table 2. Statistical analysis of explanatory variables of the EKC model.

Variable		Unit	Explanation	Mean	Std. Dev.	Min	Max
Core explanatory variable	Agricultural GDP per person/$AGDP$	10^4 CNY/Person	The ratio of agricultural GDP to agricultural employees	1.953	1.420	0.247	8.637
	Squared term of agricultural GDP per person/$AGDP^2$	10^4 CNY/Person	The square term of the ratio of agricultural GDP to agricultural employees	5.829	9.396	0.061	74.601
	Cube term of agricultural GDP per person/$AGDP^3$	10^4 CNY/Person	The cubic term of the ratio of agricultural GDP to agricultural employees	23.918	64.083	0.015	644.345

Table 2. *Cont.*

	Variable	Unit	Explanation	Mean	Std. Dev.	Min	Max
Control variable	Proportion of Agricultural Sector (*agristruc*)	-	Ratio of output value of non-planting industry to total output value of agriculture	0.477	0.086	0.260	0.661
	Crop Planting Structure (*cropstruc*)	-	Ratio of area of economic crops to total planting area of crops	0.342	0.132	0.029	0.646
	Animal farming structure (*animal*)	-	Ratio of number of herbivorous animals to total number of animals raised	0.488	0.253	0.094	0.987
	Degree of agricultural mechanization (*machine*)	kW/Person	Ratio of total agricultural machinery power to number of laborers	3.499	2.163	0.383	12.593
	Degree of Agricultural Disasters (*disaster*)	-	Ratio of disaster-affected agricultural area to total crop planting area	0.231	0.162	0.000	0.936
	Financial Support for Agriculture (*fiscal*)	-	Proportion of agricultural expenditure in total fiscal budget expenditure	0.090	0.042	0.012	0.204
	Degree of urbanization (*urban*)	-	Ratio of urban population to total population	0.506	0.166	0.131	0.896
	Intensity of environmental protection (*environ*)	-	Proportion of environmental protection expenditure in total fiscal budget expenditure	0.031	0.012	0.008	0.068
	Intensity of Technology Investment (*tech*)	-	Proportion of expenditure on scientific research activities in total fiscal budget expenditure	0.020	0.014	0.004	0.072

2.5. Data Sources and Processing

This study examined ALUCEs across 30 provinces in mainland China between 2000 and 2020. All original data were taken from statistical yearbooks, and agricultural GDP was discounted by constant prices in 2000 to account for changes in price over time. Hong Kong, Macao, Taiwan, and Tibet were excluded due to a lack of data availability.

3. Results and Analysis

3.1. Peaking Process of ALUCEs in China

3.1.1. Peaking Process of ALUCEs at the National Level

ALUCEs were calculated through the accounting inventory and are presented in Figure 4, where the annual average proportion of each carbon source decreases in the order of livestock breeding (36.6%), agricultural materials (21.3%), straw burning (17.0%), rice cultivation (16.9%), and soil management (8.2%).

The national average ALUCEs during the study period were 368.1 Mt C-eq (1349.7 Mt CO_2-eq) annually, with a peak of 396.9 Mt C-eq (1455.3 Mt CO_2 eq) in 2015. The agricultural support policy introduced in 2004 resulted in an increase in investment in agricultural materials and an expansion of livestock breeding, thus stimulating farmers' enthusiasm for production. However, from 2016 to 2020, ALUCEs in China started to decline due to low-carbon policies such as reducing chemical fertilizers and pesticides, forbidding straw burning, and green breeding of livestock. The annual change rate compared to the peak emissions reached -1.7%, indicating a plateauing period, but potential rebound momentum should still be monitored.

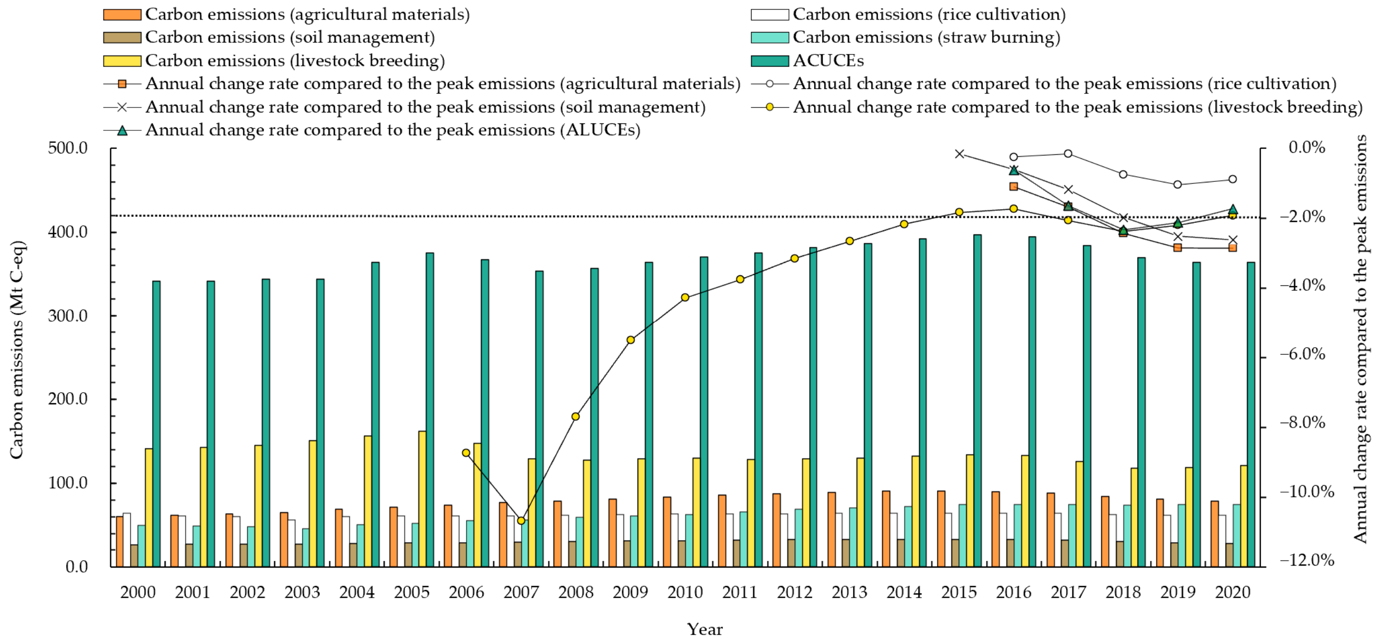

Figure 4. Temporal evolution and peaking process of ALUCEs in China from 2000 to 2020.

In regard to the peaking process of specific carbon sources, there was an increase in carbon emissions from agricultural materials from 60.4 Mt C-eq in 2000 to a peak of 90.8 Mt C-eq in 2015. However, emissions began to decline from 2016 onwards, reaching 78.5 Mt C-eq by the end of the study period. The average annual post-peak change rate reached −2% in 2018 and further decreased to −2.9% by 2020, indicating that carbon emissions from agricultural materials entered a declining phase. Emissions from rice cultivation also decreased from 63.8 Mt C-eq to 61.4 Mt C-eq, with a stable trend that was determined by its natural attributes, that is, cultivation area and local conditions. Although emissions from rice cultivation peaked in 2015, the slow yearly change rate compared to the peak emissions remained relatively unchanged and had not surpassed the −1.0% threshold by 2020; hence, they were still in the peaking stage. Carbon emissions from soil management increased smoothly from 26.7 Mt C-eq in 2000 to 33.2 Mt C-eq in 2014, but have since declined yearly, reaching 28.3 Mt C-eq in 2020. The small base contributed to the weak magnitude of the change. Soil management emission trends were similar to those of carbon emissions from agricultural materials, reaching their peak in 2014 before decreasing significantly. The rate exceeded −2% in 2018 and further dropped to −2.9% in 2020, indicating that they passed the plateauing phase and entered the declining phase. Conversely, carbon emissions from straw burning consistently increased from 49.5 Mt C-eq to 74.6 Mt C-eq, with no inflection point occurring, and it should be attributed to a rising period. The development of carbon emissions from livestock breeding differed greatly from other carbon sources; from 2000 to 2005, the total amount increased from 141.1 Mt C-eq to 161.6 Mt C-eq before declining yearly and dropping to 118.4 Mt C-eq in 2019. In 2020, there was a slight increase, leading to a rebound in its peaking process and regression from the declining period back to the plateauing phase.

3.1.2. Peaking Process of ALUCEs at the Provincial Level

After understanding the peaking process at the national level, we classified Chinese provinces into several classes according to their peaking processes and emission quantities, which are presented in Figure 5.

Different agricultural practices resulted in varying quantities and compositions of carbon emissions across provinces. Henan had the highest emissions at 34.3 Mt C-eq, followed by Hunan, Sichuan, Anhui, Shandong, Heilongjiang, Hubei, and Hebei, which all had emissions between 20 and 30 Mt C-eq. The remaining 22 provinces emitted less than

20 Mt C-eq, with Jiangsu, Xinjiang, and Jiangxi producing between 10 and 20 Mt C-eq, and Beijing, Shanghai, and Tianjin producing around 1 Mt C-eq each.

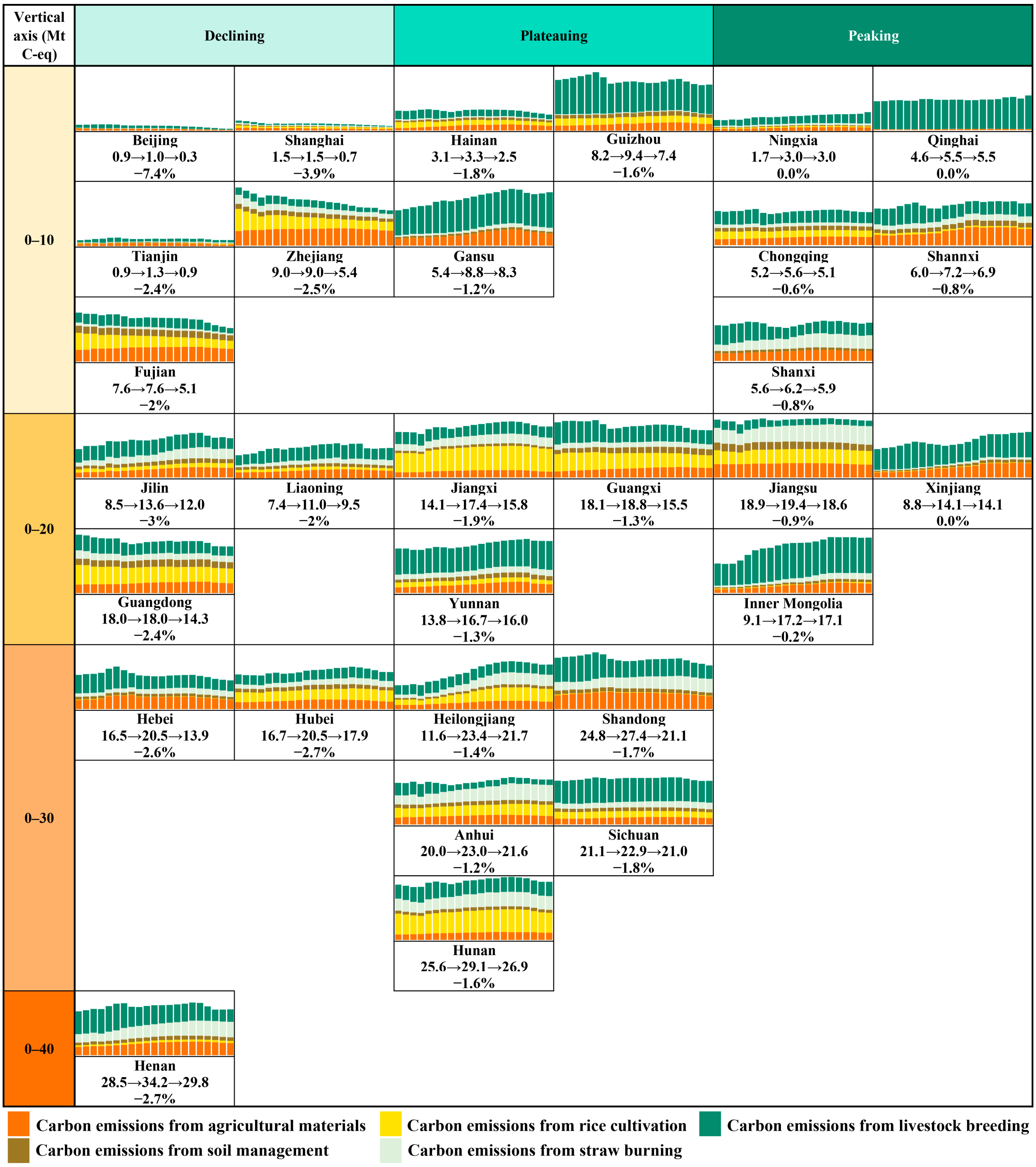

Figure 5. Peaking processes of ALUCEs in 30 Chinese provinces between 2000 and 2020. Note: each line graph features a consistent y-axis range that is marked on the far left-hand side and represents levels of ALUCEs. Meanwhile, the x-axis for all graphs depicts the years between 2000 and 2020. The figures beneath each graph denote baseline, peak, and final emissions, as well as average annual change rates, presented in sequential order.

Of all identified carbon sources, agricultural materials, rice cultivation, soil management, and straw burning are associated with crop production. Provinces where crop production accounts for over 50% of total emissions are classified as "led by crop production", while those where livestock breeding contributes more than 50% are characterized as "led by livestock breeding". We found that emissions in 21 provinces were led by crop production, with subdivisions based on individual carbon source contributions. Nine provinces, including Tianjin, Hebei, Liaoning, Shanghai, Zhejiang, Fujian, Shandong, Chongqing, and Shaanxi had emissions predominantly led by agricultural materials, which are mainly situated in northern and eastern coastal areas and some western regions. Meanwhile, Heilongjiang, Jiangxi, Hubei, Hunan, Guangdong, Guangxi, and Hainan had high carbon emissions from rice cultivation, with CH_4 emissions from rice cultivation dominating the carbon emission structure of crop production, particularly in the middle reaches of the Yangtze River. Jiangxi had the highest proportion of CH_4 emissions at almost 50%. Soil management accounted for a modest proportion of total emissions in all provinces, ranging from 5% to 15%. Straw burning was relatively prevalent in Jiangsu and Anhui, producing substantial carbon emissions due to their large straw output facing frequent treatment, leading to high emissions.

On the other hand, nine provinces were led by livestock breeding, such as Gansu, Xinjiang, and Inner Mongolia. Animal husbandry dominated agricultural production in Inner Mongolia, Sichuan, Gansu, Qinghai, Ningxia, and Xinjiang due to large-scale livestock breeding. Given the geographical conditions of mountains and plateaus, draught animals were still necessary for agricultural land use in Guizhou and Yunnan, which led to a high share of carbon emissions from livestock breeding.

During the study period, eleven provinces including Beijing and Tianjin experienced a decline in ALUCEs. The highest point of emissions was reached during this period, after which there was a steady downward trend. In 2020, the annual change rate compared with peak emissions was lower than -2%, indicating a smooth transition past the plateauing phase. Peak emissions in Beijing, Tianjin, Shanghai, Zhejiang, Fujian, Jilin, Liaoning, and Guangdong were all below 20 Mt C-eq. In regions where urban agriculture is prevalent, such as Beijing, Tianjin, and Shanghai, strict environmental regulations and greener waste disposal methods led to a smaller intensity of carbon-containing agricultural inputs and reduced emissions from various carbon sources. Meanwhile, southeastern coastal areas like Guangdong, Fujian, and Zhejiang have flat terrain and promising light and heat conditions, allowing for the application of low-carbon and efficient production technologies and large-scale operations. Jilin and Liaoning, located in the Northeast Plain with superior production conditions, had also successfully peaked and turned into a declining period thanks to increasing efforts in ecological protection and financial investment related to agriculture. Finally, Hebei, Hubei, and Henan all experienced a rapid decline after reaching their highest emissions during the study period. This indicates that low-carbon production requirements introduced by the Chinese government have been effectively implemented in these provinces, resulting in significant improvements in high input, energy consumption, and emission mitigation.

Eleven provinces including Hainan and Guizhou were in the plateauing phase, with carbon emissions reaching their highest point during this period, primarily concentrated in 2015 and 2016. Grain crops dominate planting structures in Shandong, Hunan, Anhui, Jiangxi, and Heilongjiang, with carbon emissions from straw burning mainly originating from rice, corn, and wheat grain crops. Rice cultivation was also a considerable emitter. Due to these structural characteristics, it is more difficult for local ALUCEs to peak and decline. Although emissions from all carbon sources in Hunan and Guangxi decreased to varying degrees, carbon emissions from rice cultivation still occupied a large proportion of the local emission structure and were closely related to climatic conditions, cultivation scale, field management, and other factors, making it difficult to significantly reduce them in a short period. In Guizhou, Yunnan, Sichuan, and Gansu, carbon emissions from livestock breeding have occasionally increased in recent years. The combined performance of various carbon sources led to a slower decline in ALUCEs as a whole. Despite reaching an inflection point, the average annual decline rate after reaching the peak was less than 2% in absolute terms, making it necessary to be alert to the rebound phenomenon that may occur after reaching the peak. These were key areas of concern for ALUCE reduction.

The peaking phase concerned Ningxia, Qinghai, and six other provinces, with the highest emissions levels of less than 20 Mt C-eq. Carbon emissions from agricultural materials and soil management had started to decline in all eight provinces, but at a relatively slow pace, resulting in high emissions. This indicates a need for a further reduction in fertilizer, pesticide, and mulch consumption, as well as a need to improve the efficiency of energy consumption in agricultural production activities. Carbon emissions from rice cultivation in Inner Mongolia, Chongqing, Ningxia, and Xinjiang slightly rebounded in recent years. Additionally, carbon emissions from livestock breeding were still expanding in these regions, with large volumes of enteric fermentation and waste in the process. The treatment for these emissions had yet to be transformed into more eco-friendly options, making them the most challenging areas for the low-carbon transition of China's agricultural land use.

3.2. Robustness of the Peaking Process of ALUCEs Based on Decoupling Theory

3.2.1. Decoupling Analysis of ALUCEs and Agricultural GDP at the National Level

The decoupling states were determined by examining the correlation between changes in ALUCEs and agricultural GDP from 2000 to 2020. The results are displayed in Figure 6.

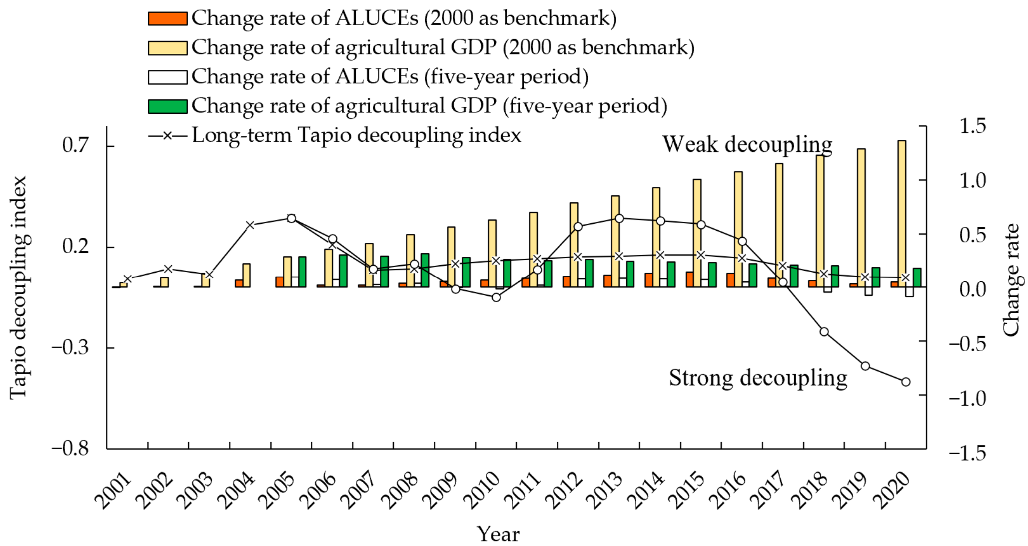

Figure 6. Decoupling of ALUCEs and agricultural GDP in China between 2000 and 2020.

In the long-term decoupling analysis, ALUCEs and agricultural GDP were predominately weakly decoupled, except for 2001, where there was a strong decoupling observed with a decrease in ALUCEs and an increase in agricultural GDP. For all other years, the rates of change for both variables were positive but remained below 0.8, signifying weak decoupling. The decoupling index was more volatile in the early period due to shorter intervals between the examined years and the base period. Over time, the growth rate of carbon emissions had a fluctuating curve, while the growth rate of agricultural GDP accumulated steadily, leading to a stable decreasing trend in the decoupling index in the later period. The continuation of both variables' respective development momentum could lead to a smooth transition in the long-term relationship between China's ALUCEs and economic development from weak decoupling to strong decoupling.

The segmented short-term decoupling index is more sensitive than long-term analysis and can indicate subtle decoupling characteristics in recent time periods. Over the period from 2005 to 2020, the relationship between China's ALUCEs and its economic output evolved from weak decoupling to strong decoupling. The rate of change for carbon emissions was mostly positive, except for 2008 and 2009, and remained stable and negative from 2018 to 2020. Meanwhile, the agricultural GDP consistently grew over the entire period under consideration. Specifically, the agricultural GDP remained positive during all years studied, leading to a strong decoupling state in 2008, 2009, and 2018–2020, and a weak decoupling in the other years. By reducing the comparison interval to five years, we observed that the negative environmental externalities of agricultural land use have significantly decoupled from agricultural economic growth in recent years. This suggests that China's agricultural land use has gradually moved away from a redundant state characterized by high resource consumption, high factor input, and high environmental cost, and toward an ideal state characterized by low carbon, conservation, and high efficiency.

The national-level decoupling analysis verified that the peaking states through the change rates between ALUCEs and agricultural GDP, and the peaking state of China's ALUCEs, that is, plateauing, were quite stable with agricultural growth.

3.2.2. Decoupling Analysis of ALUCEs and Agricultural GDP at the Provincial Level

After examining the correlation between national ALUCEs and the agricultural economy, we measured the decoupling index for each province at 5-year intervals. The decoupling states for Chinese provinces are illustrated in Figure 7.

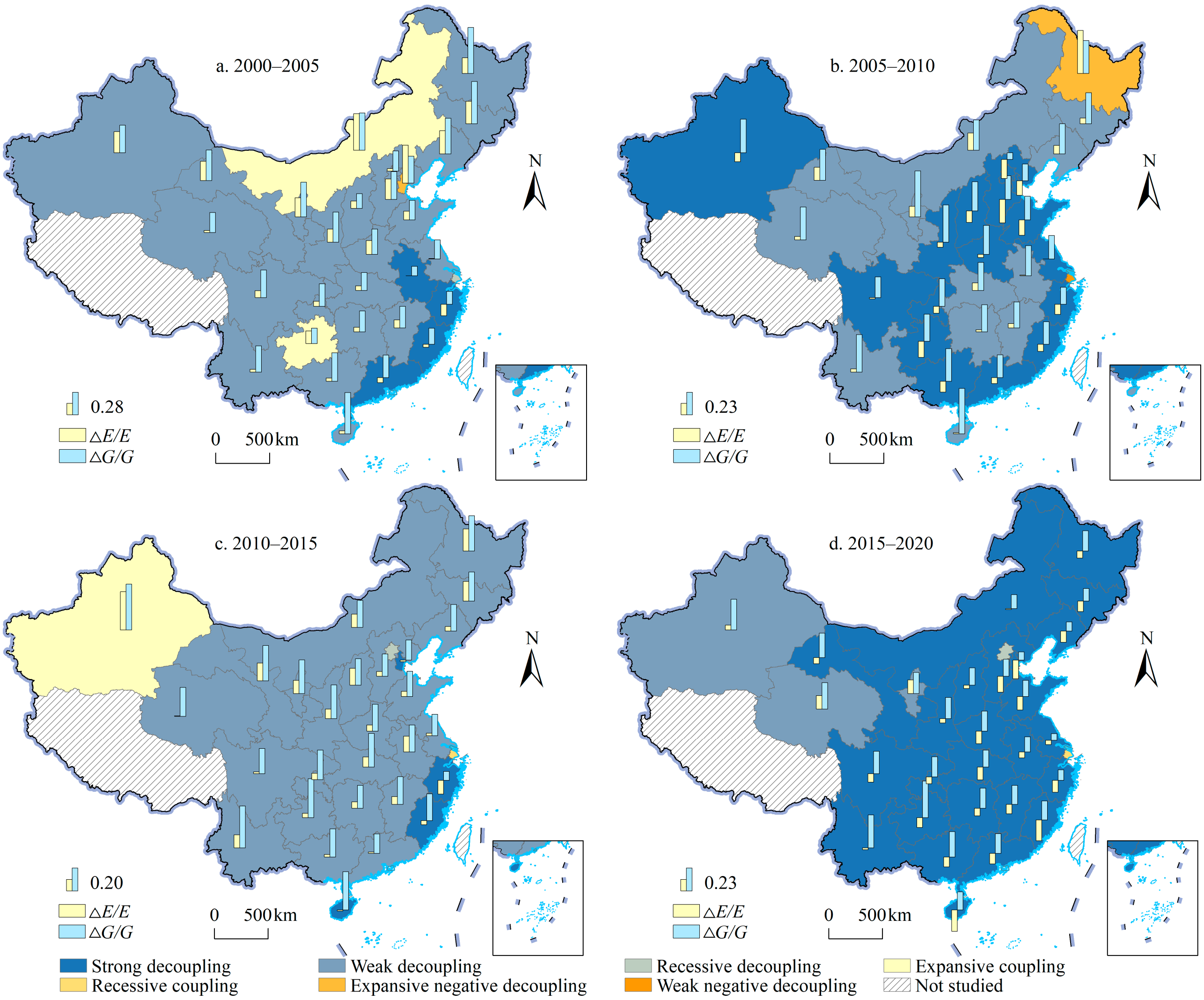

Figure 7. Spatial distribution of decoupling relationship between ALUCEs and agricultural GDP in China.

From 2000 to 2005, various relationships were observed, including weak decoupling, recessive decoupling, expansive negative decoupling, expansive coupling, and strong decoupling. In Inner Mongolia and Guizhou, the relationship between ALUCEs and economic development was identified as expansive coupling. This indicates that agricultural production in these provinces was reliant on high emissions and high material consumption as both agricultural GDP and ALUCEs increased relatively similarly. In contrast, Jiangsu, Anhui, Fujian, and Guangdong, the four southeastern coastal provinces, demonstrated strong decoupling in the same period. Their ALUCEs decreased while their agricultural GDP kept increasing. This suggests that the technological level, development orientation, and functional orientation of the southeast coastal regions played a critical role in this outcome. Additionally, weak decoupling was the dominant type during this stage as an increase in ALUCEs in most regions was lower than that of their agricultural GDP.

From 2005 to 2010, Heilongjiang experienced negative decoupling as the growth rate of ALUCEs exceeded that of agricultural GDP. Shanghai was in a state of weak negative decoupling, with both indicators showing a negative change rate. The rest of the provinces were distributed across states of strong and weak decoupling, with weak decoupling primarily in the northeastern provinces such as Liaoning and Jilin, the northwestern provinces such as Gansu and Ningxia, and the middle reaches of the Yangtze River, including Hunan and Hubei. The strong decoupling area extended from the southeast coastal region to some central and western regions. This indicates that during this period, most provinces had declining momentum of ALUCEs and stable growth of the agricultural economy.

From 2010 to 2015, Beijing and Shanghai were in states of recessive decoupling and recessive coupling, respectively. This reflects the gradual reduction in agricultural production in these two provinces. Xinjiang returned to the expansive coupling state as its agricultural economy and carbon emissions grew at the same rate. The strong decoupling area shrunk again to the southeast coastal area plus Tianjin. Weak decoupling was predominant among the provinces, with 23 provinces in this state, reflecting the repetitiveness and volatility of decoupling states.

Based on observations from the last period (2015–2020), Beijing and Shanghai remained stable in their previous states, while Xinjiang transitioned from expansive coupling to weak decoupling. Ningxia and Qinghai also maintained weak decoupling, whereas the remaining 25 provinces smoothly transitioned to strong decoupling, successfully avoiding the high-pollution and low-output dilemma. This trend can be attributed to the increasing ecological protection awareness among agricultural producers, leading to more efficient and intensive production methods that prioritize resource conservation. Additionally, there has been a reduction in the consumption of high-carbon agricultural materials and energy, along with advancement in waste management and clean treatments. Consequently, in most provinces, the previously observed link between ALUCEs and economic development had been broken.

In China, the relationship between ALUCEs and economic development exhibited a geographically clustered pattern. After 21 years of evolution, this pattern had polarized into a “strong decoupling dominated” distribution, indicating ongoing improvement and progress towards absolute decoupling across the region. This also confirmed the stability of the peaking states of ALUCEs in each province.

3.3. Robustness Test of ALUCE Peaking Process Based on Spatial Durbin Model

The Tapio decoupling index verified that ALUCEs’ plateauing state was stable. To specifically describe the relationship between ALUCEs and agricultural GDP, we further constructed a spatial EKC model. To account for the smoothness and cointegration relationship of each panel series, we performed a unit root test using the HT test, with both constant and trend terms applied to the panel data. The results indicate that all variables were first-order single integers. Additionally, the KAO cointegration test showed that the Modified Dickey–Fuller t was 2.1863 and the Dickey–Fuller t was 2.5409. These values rejected the original hypothesis of no cointegration relationship between variables, at both the 1% and 5% significance levels. Therefore, we can conclude that a stable equilibrium existed between the variables. We then conducted a regression analysis, presenting the EKC estimation results based on the SDM of the relationship between ALUCEs and agricultural GDP in Table 3.

Table 3. Spatial EKC estimation results of the relationship between ALUCEs and agricultural GDP.

Variable	Model 1 (Classical Squared Function)		Model 2 (Cubic Function without Control Variables)		Model 3 (Cubic Function with Control Variables)	
	Coefficient	z-Score	Coefficient	z-Score	Coefficient	z-Score
AGDP	0.835 ***	5.33	1.563 ***	4.07	0.967 ***	3.32
$AGDP^2$	−0.063 ***	−3.60	−0.262 ***	−3.02	−0.150 ***	−2.67
$AGDP^3$			0.016 ***	2.58	0.008 **	2.25
agristruc					−0.702	−1.05
cropstruc					−0.465	−1.22
animal					0.941 **	2.53
machine					0.145 ***	3.39
disaster					−0.079	−0.95
fiscal					−1.798 *	−1.77
urban					−1.290 ***	−3.43
environ					−4.998 **	−2.32
tech					3.124	0.98
W × *AGDP*	−0.225	−1.46	−0.718	−1.38	−0.801 **	−2.34
W × $AGDP^2$	0.008	0.42	0.102	0.73	0.191 **	2.21
W × $AGDP^3$			−0.005	−0.45	−0.014 *	−1.97
W × *agristruc*					2.318 ***	3.86
W × *cropstruc*					−0.185	−0.29
W × *animal*					0.742	1.01
W × *machine*					−0.078	−1.12
W × *disaster*					−0.253 *	−1.68
W × *fiscal*					3.099 *	1.71
W × *urban*					1.373 **	2.29
W × *environ*					−9.255	−1.16
W × *tech*					0.134	0.02
ρ	0.196 **	2.57	0.213 **	2.25	0.106	1.22
Hausman	24.01		29.19		27.05	
Wald-SAR	28.52		48.11		71.87	
Wald-SEM	21.92		36.69		71.37	
LR-SAR	27.46		45.44		67.88	
LR-SEM	21.45		39.93		68.24	
R^2	0.6368		0.672		0.7928	
Log-pseudolikelihood	−47.7003		−15.8746		126.1126	
Observations	630		630		630	

Note: *, **, *** indicate that the estimated coefficients pass the *t*-test at the 10%, 5%, and 1% significance levels, respectively.

As shown in Table 3, the Wald-lag, Wald-err, LR-lag, and LR-err tests rejected the null hypothesis that the SDM degenerated into the SAR or SEM, indicating that the SDM was the most appropriate model. Model 1 found that both the logarithm of agricultural GDP and its squared term passed the *t*-test at a 1% significance level, confirming the ALUCEs had reached a peak with agricultural GDP growth. Further, Model 2 found that the linear, quadratic, and cubic terms of agricultural GDP were all significantly validated by the z-test, with the cubic term being negative, indicating a significant N-shaped relationship between ALUCEs and agricultural GDP. To investigate the possible impact of several factors on the peak of ALUCEs, Model 3 introduced a series of control variables related to the agricultural sector's characteristics. The results indicated that the coefficients of the three terms of agricultural GDP remained significant. Therefore, we can conclude that there was an N-shaped relationship between ALUCEs and agricultural GDP, which held true with additional controls. Taken together, the three models indicated that ALUCEs had rebounded after meeting the inflection point with the expansion of agricultural production, and if the current trend continued, a second inflection point could occur. In other words, this finding confirmed that China's historical maximum of ALUCEs in 2015 may not be the emission peak. Consequently, more efforts should be put into ALUCE mitigation for smoothly passing the plateauing phase and turning to decline over time.

The estimated results revealed that the spatial autoregression coefficient ρ passed the z-test at the 1% significance level in Model 1 and Model 2, and some variables' cross-products with the spatial weight matrix were also significant. This observation signified that the peaking process of ALUCEs had spillover effects between provinces. These effects were attributable to similarities in the geographic environment, land endowment, and agricultural structure among geographically close areas, as well as increasing factor flow, technological diffusion, and policy emulation. It is worth noting that in Model 3, both the degree of agricultural mechanization (*machine*) and animal farming structure (*animal*) were found to have a significant positive impact on carbon emissions from land use. This suggests that the increased usage of agricultural machinery power will significantly increase greenhouse gas emissions, reflecting the energy-consumption nature of agricultural machinery. The emission coefficients of herbivores on fermentation and manure management are commonly a larger share of ALUCEs than omnivores, and therefore, the rise in herbivore proportion in animal structure had a positive impact on ALUCEs. On the other hand, the degree of urbanization (*urban*) and the intensity of environmental protection (*environ*) contributed to mitigating carbon emissions from land use. Urbanization signifies a process of technological advancement, leading to the accumulation of human capital, innovative knowledge, and the diffusion of technological progress effects on the agricultural sector. Additionally, enhancing environmental protection measures will effectively prompt producers to reduce high-carbon production practices such as wastage of agricultural resources and accumulation of waste during land use, thereby achieving carbon emission reduction from agricultural land use.

4. Discussion

4.1. Discussion of ALUCE Accounting

To compare ALUCE estimation results, we selected relevant studies from recent years. Based on their findings and the results of this study, a time-series evolution line chart was generated, which is presented in Figure 8.

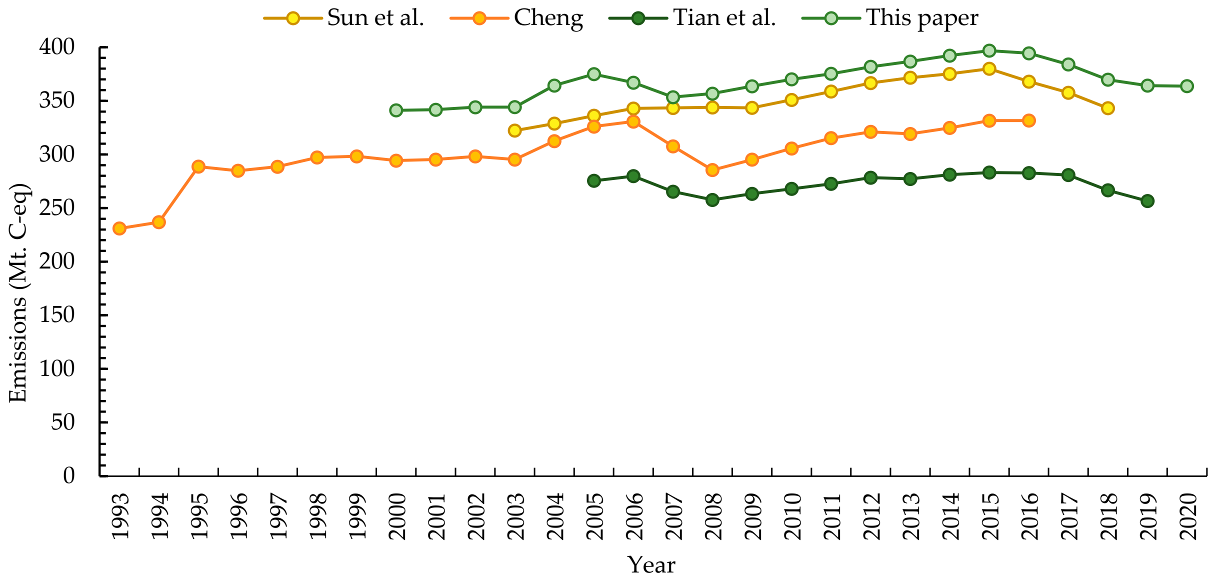

Figure 8. Comparison of ALUCEs in China estimated by relevant studies [27,29,30].

The primary conclusion that ALUCEs peaked at a historical point in 2015 aligns with existing literature [27,29,30]. Nevertheless, subtle differences persist among the studies examined. For instance, Cheng's study [29] focused on China's ALUCEs spanning 1993–2016 and observed that emissions (331.6 Mt C-eq, 1215.9 Mt CO_2-eq) reached their highest point in 2015, which were at a lower level than those measured in this study (396.9 Mt C-eq, 1455.3 Mt CO_2-eq). This disparity can be attributed to the different accounting inventories used in the two studies, as Cheng's list excluded agricultural materials such as fertilizers and pesticides that contribute significantly to China's ALUCEs. In contrast, Tian et al.'s [30] study identified peak ALUCEs (283.2 Mt C-eq, 1038.4 Mt CO_2-eq) in China in 2015, which were much lower than those measured in this study. This difference can also be explained by the variation in the carbon-accounting inventory. This study's accounting inventory considered two additional emission sources—soil management and straw burning—that accounted for an average of 25.2% of China's ALUCE composition. If these emissions were added, the results from Tian et al.'s study would closely resemble ours. Sun et al.'s [27] carbon-accounting inventory encompassed agricultural materials, rice cultivation, straw burning, and livestock breeding but excluded soil management compared to the accounting inventory developed in this paper. Since the proportion of carbon emissions from soil management in the composition of carbon emissions is generally low (7.9%), its impact on the final emission accounting results is relatively minor. Therefore, the difference between the results of Sun et al. [27] and those of this study is much lower than that of other studies.

4.2. Discussion on the Peaking Process of ALUCEs

Compared to previous studies that directly concluded that "ALUCEs peaked in 2015", this study proposed an analytical framework for evaluating the process of ALUCE peaking, exploring different peaking states through quantitative assessment and statistical testing.

Regarding quantitative assessment, we extended the study period up to 2020 and analyzed the peaking process using criteria. The results indicate that ALUCEs have reached an inflection point, with an average rate of annual change after peaking at −1.7%, suggesting a plateauing period. Unlike industrial and energy carbon emissions, ALUCEs remain relatively stable across provinces due to their close association with production scale, technology, and agricultural structure. Eleven provinces had already entered the plateauing period, while eight provinces were still in the peaking period. As such, continuing low-carbon transition efforts in agriculture is essential for ensuring a seamless transition through the peaking and plateauing periods. These findings contribute to the field of emission-peaking research from an agricultural perspective.

In addition to quantitative assessment, the robustness of the peaking process was also assessed using Tapio decoupling analysis and the spatial EKC model. The results reveal that most provinces have achieved decoupling between ALUCEs and the agricultural economy over both short- and long-term periods. However, the EKC model showed an N-shaped relationship between ALUCEs and the agricultural economy, indicating that though ALUCEs showed a decreasing trend after an inflection point occurred, they may still rebound due to the expansion of agricultural economic development. The combination of statistical testing and econometric analysis ensured the reliability of the peaking process judgment.

4.3. Limitations and Future Directions

The emission coefficients for ALUCEs were primarily derived from the data published by the Chinese government and widely cited literature in the field. However, the results still have uncertainties, particularly in accounting for carbon emissions resulting from straw treatment, including both straw burning and straw returning to the fields. Carbon emissions from straw burning involve the burning efficiency of major crops and the proportion of open burning, which may change over time due to technological progress and stricter bans. Due to limited data availability, this study used fixed straw open-burning rates for all years, potentially underestimating carbon emissions from straw burning in earlier years and overestimating them in recent years. Carbon emissions from soil management also include direct and indirect emissions of nitrous oxide caused by nitrogen input from straw returning to the fields. The straw return rate was based on data published by the Chinese government in 2011, leading to some bias in the time-series analysis. Despite these limitations, carbon emissions caused by straw disposal were included in the accounting system due to their significance. Future research can broaden perspectives and enhance data acquisition methods, such as integrating sample field observations, field trials, model simulations, farmer surveys, and statistical data to improve assessment models. Remote sensing technology can also be utilized to measure carbon emissions caused by straw treatment, increasing the degree of localization and accuracy of parameters in ALUCE-accounting research.

This paper aims to analyze past ALUCEs in China while summarizing the peaking process and evaluating their robustness without discussing the potential space for emission reduction. Given China's vision for emission peak and carbon neutrality, exploring ways to reduce agricultural emissions is crucial to achieving the "double carbon" target. Future research should focus on scenario simulations that project both temporal and spatial changes in ALUCEs. Such simulations could take into account factors like per capita consumption of major agricultural products in urban and rural areas, total population, and changes in urban and rural structures, as well as self-sufficiency rates of major agricultural products. By doing so, we can forecast the contribution of ALUCE reduction and explore ideal scenarios of low-carbon agricultural land use for the future.

5. Conclusions and Policy Recommendations

5.1. Conclusions

(1) Over 21 years, China's ALUCEs averaged 368.1 Mt (1349.7 CO_2-eq), with a historical maximum of 396.9 Mt C-eq (1455.3 CO_2-eq) occurring in 2015. The annual change rate compared with the peak emissions was −1.7%, indicating that ALUCEs have entered the plateauing phase. In terms of emission structure, each carbon source's annual average share decreased in the order of livestock breeding (36.6%), agricultural materials (21.3%), straw burning (17.0%), rice cultivation (16.9%), and soil management (8.2%). Emissions from agricultural materials and soil management had entered the declining period, while those from rice cultivation were in the peaking period, those from straw burning were still rising, and those from livestock breeding remained at the plateauing phase.

(2) Based on the overall development and annual change rate after reaching the peak, ALUCEs in Beijing, Tianjin, and nine other provinces had been declining. Conversely, in Hainan, Guizhou, and nine other provinces, ALUCEs had plateaued, while those in Ningxia, Qinghai, and six other provinces were still peaking.

(3) At a national scale, the long-term relationship between ALUCEs and agricultural GDP was weak decoupling. The short-term relationship was gradually moving towards strong decoupling from weak decoupling. At a provincial level, the connection changed from a diverse pattern to a polarized distribution pattern in which strong decoupling prevailed. The decoupling analysis verified that the emission-peaking states were stable even with agricultural growth.

(4) Instead of an inverted U-shaped relationship between ALUCEs and economic development, there existed an N-shaped relationship. Consequently, more efforts should be paid to ALUCE mitigation to smoothly pass the plateauing phase. Additionally, the peaking process of ALUCEs had spillover effects between provinces, suggesting an opportunity to make spatial-coordinating policies to achieve emission peaking.

5.2. Policy Recommendations

At the national level, ALUCEs had reached a plateau and were weakly decoupled from economic development in the long term and strongly decoupled in the short term. The EKC relationship between them was N-shaped. While agricultural materials and soil management had consistently reduced these emissions, there was still cause for concern regarding the expansion of straw burning causing a rebound effect. Therefore, it is necessary to continue prohibiting the open burning of straw and accelerate the resource utilization of straw. The application of low-carbon planting and breeding technology should be implemented to address high-carbon emission sources such as rice cultivation and livestock breeding. At the same time, promoting the transformation of livestock breeding from decentralization to intensification and applying low-carbon rice crop and field management can ensure stable production while achieving the low-carbon transition of agricultural land use.

At a provincial level, the quantity relationship between ALUCEs and economic output has generally been strongly decoupled. However, this relationship has not yet demonstrated a statistically stable trend. To accelerate the process of reducing ALUCEs in China, it is not only necessary to harness the potential spatial spillover effects across provinces, but an emission reduction strategy by area should also be formulated based on the peaking process and emission characteristics.

Firstly, within the eight provinces in the peaking phase, the annual average rate of change still has a large gap from the critical value (−2%). Without policy intervention, it would take a long time to enter the plateauing phase and then transition to the declining phase. Therefore, accelerating the adjustment and optimization of livestock breeding structures aligned with market orientation can influence the overall trend of ALUCEs, particularly as the scale and level of livestock breeding significantly affect this trend. In Jiangsu, CH_4 emissions from rice cultivation were high, and there was considerable reliance on high-carbon agricultural inputs. To achieve an earlier peak in ALUCEs, innovation and application of nitrification inhibitors and supportive management measures, development and introduction of new varieties of low-methane high-yield rice, and promotion of low-carbon field management suitable for local conditions are necessary.

Secondly, among the eleven provinces in the plateauing phase, especially those at medium to high emission levels (Heilongjiang, Shandong, Anhui, Sichuan, and Hunan), their subsequent development affects national emission reduction trends. The annual change rate compared to the peak emissions of six provinces (Hainan, Guizhou, Jiangxi, Shandong, Sichuan, and Hunan) has crossed −1.5% and that of Jiangxi has dropped to −1.9%. To accelerate the transition to the declining period, it is necessary to strengthen the application of low-carbon and high-efficiency technologies and improve the effective utilization rate of high-carbon agricultural materials.

Thirdly, in the provinces in the declining phase, Hebei, Hubei, and Henan have positive agricultural structures and technologies despite standing out as high-emission areas. These provinces have sustained a positive momentum of emission mitigation, demonstrating their potential for guiding provinces with similar production conditions. Other provinces with lower to moderate emission levels, characterized by small-scale crop cultivation and limited local agriculture in the economic structure, may benefit from flexible adjustment measures.

Supplementary Materials: Supplementary Materials about the equations and coefficients for calculating ALUCEs in China have been uploaded to the submission system along with this manuscript, which can be downloaded at https://www.mdpi.com/article/10.3390/land13050585/s1 [29,40,42–44].

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