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Investigation into the Performance Characteristics of the Organic Dry Farming Transition and the Corresponding Impact on Carbon Emissions Reduction

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Abstract: Global warming affects food security and ecological security, and it threatens economic stability and sustainable agricultural development. The transformation and development of agriculture have significant implications for the achievement of the "dual-carbon" goals and the promotion of sustainable agricultural development. Based on panel data on organic dry farming in China from 2005 to 2020, this study aimed to comprehensively assess the transformation performance of organic dry farming (TRODF) in 15 provinces. It explored the impact of the transformation of organic dry farming on carbon emissions by utilizing a spatial Markov chain and spatial measurement models. Our findings are as follows: (1) The performance of the organic dryland agriculture transformation has gradually improved and is accompanied by a corresponding trend of fluctuating regional disparities, which are on the rise. Moreover, the disparities between the five major regions mainly stem from intra-regional differences. (2) TRODF agriculture presents the possibility of state transfer during different periods, featuring four convergent zones: a lagging zone, a starting zone, a crossing zone, and an advanced zone. The spatial Markov chain indicates that state transitions typically occur between adjacent levels, with fewer instances of "jump"-type transitions. Moreover, there is a clear trend of differentiation in the state transitions between non-adjacent areas. (3) The organic dry farming transformation exhibits a significant carbon reduction effect, which is characterized by heterogeneity across different stages of agricultural development, provinces, and time periods. This study emphasizes that economic and industrial transformation, along with the transformation of the ecological environment, represents a crucial direction for conserving resources and achieving a further reduction in carbon emissions.

Keywords: organic dry farming; transformation performance; carbon emissions reduction

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Citation: Wang, G.; Zhao, B.; Zhao, M. Investigation into the Performance Characteristics of the Organic Dry Farming Transition and the Corresponding Impact on Carbon Emissions Reduction. *Agriculture* **2024**, *14*, 459. https://doi.org/10.3390/agriculture14030459

Academic Editor: Roberto Mancinelli

Received: 25 January 2024
Revised: 8 March 2024
Accepted: 8 March 2024
Published: 12 March 2024

1. Introduction

The 20th annual report of the Party highlights the need for China's agricultural development to steadfastly adhere to the red line of 1.8 billion mu of arable land, ensuring the secure control of the Chinese people's food supply [1]. To comprehensively fortify the foundation of food security and effectively implement measures to this end, it is essential to chart a new course for modern agriculture and rural development [2]. This involves bolstering the technical framework of organic dry farming, positioning it as a pivotal brand within modern agriculture. As per the Main Data Bulletin of the Third National Land Survey, China's total arable land of 1.918 billion mu comprises 965 million mu, constituting 50.33% of the total amount. Notably, 64% of this arable land is concentrated in regions north of the Kunlun Mountains, Qinling Mountains, and Huaihe River [3]. In the context of green development, the transformation and enhancement of traditional rainfed agriculture towards modern organic rainfed agricultural systems are imperative. The widespread application of modern agricultural elements has continuously weakened or even led to the disappearance of traditional rainfed agriculture. This transition not only aims to produce high-quality agricultural products that improve people's lives but also contributes to a reduction in carbon dioxide emissions. The organic transition is the period in which crops and livestock are managed according to the requirements of the USDA National Organic Program (NOP), prior to being granted organic certification. Agriculture represents the second-largest contributor to greenhouse gas emissions, as a significant source of carbon dioxide emissions. The transition to organic dryland farming must play a crucial role in achieving the "dual carbon" goals and promoting the sustainable development of agriculture. By elucidating the performance and carbon reduction mechanisms underlying the transition to organic dryland farming, as well as exploring its spatiotemporal evolution characteristics and spatial effects on reducing carbon emissions, we can further propel the transformation of traditional dryland agriculture.

The scientific evaluation of the transition performance is a critical approach to assessing the effectiveness of transition policies and constitutes a prerequisite for appraising their impact on reducing carbon emissions. The performance characteristics of the transformation refer to the precise summarization of its performance features based on the connotations of transformation. It involves the application of performance evaluation methods that are capable of reflecting the logical realities of an economic transformation. These methods assess the performance of the research subjects across various dimensions of economic transformation within a certain time frame. This assessment involves analyzing whether economic transformation behaviors have yielded significant effects, evaluating the quality of the economic, social, and ecological aspects of the transformation process, and assessing the degree to which the ultimate goals of economic transformation have been achieved. During this process, evaluation results consistent with the genuine mechanisms of transformation are obtained. Domestic and international research methodologies related to transformation performance and carbon emission effects are characterized by two main dimensions. The examination of transformation performance encompasses resource-based transformation and digital-intelligent-service-oriented transformation. Research on resource-based transformation delves into the characteristics and evaluation of the transformation performance [4–6], carbon emission reduction effects [7], and dynamic assessments [8] of resource-based cities. Meanwhile, digital-intelligent-service-oriented transformation focuses on the influence of big data resources [9,10] and data empowerment [8,11] on transformation performance. There is an urgent need for further exploration of TRODF agriculture.

The research on the measurement and evaluation of transformation performance employs two distinct methodologies. (1) The index system method is utilized, wherein scholars establish sustainable development policy systems to assess the impact of local industrial transformations in resource-based cities [12]. Scholars have also devised a corresponding evaluation index system for the ecological transformation of China's Mekong River, which is grounded in the innovative segmentation of the Mekong River ecosystem's transformation stages: these include the transition recovery period, the transition adjustment period, and the transition innovation period [13]. (2) The single-index method is applied to evaluate key aspects of transformation performance in resource-based cities. This method encompasses the assessment of sustainable development [14], industrial upgrading [15], improvements in economic quality and efficiency, and the promotion of low-carbon development [16]. (3) The input–output method, utilizing the DEA (Data Envelopment Analysis) model, evaluates the efficiency of resource-based urban transformations from an efficiency perspective [17,18].

The third area involves the proposal of and impetus for the development of low-carbon agriculture based on the "dual-carbon" target, encouraging the academic community to focus their attention on research related to carbon emission reduction pathways. Research indicates that agricultural insurance restrains carbon emissions by influencing green-agricultural-total-factor productivity and insurance transfer [19,20]. Additionally, green-agricultural-production technology plays a pivotal role in carbon reduction efforts [21]. The pathways for the low-carbon transformation of Chinese cities encompass the digital economy, industrial transformation and upgrading, and the spatial transfer of carbon emissions [22]. Furthermore, a comprehensive approach to straw utilization [12], investment in technological innovation [23], the enhancement of agricultural land-use types [24], economic and technological cooperation [25] and conservation tillage [26] can also make major contributions to reducing carbon emissions.

In the academic research on transformation performance, two main lines of inquiry have emerged: impact evaluation and measurement. However, the existing research still has some shortcomings and areas for improvement. First, the scope of the research on transformation performance is limited, often focusing on the transition from resource-based cities to smart services, with a lack of comprehensive studies of regional variations and spatiotemporal evolution, particularly in organic dryland agriculture. The relevant dynamic evolutionary characteristics require further exploration. Second, systematic measurement methods used to assess the transformation performance of organic dryland agriculture are lacking in the existing research. While the existing studies emphasize the pathways for the enhancement of organic dryland agriculture, insufficient attention is paid to its carbon emission reduction effects. Third, in the existing research, there is a lack of theoretical interrogation regarding the impact of the development of the transformation of organic dryland agriculture on carbon emissions reduction, with a dearth of empirical studies on its spatial effects. Therefore, this paper constructs indicators to evaluate the transformation performance of organic dryland agriculture, encompassing industrial upgrading, social life transformation, and environmental improvement. We focus on elucidating the characteristics of the transformation performance of organic dryland agriculture, identifying its carbon emissions reduction effects, and making policy recommendations to further promote its development.

2. Materials and Methods

Of the country's dry cultivated land, 64% is concentrated in the regions north of the Kunlun Mountains, Qinling Mountains, and Huaihe River. Consequently, this paper focuses on these areas, covering the period from 2005 to 2020. The selected region encompasses 15 provinces, municipalities, and autonomous regions: Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Shandong, Henan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. The details are shown in Table 1.

Table 1. Overview of the study area.

	Numerical Value	Unit	National Share
Area	579.09	10^4 km^2	60.32%
GDP	354,784.37	10^8 CNY	35%
Cropland area	82,799.06	10^4 hm^2	64.7%
Gross agricultural product	33,024.21	10^8 CNY	46.03%
Total grain output	39,646.71	10^4 t	59.22%
Population	57,224	10^4	40.53%

2.1. Theoretical Analysis

(1) The industrial upgrading effect of organic dryland agriculture. The transformation of agricultural industries serves as a critical foundation for the development of organic dryland agriculture and constitutes the fundamental basis for carbon emission reduction in organic dryland agriculture. This transformation primarily occurs through the rationalization and upgrading of agricultural structures. Regarding the rationalization of agricultural structures, enhanced coordination among various elements facilitates the redistribution of agricultural factors across sectors, thereby promoting the restructuring of agricultural sectors. Concerning the upgrading of industrial structures, agriculture transitions towards high technology and high value-added processes, directing factors towards high value-added agricultural sectors and consequently reducing agricultural carbon emissions.

(2) The societal impact of organic dryland agriculture. The societal transformation induced by organic dryland agriculture is primarily manifested in the enhancement of economic development efficiency and livelihood security. Technological advancements and educational initiatives accelerate the accumulation of agricultural production factors. The application of advanced agricultural production technologies improves agricultural resource-utilization efficiency and reduces agricultural carbon emissions. The transformation to organic dryland agriculture compels agricultural enterprises to reduce carbon emissions and pollution, fostering economic quality enhancement and efficiency improvement. As living standards rise, awareness of low-carbon practices increases, thereby promoting carbon emission reduction with heightened public environmental consciousness.

(3) The environmental synergistic effects of organic dryland agriculture. The collaborative improvement of the environment by organic dryland agriculture stems from the management of agricultural resource consumption and environmental pollution control. On one hand, reductions in pollutant emissions and resource consumption during the development of agricultural environmental transformations contribute to energy conservation and emission reduction, thereby positively impacting carbon emission reduction. On the other hand, environmental pollution control during agricultural environmental transformations plays a constructive role in carbon emission reduction. For instance, ecosystem protection and restoration facilitate the formation and development of ecological balance, significantly contributing to environmental improvement and achieving carbon emission reduction effects (Figure 1).

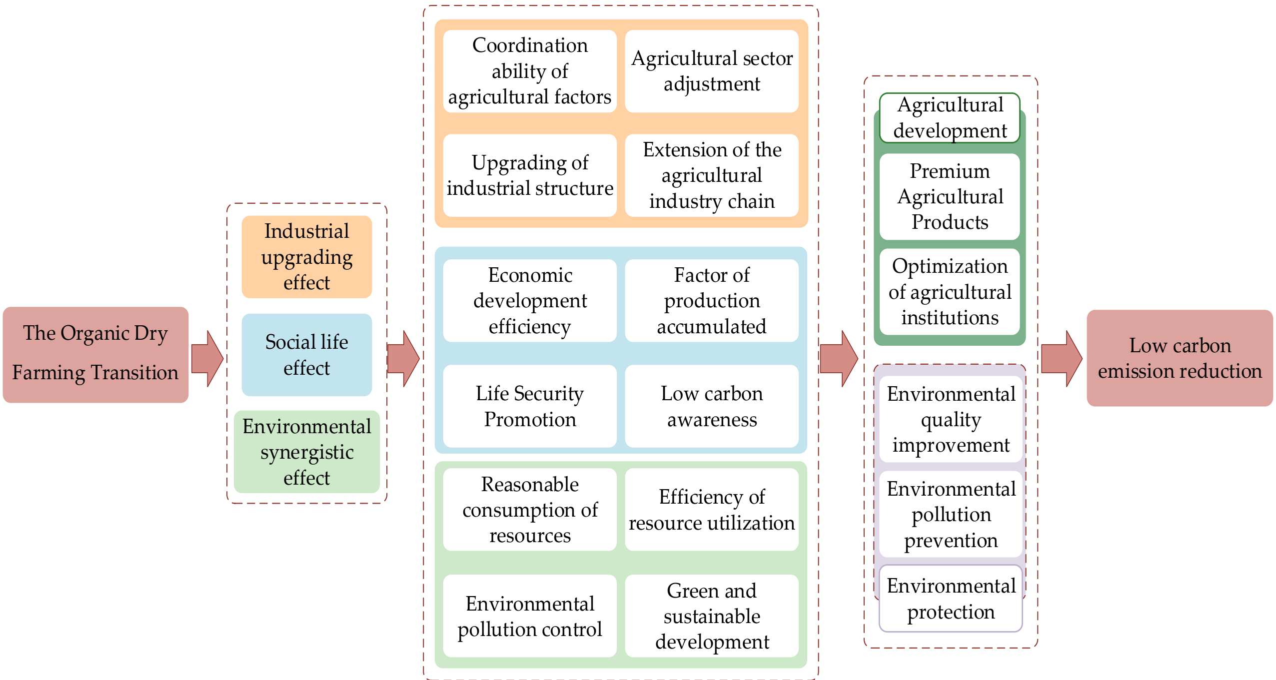

Figure 1. Mechanism of Organic Dry Farming Transformation.

2.2. Materials

The performance index system and control variable data related to the transformation of organic dry farming used in this study primarily derive from the National Statistical Yearbook spanning the years from 2005 to 2020. The data collected from the Statistical Yearbook underwent preprocessing, wherein missing values for individual years are interpolated to ensure completeness and accuracy. Based on the average transformation performance of the 15 provinces engaged in organic dry farming from 2005 to 2020, this study categorizes them into four grades: the lag zone (performance value below 60% of the mean), the starting area (performance value between 60% and 80% of the average), the spanning area (performance value between 80% and 120% of the average), and the leading zone (performance value exceeding 120% of the average). Employing spatial Markov chain analysis, this research aims to investigate the evolutionary characteristics of the transformation performance of organic dry agricultural areas. This involves establishing a spatial Markov probability transfer matrix with four distinct types and analyzing the probability of transfer trends associated with the four transformation-performance categories across different time periods.

2.3. Methods

2.3.1. Performance Evaluation Index System for the Transformation of Organic Dry Farming

This study constructs a comprehensive performance evaluation index system for the organic dryland agriculture transformation, drawing upon existing research achievements related to transformational performance evaluation indicators [9]. The constructed system encompasses three key dimensions: economic and industrial transformation, transformations in social life, and the transformation of the ecological environment. Regarding index measurement, the initial index data undergo a standardization process. Subsequently, the entropy method is employed to assign scores to each index, thereby determining their respective weights. The culmination of these steps results in the formulation of the performance index system for the transformation of organic dry farming.

2.3.2. Spatiotemporal Characteristic Analysis Method for the TRODF

(1) Theil index

To elucidate the temporal disparities and spatial variations in the TRODF, the Theil index for regional differences is employed. This calculation facilitates the decomposition of these differences into regional variances and intra-regional distinctions, enabling a comprehensive comparative analysis as follows:

$$T = \frac{1}{n}\sum_{i=1}^{n}(\frac{TRA_i}{\overline{TRA}} \times \ln\frac{TRA_i}{\overline{TRA}}) \tag{1}$$

$$T_r = \frac{1}{n}\sum_{i=1}^{n_r}(\frac{TRA_{ri}}{\overline{TRA}} \times \ln\frac{TRA_{ir}}{\overline{\overline{TRA_r}}}) \tag{2}$$

$$T = T_a + T_b = \sum_{r=1}^{5}(\frac{n_r}{n} \times \frac{\overline{TRA_r}}{\overline{\overline{TRA}}} \times Tr) + \sum_{r=1}^{5}(\frac{n_r}{n} \times \frac{\overline{TRA_r}}{\overline{TRA}} \times \ln\frac{\overline{TRA_r}}{\overline{TRA}}) \tag{3}$$

In the presented framework, let T denote the Tyre index representing the TRODF, with its values confined to the interval (0, 1), thereby reflecting the magnitude of the overall regional differences. TRA signifies the transformation performance value of organic dry farming, where T_r (r = 1, 2, 3, 4, 5) designates the Theil index of the transformation performance in the northeast, north, east, northwest, and central-southern regions, respectively. Here, i refers to the province, n denotes the total number of provinces under consideration for organic dry farming studies, and T_a and T_b represent intra-regional and inter-regional differences, respectively. The parameter n_r signifies the number of provinces engaged in organic dry agriculture (PCS) in the regions of northeast China, north China, east China, northwest China, and central China. TRA_i represents the transformation performance of province i, while TRA_{ri} denotes the transformation performance of the organic dry farming province i in the region. Additionally, the mean values of the transition performance for both organic dry farming and the provinces engaging in organic dry farming within region r are denoted as $\overline{TRA}$ and $\overline{TRA_r}$, respectively. The origins of the overall regional differences can be dissected at two levels: the intra-regional variation Theil index (T_a) and the inter-regional differences Theil index (T_b). T_a/T and T_b/T signify the contributions of intra-regional and inter-regional differences to the overall disparities, respectively. Furthermore, $(TRA_r/TRA) \times (T_r/T)$ represents the contribution of the five regions to the intra-regional variation in organic dry farming provinces within the northeast, north China, east China, the northwest, and the central-southern region. This includes TRA_r and TRA, which represent the sums of the transformation performance of organic and organic dry farming in the five regions, respectively.

(2) Spatial Markov chain

To delve deeper into the spatial correlations of TRODF agriculture across neighboring provinces over time, the selected provinces are classified into k types based on the initial-year spatial lag values of each province's transition performance. The performance type of the neighboring provinces is denoted by the spatial lag value of province i in a given year. Subsequently, k × k order probability transfer matrices are constructed by integrating these spatial lag values into the conventional Markov chain framework. The calculation of spatial lag values is carried out as follows:

$$Lag = \sum x_i W_{ij} \tag{4}$$

where x_i represents the transformation performance of province i, and W_{ij} stands for the adjacency spatial weight matrix.

2.3.3. Method for the Analysis of the Carbon Emission Reduction Effect of the Transformation of Organic Dry Farming

(1) Panel fixed-effect model

To investigate the correlation between TRODF agriculture and carbon emissions, we constructed an econometric model for testing as follows:

$$EMI_{it} = \alpha + \beta TRA_{it} + \delta X_{it} + \mu_i + v_i + \varepsilon_{it} \tag{5}$$

where t represents time, EMI_{it} denotes provincial carbon emissions measured in 100 million tons, X_{it} serves as the control variable, μ_i represents the provincial fixed effect, ν_i corresponds to the time-fixed effect, and ε_{it} represents the random interference term. Additionally, α represents the constant term, while the estimated coefficients pertain to the core explanatory and control variables.

In this paper, the following variables are selected as control variables: ① Government intervention (GOV): the ratio of the general budget expenditure of local finance to GDP is used to reflect the degree of government intervention; ② population size (POP), which is characterized by the permanent urban resident population; ③ environmental regulation (ENR), using the proportion of employees in water conservation, environment, and public facilities management in the total population; ④ infrastructure (INF), which is characterized by the ratio of the urban road area to the total population; and ⑤ market size (SIZ), which is characterized by the product of population per square kilometer and GDP per capita.

(2) Spatial econometric model

TRODF agriculture was incorporated into the STIRPAT model to analyze the impact pathway of organic dry agriculture on carbon emissions, along with the demonstrated spatial effects. The spatial Durbin model (SDM) can be simplified into both the Spatial Error Model (SEM) and the Spatial Lag Model (SLM):

$$EMI_{it} = \alpha TRA_{it} + \beta X_{it} + \rho \sum_{i=1}^{n} W_{ij} EMI_{it} + \gamma \sum_{i=1}^{n} W_{ij} TRA_{it} + \varphi \sum_{i=1}^{n} W_{ij} X_{it} + \mu_i + v_i + \varepsilon_{it} \tag{6}$$

where ρ, γ, and ϕ represent the spatial lag coefficients of the variables. Additionally, to enhance data stability and alleviate heteroscedasticity, the respective variables undergo logarithmic transformations to standardize the variable scale.

3. Results

3.1. Spatiotemporal Evolution Characteristics of the Transformation Performance of Organic Dry Farming

3.1.1. Regional Differences and Structural Decomposition

In Figure 2, the overall volatility (as depicted by the Theil index) of TRODF in agricultural provinces from 2005 to 2020 exhibited an increase from 0.0486 in 2005 to 0.1436 in 2006, followed by a decrease to 0.0590 in 2020. This pattern indicates an initial rise and subsequent fall in the overall difference in TRODF across China. The minimum difference was observed in 2008, at 0.0143, while the maximum difference occurred in 2006, with a Theil index value of 0.1436.

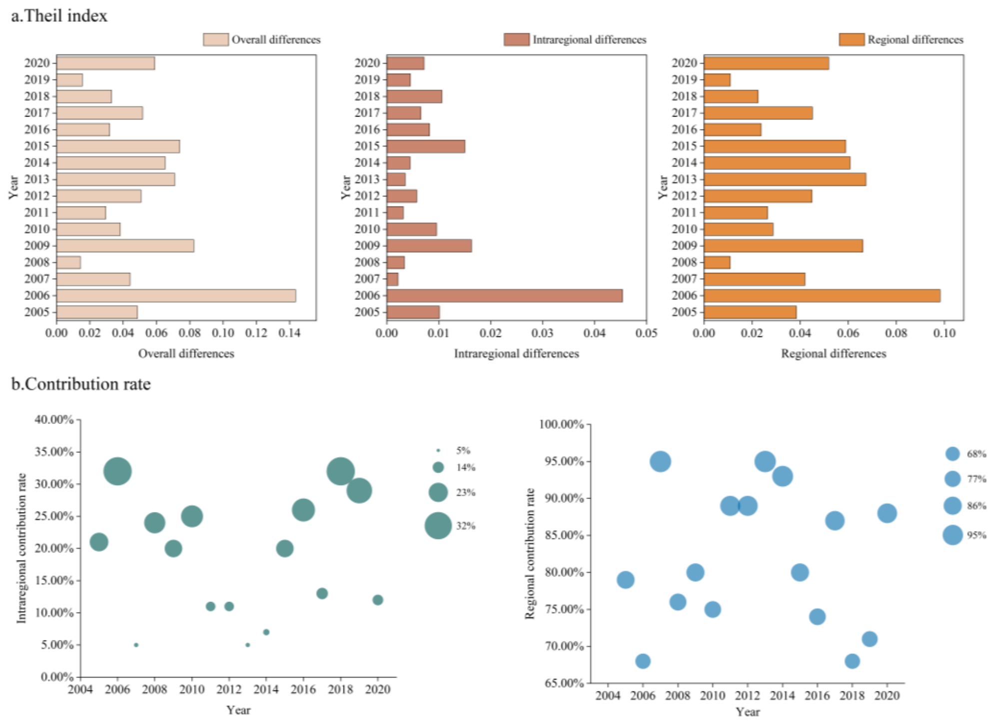

Figure 2. Theil index of the organic dry farming transformation performance from 2005 to 2020 ((**a**): Theil index; (**b**): Contribution rate).

Regarding regional decomposition, the contribution rate of regional differences from 2005 to 2020 exceeded 70%. In 2007 and 2013, the contribution rate reached its peak at 95%, while, in the other years, the contribution rate of regional differences was less than 35%, except for the maximum value of 32%, which was reached in 2006. This suggests that regional differences predominantly account for the overall disparity in organic dry farming, with 2007 and 2013 standing out as the years with the most significant regional contributions.

Upon decomposing the regional difference index, we discerned that the average transformation performance indices for northeast China, north China, east China, northwest China, and central China from 2005 to 2018 were 0.0083, 0.0055, 0.0173, 0.0073, and 0.0247, respectively (Figure 3).

Furthermore, the northeastern, northern, eastern, northwestern, and central-southern regions exhibit average contributions to the overall variation of 1.88%, 2.95%, 9.15%, 3.06%, and 9.67%, respectively. Notably, the northeastern, northern, and northwestern regions display discernible fluctuation trends. The contribution rates of the eastern and central-southern regions, averaging above 9%, position them as the primary contributors to the overall variation. The northern and northwestern regions follow, while the northeastern region makes the smallest contribution to the overall variation.

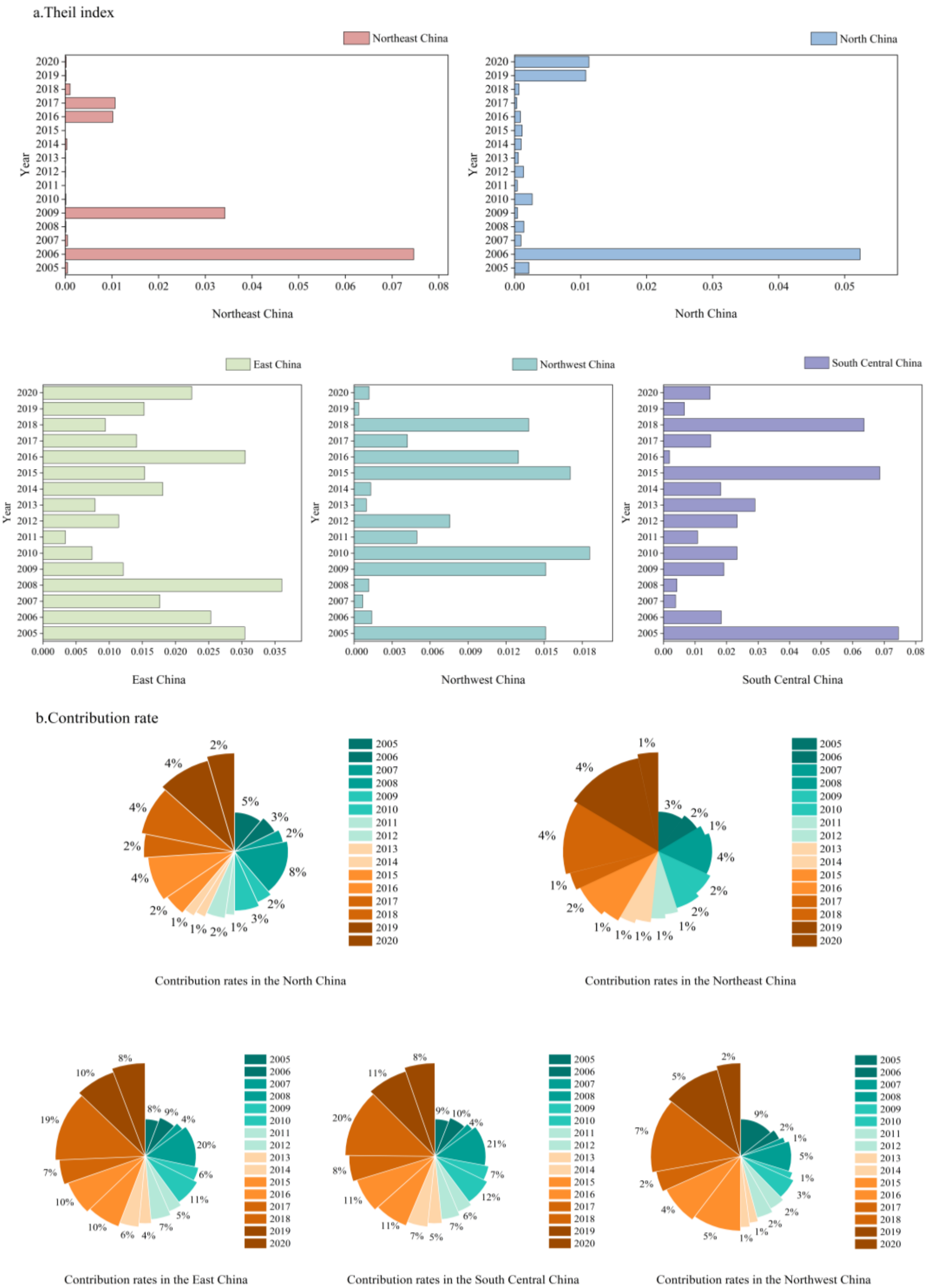

Figure 3. Theil index and structural decomposition of the transformation performance of organic and dry farming ((**a**): Theil index; (**b**): contribution rate).

3.1.2. Dynamic Transfer Characteristics

The overall transformation performance of the organic dry farming area can be categorized into the lag area, starting area, crossing area, and pilot area (Figure 4). Generally, with the exception of the pilot zone, the probability values along the diagonal of each regional level are higher than those off the diagonal, indicating that the transformation performance of each province is relatively stable, with strong internal dynamics. However, there is a notable probability of the initial state being maintained.

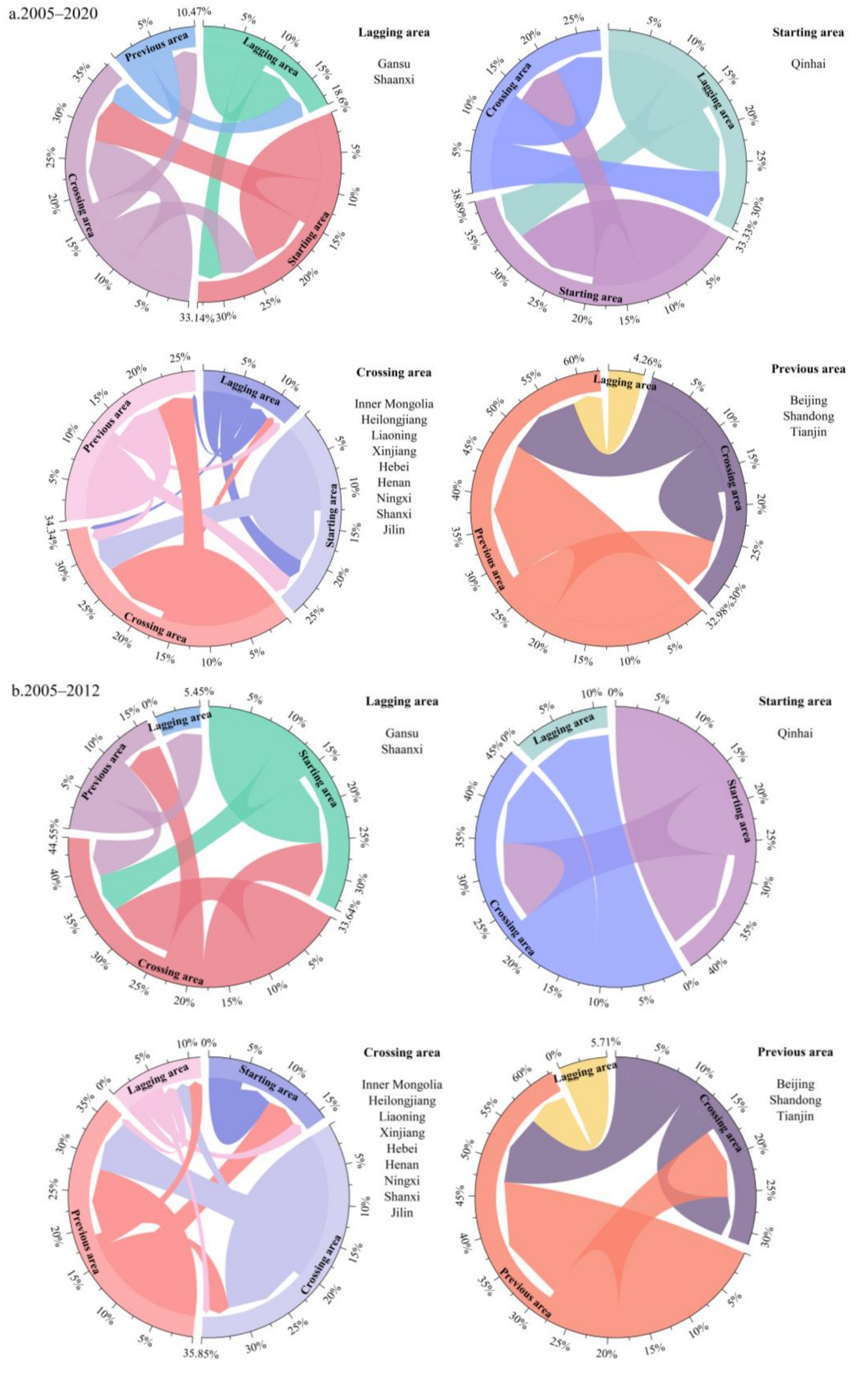

Figure 4. *Cont.*

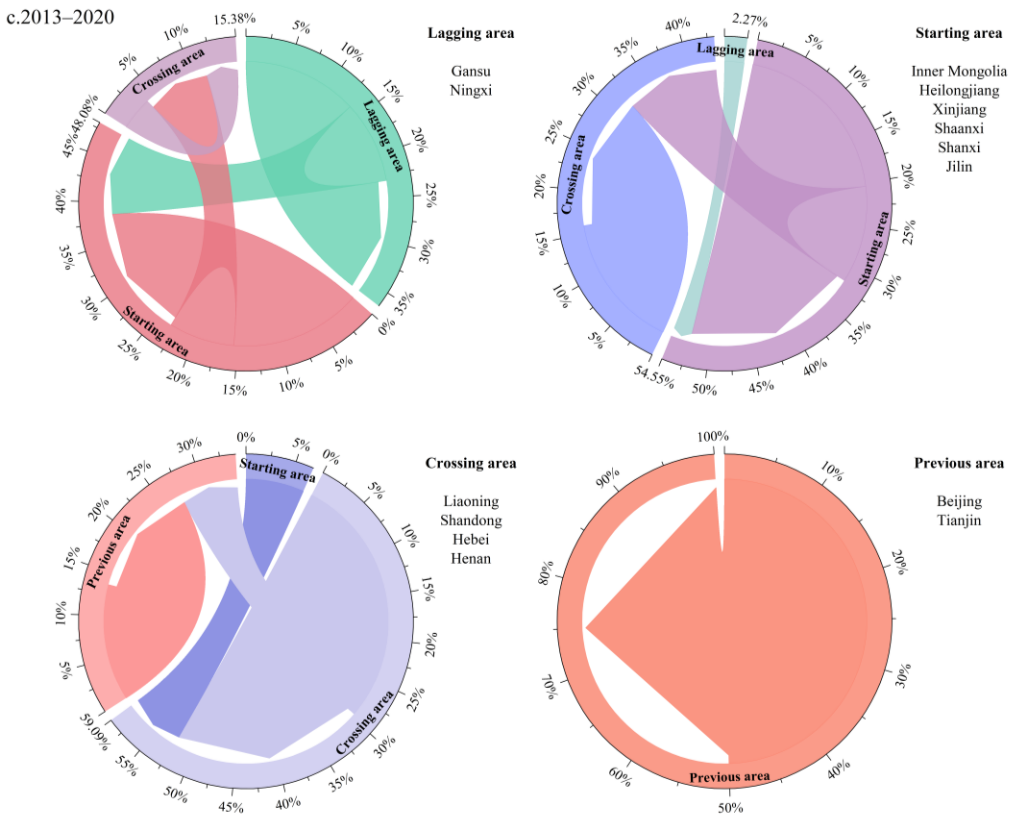

Figure 4. Spatial Markov transition probabilities ((**a**): 2005–2020; (**b**): 2005–2012; and (**c**): 2013–2020).

In the state transition probability matrix, the state transfer of the TRODF mainly leans towards the crossing zone, followed by the starting zone, while the probability of state transfer to the lag zone and the pilot zone is minimal. State transfer of the transformation performance usually occurs between adjacent grades, and the occurrence of the "jump" transfer phenomenon is infrequent. Numbers off the diagonal are distributed on both sides and are concentrated above it, indicating that the transition performance has the potential to shift to higher-ranking types.

Between 2005 and 2012, there is a notable trend in state transfer from the crossing area to lower types, which is higher than the transfer to higher-grade types. The transformation of organic dry farming exhibits a certain "path dependence", displaying long-term and persistent characteristics, making it difficult to achieve leapfrog development.

The process of state transfer in the transformational performance of organic dry farming displays a strong spatial proximity. Provinces that are adjacent with different transformation performance types exhibit varying transfer probabilities. Generally, the higher the transformation performance of neighboring provinces, the greater the probability of upward transfer for a given province. Conversely, if a neighboring province has lower transformation performance, the probability of downward transfer for that province is higher. This suggests that the transformational development of a province in organic dry-crop agriculture is distinctly correlated with the transformation performance type of the neighboring provinces.

3.2. Impact of the Regional Transformation of Organic Dry Farming on Carbon Emissions

3.2.1. Spatial Correlation Test

Prior to conducting the spatial measurement analysis of regional transformation and carbon emissions, this paper utilized the univariate Moran's I index to examine the spatial correlation between the regional transition performance (TRA) and carbon emissions (EMI). Additionally, the bivariate value of the regional transition performance and Moran's I was calculated to investigate the spatial correlation characteristics between the two variables (Table 1).

The Moran's I values for the TRODF areas exhibited fluctuations ranging from 0.270 to 0.634. Significance was observed at the 1% level for all years, indicating robust spatial agglomeration. This suggests that areas with higher levels of transformation performance tended to be spatially adjacent, while lower-performing regions also exhibited spatial adjacency. The trend of the Moran's I values for carbon emissions in organic dry farming areas showed less apparent changes, implying strong spatial agglomerations in carbon emissions within these areas.

An analysis of the bivariate Moran's I value for transformation performance and carbon emissions revealed that, although significance was not observed in some years, the overall relationship was significantly positive. This indicates pronounced spatial agglomeration and dependence characteristics between the TRODF agricultural areas and carbon emissions. These findings suggest a mutual influence among neighboring provinces, with notable clustering characteristics (Table 2).

Table 2. Results of the Moran's I statistic test.

Year	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
TRA	0.439 ***	0.450 ***	0.438 ***	0.540 ***	0.476 ***	0.322 ***	0.434 ***	0.384 ***
EMI	0.346 ***	0.348 ***	0.332 ***	0.323 ***	0.318 ***	0.306 ***	0.290 ***	0.264 ***
Year	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
TRA	0.440 ***	0.420 ***	0.634 ***	0.386 ***	0.396 ***	0.270 ***	0.469 ***	0.303 ***
EMI	0.250 ***	0.214 ***	0.201	0.200	0.199	0.187	0.178	0.183

Note: *** represent the significance levels of 1%.

3.2.2. Parameter Estimation and Analysis of Results

After the initial examinations, the panel FE model was used for the basic regression, and the reliability of this study's conclusions was verified using the endogeneity test and the robustness test. Furthermore, the spatial Durbin model was used to analyze the spatial spillover effect. Table 3 shows the estimated results of the model basis.

Table 3. Parameter estimation and results.

Variable	**Panel FE Model**	**Endurance Test**	**Robustness Test**		**Spatial Durbin Model**	
	lnEMI	**lnEMI**	**lnCOG**	**lnEMI**	**Main**	**W × X**
TRA	−2.022 *** (−6.55)	−2.022 (−2.02)	−0.490 * (−1.84)	−0.424 * (1.83)	−0.309 *** (−3.93)	−0.005 (−0.03)
GOV	3.496 *** (−6.92)	3.496 (3.50)	0.230 (1.06)	0.859 ** (2.66)	0.0121 (0.08)	0.268 (0.69)
POP	0.000 *** (11.97)	0.000 *** (0.00)	−0.000 ** (−2.53)	−0.000 * (−2.03)	−0.000 *** (−6.01)	−0.001 ** (−2.50)
ENR	123.166 * (−1.91)	123.166 (123.17)	27.538 (0.49)	113.670 * (2.09)	42.268 ** (2.22)	312.711 *** (4.47)
INF	0.038 * (−1.93)	0.038 ** (0.04)	0.027 ** (2.25)	0.027 (1.62)	0.015 (1.38)	−0.064 *** (−4.57)
SIZ	−65.310 *** (−10.11)	−65.310 (−65.31)	9.354 (1.74)	0.940 (0.12)	−3.203 (−1.36)	−72.095 *** (−10.56)

Table 3. *Cont.*

Variable	Panel FE Model	Endurance Test	Robustness Test		Spatial Durbin Model	
	lnEMI	lnEMI	lnCOG	lnEMI	Main	W × X
cons/rho	6.668 *** (20.91)	6.668 (6.67)	8.563 *** (14.15)	6.138 *** (7.2)	−0.742 *** (−4.08)	
N/individual	240	210	240	240	240	
R^2	0.44	0.00	0.43	0.54	0.68	

Note: the t-value is given in parentheses; in the endogeneity test model, the AR (1) test result is −1.99 (p = 0.046), the AR (2) test result is 0.90 (p = 0.366), and the Hansen test result is 5.60 (p = 1.000). Cons represents the constant term in the non-spatial measurement model (panel FE, endogeneity, robustness), and the rho in the spatial measurement model represents the spatial lag term, the same as below. And *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively.

(1) Panel fixation effect

Initially, the analysis employed the panel fixed effects model as the foundational framework. The results indicate that the TRODF exerts a notable negative influence on carbon emissions. This suggests that the TRODF is conducive to reducing carbon emissions. Furthermore, provinces engaging in economic, social, and ecological transformations related to organic dry farming demonstrate pronounced energy-saving and emissions-reduction effects, as highlighted in Table 3.

(2) Endurance test

To address the endogeneity problem resulting from omitted variables and reverse causality, the model undergoes an endogeneity test, as shown in Table 4. In consideration of the presence of heteroscedasticity, the Generalized Method of Moments (GMM) remains robust and optimal. Estimates are made using the differential GMM model, assuming no autocorrelation for the disturbance term and employing the first order of the transition performance lag as the instrumental variable.

Table 4. Model-based estimation results.

Order	Z	Prob > z
1	−0.21438	0.8303
2	−0.10131	0.9193

The p-value of 0.777, which exceeds the threshold of 0.05 for AR (1), leads to the rejection of the null hypothesis, signifying the absence of first-order autocorrelation in the disturbance term. The difference GMM, which is reliant on the assumption of no autocorrelation in the disturbance term, provides a consistent estimate. The Arellano–Bond test reveals no autocorrelation in the disturbance items, confirming the consistency of the difference GMM estimator. This emphasizes the validity of the previously established conclusion regarding the dampening effect of the performance of the organic dry farming transition on carbon emissions.

(3) Robustness test

To some extent, the endogeneity test helps us to elucidate the model's robustness. Furthermore, this study extends the robustness testing by substituting and constraining the explanatory variables. Initially, the explanatory variable was substituted with carbon intensity, revealing that the TRODF remained significantly negative at the 10% significance level. This reaffirms the reliability of the conclusion that provincial transformation is conducive to reducing carbon emissions.

Additionally, in light of the potential impact of excluding extreme values, the carbon emission level of the dependent variable experiences a 1% reduction at both ends. The data demonstrate that the original results remain credible, underscoring the high robustness of this paper's findings. This implies that the transformation of organic dry farming agriculture indeed yields a carbon emissions reduction effect.

(4) Spatial Durbin model

In order to generate a deeper understanding of the spatial impact of the transformation performance of organic dry farming on carbon emissions, we utilize a spatial measurement model to extend the original model (refer to Table 4). Initially, both the LM lag and LM error successfully pass the significance test—Lagrange multipliers and lag factors—with p-values well below 0.05, indicating the presence of spatial autocorrelation in the model. Moreover, both the Wald test and the LR test, which assess significance, confirm that the SDM model cannot be simplified into an SLM model or a SEM model. Subsequently, the results of the Hausman test reveal a negative statistic, the correction of the variance and covariance matrix, and an infinitesimally close-to-zero p-value for the corrected estimator, signaling the absence of random effects. Consequently, we confirm the validity of the fixed-effect model.

When examining the outcomes of the spatial Durbin model, the coefficient rho for the spatial lag term of the explained variable is significantly negative. This indicates the notable positive spillover effect of organic dry farming carbon emissions from neighboring areas and the significant negative impact of the organic dry farming transformation performance on carbon emissions. However, at the level of the overall transformation performance, the spatial lag term coefficient is not statistically significant.

Further exploration of the impact of the organic dry farming transformation on carbon emissions is conducted via province classification and performance zoning. The primary reasons for these effects relate to the facilitation of the break from traditional agriculture, which promotes the vertical extension and high-quality development of the agricultural industrial chain, and especially the green development of the industrial structure. This, in turn, encourages the rational development and utilization of agricultural input elements, alleviates pressure on the ecological environment, and reduces carbon emissions. Moreover, the transformation and development of organic dry farming represent a comprehensive process involving economic, social, and environmental transformations. This process promotes enhanced social functionality, fosters a positive environmental protection mindset throughout society, improves farming techniques in order to reduce pollution emissions, and encourages consumers to adopt energy-saving and emission-reducing measures in daily life—all contributing to the mitigation of agricultural carbon emissions.

Regarding the control variables, the influence of government intervention on carbon emissions appears to be insubstantial. This suggests that the macro-control impact of government intervention on organic dry farming has not significantly elevated carbon emissions. Nevertheless, an excess of interventionist policies may potentially result in diminished resource allocation within the market, thereby causing an upsurge in carbon emissions due to a resource mismatch.

The size of the population exhibits a negative correlation with carbon emissions, which is primarily attributed to the diminishing effects of population growth. As the population reaches a certain threshold, per capita carbon emissions experience a relative reduction. The impact of infrastructure on carbon emissions is positive but lacks statistical significance. This can be attributed to the current developmental stage of the organic dry farming infrastructure, which may pose risks to the existing ecosystem, consequently contributing to heightened carbon emissions.

On the other hand, the negative correlation between the market size and carbon emissions implies that a robust market economy has the potential to attract skilled individuals. This, in turn, fosters a spillover of knowledge and technology, thereby exerting a discernible impact on reducing carbon emissions (Table 5).

Table 5. Basic estimation results of the spatial Durbin model.

Test	Statistic	df	*p*-Value
Spatial error:			
Lagrange multiplier	14.369	1	0.000
Robust Lagrange multiplier	22.708	1	0.000
Spatial lag:		1	
Lagrange multiplier	3.826	1	0.050
Robust Lagrange multiplier	12.165	1	0.000

3.2.3. Heterogeneity Analysis

To investigate the heterogeneity of the carbon emission reduction effects across various development stages and spatial locations, we categorized the development stages based on the midpoint year, focusing specifically on the stage of performance in 2013. Additionally, spatial locations were delineated according to the national standard (Table 6).

Table 6. Results of the heterogeneity analysis.

Variable	Different Stages of Development			Different Spatial Locations			Different Time Stages	
	Lag Area	Start Area	Across the Area	NC	Northeast	Northwest	2005–2013	2014–2020
TRA	0.319 ** (2.11)	−0.036 (−0.57)	−0.019 (−0.07)	−0.252 *** (−3.74)	0.292 * (1.75)	−0.034 (−0.18)	0.05 (1.489)	−2.59 *** (−113.376)
W × TRA	−0.407 *** (−2.87)	−0.039 (−0.38)	−0.049 (−0.16)	−0.376 *** (−2.85)	−0.278 * (−1.66)	0.0133 (0.006)	—	—
Controlled variable	yes	yes	yes	yes	yes	yes	yes	yes
rho	−0.149 (−1.09)	0.006 (0.04)	−0.593 *** (−3.51)	−0.616 *** (−4.83)	−0.033 (−0.24)	0.161 (1.08)	20.29 (314.22)	436.505 (18.83)
N/individual	48	96	64	80	48	80	210	105
R^2	0.957	0.944	0.710	0.808	0.977	0.925	0.537	0.436

Note: *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively.

(1) Different development stages of organic dry farming areas

Building on the findings of the previous study, the 15 provinces engaged in organic dry farming are categorized into lag, starting, spanning, and pilot areas. Provinces within the lag zone include Gansu, Ningxia, and Qinghai. The starting area comprises Heilongjiang, Jilin, Inner Mongolia, Shanxi, Shaanxi, Xinjiang, Hebei, Henan, Liaoning, and Shandong. Lastly, the pilot area includes Beijing and Tianjin. Given the limited number of provinces in the pilot zone, the spatial measurement model is not applicable to this subset. Consequently, the spatial Durbin Model (SDM) results for the lag, starting, and spanning areas are exclusively examined in this context.

Regarding the spatial impact of overall carbon emissions, the rho coefficient of the spanning provinces is significantly negative. Notably, the carbon emissions from provinces within the spanning regions exhibit a significant positive spillover effect on neighboring regions. In lagging areas, the development of organic dry farming demonstrates a significant positive impact on local carbon emissions, and its influence on the carbon emissions of nearby provinces is also notably positive. This is likely due to the fact that lagging areas, being in the early stages of development, possess significant development potential. The primary developmental focus involves enhancing the construction of upstream and downstream infrastructure. In the process of advancing agriculture to meet basic food demands, the use of chemical fertilizers, pesticides, and other agricultural inputs in lagging areas contributes to increased carbon emissions in the province.

However, due to the imperative for transformation and economic development, these areas undertake agricultural and industrial development for neighboring provinces. This, in turn, promotes the enhancement of resource processing and utilization levels in neighboring provinces, fosters the construction of new urban areas, encourages the development of strategic emerging industries, and facilitates the transformation and development of neighboring provinces, thereby exerting a noteworthy carbon emissions reduction effect.

In starting areas, the impact of provincial transformation development on carbon emissions is not deemed significant. This could be attributed to the ecological challenges faced by starting area provinces during the promotion of economic development. These areas face severe talent shortages and funding constraints. Furthermore, the establishment of a robust organic dry farming transformation system is still in progress, and the transformative impact on agricultural development is not yet sufficient to significantly reduce carbon emissions.

For provinces in a transitional development phase that spans regions, there is no discernible significant impact on carbon emissions in the region and neighboring cities. This is likely due to the fact that economic growth in cross-regional provinces predominantly relies on tertiary industry. The emphasis in these provinces is on quality and efficiency, with traditional agricultural development constituting a small proportion of overall development. As a result, the impact on carbon emissions reduction in agriculture is considered insubstantial. The modest share of traditional agricultural development in these provinces translates to a limited driving effect on neighboring regions, further diminishing the significance of carbon emissions reduction in agriculture.

(2) For provinces with different locations

The impact of the transformation of organic dry farming in agricultural provinces on carbon emissions was examined separately in north China, northeast China, and northwest China. The transformation of organic dry farming in the provinces of north China significantly suppressed carbon emissions in the region and in its neighboring provinces. In contrast, the transformation of organic dry farming in northeast China resulted in a notable increase in carbon emissions within the region but significantly inhibited carbon emissions in neighboring provinces. Meanwhile, the carbon reduction effect in northwest China and adjacent regions was not pronounced.

This discrepancy may be attributed to the relatively limited diversity of agricultural types in north China. Beijing and Tianjin, in particular, possess distinct advantages in terms of resources for innovation, attracting a considerable number of innovative talents and a good deal of innovation capital. This dynamic exerts a robust influence on agricultural transformation and development in the region, resulting in a discernible reduction in carbon emissions. Northeast China, serving as China's traditional and stable commodity grain base, is also the nation's largest commodity grain base. To a certain extent, the scale of organic dry farming development in this region diminishes agricultural inputs in neighboring provinces, thereby yielding a significant carbon reduction effect.

In contrast, traditional agriculture in northwest China is characterized by widespread distribution, with organic dry farming constituting a relatively small proportion of the total. Additionally, the agricultural development conditions in this region are challenging, potentially leading to substantial resource consumption during the agricultural development process. Consequently, the transformation and development of organic dry farming may not exhibit a conspicuous inhibitory effect on carbon emissions at this stage.

(3) Provinces at different stages

Considering the different stages of temporal development, with 2013 as the delineating point, the impact of the transformation of organic dry farming on carbon emissions was not significant prior to 2013. However, after 2013, the overall transformation performance in each province exhibited a noteworthy reduction in local carbon emissions. During the period of 2005–2013, China underwent a shift from economic accumulation to a growth rate transition, experienced structural adjustment challenges, and navigated the early phase of stimulus digestion. Organic dry farming, being in its nascent stage of development during this period, primarily focused on dryland agriculture. TRODF remained at a low level, as is indicative of its position in the traditional dry farming development stage. This phase was characterized by the dual challenges of economic development and environmental pollution, resulting in the limited effectiveness of carbon emissions reduction through the organic dry farming transformation.

The 2012 report to the 18th National Congress of the Communist Party of China emphasized the need to expedite the development of modern agriculture, enhance the comprehensive agricultural production capacity, and ensure national food security along with the effective supply of critical agricultural products. The state strongly supported the modern agriculture initiative, leading local governments to implement preferential subsidy policies for organic dry farming and enterprises. This proactive approach attracted a significant influx of innovative talents, contributing to substantial carbon emissions reduction effects across economic, social, and ecological boundaries.

3.2.4. Decomposition of the Transformation Effect of Agricultural Provinces

In terms of economic industrial transformation (Table 7), the impacts of the organic dry farming agricultural economy, industrial transformation, and ecological transformation on carbon emissions appear to be insignificant. This may be attributed, in part, to the influence of economic and industrial transformation, wherein issues related to balanced industrial development, rational allocation, and sustainable development remain unresolved. Moreover, industries and enterprises are confronted by the challenges posed by a new round of technological and industrial revolutions, resulting in difficulties related to technological innovation and transformation, thereby impeding the effective reduction of urban carbon emissions.

Table 7. Decomposition of the transformation of organic dry farming provinces.

Variable	Economic and Industrial Transformation		Transformation of Social Life		Ecological Transformation	
	Main	Wx	Main	Wx	Main	Wx
TRA	0.329 (0.91)	0.073 (0.06)	−2.559 *** (−5.92)	−5.283 *** (−2.67)	−0.394 (−0.98)	−0.249 (−0.49)
GOV	0.055 (0.34)	0.453 (1.14)	−0.090 (−0.60)	0.390 (1.10)	0.016 (0.10)	0.204 (0.50)
POP	−0.001 *** (−6.36)	−0.001 *** (−3.10)	−0.001 *** (−5.10)	−0.001 *** (−2.17)	−0.001 *** (−6.19)	−0.001 *** (−2.62)
ENR	41.558 ** (2.11)	390.727 *** (5.82)	65.280 *** (3.60)	465.918 *** (7.14)	43.040 ** (2.13)	327.269 *** (4.45)
INF	0.029 *** (2.76)	−0.074 *** (−5.27)	0.017 * (1.75)	−0.0024 (−0.10)	0.0245972 ** (2.28)	−0.080 *** (−5.43)
SIZ	−3.054 (−1.26)	−71.476 *** (−9.98)	−3.294 (−1.48)	−77.055 *** (−11.37)	−3.548 (−1.47)	−72.782 *** (−10.17)
Controlled variable	yes		yes		yes	
rho	−0.749 *** (−3.97)		−1.030 *** (−5.68)		−0.753 *** (−4.05)	
R^2	0.653		0.695		0.661	

Note: *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively.

From the perspective of social transformation, it is clear that advancements in social life can significantly reduce carbon emissions in the region and neighboring cities. This suggests that, as residents experience an improvement in living standards, there is a heightened demand for high-quality public services and a better living environment. Simultaneously, residents gradually shift their consumption patterns, raising awareness of low-carbon consumption and thereby reducing the carbon emissions associated with daily life. The enhancement of residents' quality of life demonstrates a substantial carbon emissions reduction effect, fostering green and low-carbon urban development.

Finally, the transformation of the environment does not exhibit a pronounced inhibitory effect on carbon emissions in this region or in neighboring provinces. This could be attributed to the relatively slow progress made in the environmental protection industry, the circular economy, and the low-carbon economy during the process of ecological transformation. Additionally, the growth potential of new agriculture and the capacity of organic dry farming have not made notable contributions to reducing carbon emissions.

4. Discussion

Organic dry farming represents an environmentally sustainable, health-conscious, and high-quality mode of agricultural production. It constitutes a pivotal approach to fostering high-quality agricultural development and advancing low-carbon agricultural practices. To advance the progress of organic dry farming, it is imperative to conduct a comprehensive analysis of both the three-dimensional aspects of production and the associated production relations. This analytical approach aims to produce insights into the principles guiding high-quality and low-carbon development within the realm of organic dry farming.

This study aimed to enhance the system used to assess economic development and facilitate the multifaceted evolution of organic dry farming. This involves, firstly, optimizing the agricultural production mode and enhancing both the efficiency and quality of agricultural products in order to achieve a three-dimensional agricultural production paradigm. The advancement of new agricultural machinery and equipment, which are integral to the promotion of organic dry farming, necessitates a substantial labor force. To bolster agricultural production efficiency, the adoption of innovative agricultural machinery, particularly intelligent and automatic systems, can be encouraged.

Furthermore, the promotion of organic dry farming requires robust support from scientific and technological innovation. It is necessary to intensify efforts related to scientific and technological innovation, fostering the development of new technologies and varieties tailored to the specifics of organic dry farming. This approach is essential for augmenting the efficiency of agricultural production and improving product quality. Realizing the three-dimensional production of organic dry farming entails embracing ecological agricultural practices. This includes promoting methods such as ecological breeding and ecological planting, which aim to safeguard the ecological environment and enhance the quality of agricultural products.

The transformation of organic dry farming in provinces should be conducted according to local conditions, promoting the three-dimensional development of production relations. Considering the variations in production conditions across different regions, it is imperative to tailor the approach to the specific needs of each province at the various stages of the development of organic dry farming. This involves further enhancing the transformation performance in lagging and starting areas, continuously promoting the transition in spanning regions, and emphasizing the optimization of planting structures.

To promote agricultural transformation upgrading and carbon emission reduction, it is crucial to focus on the development of advanced technology and modern agriculture, fostering economic growth, improvements in quality, and enhanced transfer efficiency. Climate-Smart Agriculture Investment Plan and Conservation Farming Systems developed in Bangladesh can be used to increase crop productivity, agricultural transformation, and carbon reduction in the context of environmental sustainability. Additionally, provinces engaged in organic dry farming that are situated in different spatial locations should adopt region-specific strategies. For instance, cities in northern China should leverage their geographical advantages and knowledge-based innovation to play a driving and radiating role in the development of northeast and northwest China. Meanwhile, northwestern provinces should capitalize on national policies that favor the development of the western region, aiming to achieve robust growth in this region.

The three-dimensional transformation of agricultural production relations should be facilitated via the adjustment of production relations, the optimization of agricultural resource allocation, and the enhancement of farmers' incomes. Strengthening agricultural policy support is crucial here, and financial subsidies, rural credit, and other methods are required to foster the development of organic dry farming and augment farmers' incomes. The establishment and promotion of agricultural cooperatives are instrumental in realizing the three-dimensional production relations of organic dry farming. The adjustment of cooperative production relations, facilitated through the organizational structure of cooperatives, aims to maximize farmers' interests and enhance agricultural production efficiency.

The three-dimensional production relations of organic dry farming necessitate the implementation of land circulation. This can be achieved by optimizing the allocation of agricultural resources through land circulation, thereby improving the efficiency of agricultural production and increasing farmers' incomes. Moreover, the reduction in carbon emissions resulting from the transformation and development of organic dry farming primarily stems from the transformation of social life. Structural adjustment strategies are employed to reform and upgrade traditional agriculture, promote agricultural modernization, and reduce the reliance of agriculture on chemical agents.

The implementation of green agriculture strategies is integral to this process, involving the reinforcement of ecological reconstruction and environmental protection. The establishment of green ecosystems in agriculture should be pursued to vigorously promote ecological transformation.

According to the announcement issued by the Food and Agriculture Organization of the United Nations (FAO), approximately 81% of the global cultivated land area is under rainfed agriculture, yet it produces 60% of the world's grains and 50% of its livestock. The findings of this study hold certain reference significance for arid regions worldwide, especially those similar to the arid regions in China.

While focusing on the benefits of organic dryland agriculture, it is important to acknowledge the negative impacts it can have on biodiversity and resources. From a biodiversity perspective, some organic farming practices may involve the use of natural or organic pesticides to control pests. These pesticides can potentially affect non-target species. Additionally, over-reliance on certain plant species for cultivation may disrupt ecological balances within local ecosystems. In terms of resources, organic dryland agriculture typically requires more land to produce the same quantity of crops and consumes more energy for activities such as tillage, planting, weeding, and organic waste management. This increased demand and consumption of energy may reduce resource efficiency. The application of spatial analysis techniques provides a theoretical and methodological foundation for addressing the development of organic dryland agriculture in China. However, organic dryland agriculture involves multiple geographical elements, and in nations and regions lacking sufficient spatial data, the application scope and accuracy of spatial analysis techniques may be constrained. The present study did not fully address the potential issues of multicollinearity, autocorrelation, and heteroscedasticity in the data. However, the endogeneity and heteroscedasticity tests performed well, enhancing the accuracy and reliability of the model.

5. Conclusions

TRODF agriculture exhibits an initial ascent followed by a subsequent decline, contributing to an overall upward trajectory. The value increased from 0.0486 in 2005 to 0.1436 in 2006 and then decreased to 0.0590 in 2020. Correspondingly, regional disparities exhibited a fluctuating upward trend, with the contribution rates of intra-regional disparities from 2005 to 2020 consistently remaining above 70%. Intra-regional variances emerge as the primary drivers of the overarching distinctions observed in organic dry farming. In particular, eastern China, central China, and southern China emerge as the principal contributors to the overall differences, followed by northern China and northwest China. Northeast China, on the other hand, makes the smallest contribution rate to the overall differences.

The transformation performance of organic dryland agriculture is distinguished by conspicuous spatial differentiation, showing differences between the lagging, starting, and leaping zones. Most provinces experience a discernible upward leap in their transformation performance, exhibiting a notable positive trend in this regard.

The transformation of performance in organic dry agriculture across different periods presents the possibility of state transfer, primarily favoring cross-regional transitions, followed by transitions in starting areas. The provinces' transformation performance demonstrates relative stability, with strong internal liquidity. However, there is a greater likelihood of maintaining the initial state. State transfer in TRODF typically occurs among neighboring grades, with infrequent instances of "jumping" transfers. This process is characterized by long-term and persistent traits, making leapfrog development difficult to achieve. The transitional development of provinces engaged in organic dry farming exhibits a discernible correlation with the type of transition performance observed in the neighboring provinces.

The transition of organic dry farming leads to a conspicuous reduction in carbon emissions, exerting a significant impact on the mitigation of carbon emissions. Furthermore, a pronounced spatial spillover effect is observed in the process of the organic dry farming transformation. Agricultural transformation in lagging areas significantly reduces carbon emissions, exhibiting a substantial carbon emissions reduction effect on neighboring regions. In northern China, the transformation performance not only significantly influences the carbon emissions within the region but also exerts a substantial inhibitory effect on carbon emissions in neighboring provinces. Similarly, agricultural transformation and development in northeast China exhibit a significant inhibitory effect on the carbon emissions of adjacent regions. After 2013, the development of organic dry farming had a notable carbon emissions reduction effect on the region, and the transformation and development of social life exhibit a substantial capacity to reduce carbon emissions in the provinces within the region.

Author Contributions: Conceptualization, G.W.; methodology, B.Z.; software, B.Z.; validation, G.W., B.Z. and M.Z.; formal analysis, B.Z.; investigation, M.Z.; resources, B.Z.; data curation, B.Z.; writing—original draft preparation, G.W and B.Z.; writing—review and editing, G.W. and M.Z.; visualization, B.Z.; supervision, G.W.; project administration, G.W.; funding acquisition, G.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China (72003111).

Institutional Review Board Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy issues.

Acknowledgments: We thank the anonymous reviewers for their efforts to improve this paper.

Conflicts of Interest: The authors declare no conflicts of interest.

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