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Spatiotemporal Characteristics and Reduction Pathways of County-level Agricultural Carbon Emissions for Shanxi Province in China

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ABSTRACT

Agriculture is the main source of greenhouse gas emissions second only to energy activities and industrial production. Agricultural carbon emission reduction can effectively alleviate the negative impact of greenhouse effect. Using the emission factor method, this paper combs four types of agricultural production activities, including agricultural inputs, farmland management, animal intestinal digestion and fecal management, calculates the county-level agricultural carbon emissions quantity and intensity in Shanxi Province from 2018 to 2022, and uses GeoDa software and spatial autocorrelation model to estimate the Global Moran's index, revealing the spatial agglomeration characteristics of county-level carbon emissions. From the perspective of changing trend, agricultural carbon emissions show an increase for 64.10% in total counties. It is quite limited for the reduction of carbon emission intensity on county-level agriculture, and the potential compression space is large. Animal intestinal fermentation became the primary source of county-level agricultural carbon emissions during the study period. From the perspective of spatial distribution, the agricultural carbon emissions are relatively high for the northern and central counties of Shanxi Province. The counties with high carbon emission intensity are also mainly distributed in northern and central Shanxi Province. In 2022, the Global Moran's index of county-level agricultural carbon emissions quantity and intensity were 0.4918 and 0.4933 respectively. This shows that both indicators for county-level agricultural carbon emissions have spatial autocorrelation. The spatial distributions scale was slightly expanded for carbon emission intensity in significantly agglomerated counties, and the spatial homogeneity was slightly enhanced. This has practical guiding significance for formulating more targeted differentiated policies and accelerating the realization of carbon emission reduction targets.

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KEYWORDS: Agricultural carbon emissions, Spatiotemporal characteristics, Carbon emission reduction, Spatial agglomeration, Global Moran's index

1. INTRODUCTION

With the intensification of global warming, reduction of greenhouse gas emissions has become an important issue facing the world (Moucheng, 2021; Yang, 2022). In this context, governments and international organizations have proposed low-carbon development goals and policies to reduce carbon emission intensity and carbon emission quantity. Agriculture is one of the important emission sources of greenhouse gases, including carbon dioxide, methane and nitrous oxide. Agricultural carbon emission reduction can reduce carbon emissions and contribute to mitigate global climate change (Uttaruk, 2019; Wu, 2022).

It is deeply affected by the adverse effects of climate change such as insufficient precipitation and high temperature rise in Shanxi Province. This poses a challenge to agricultural production, and also requires the agricultural sector to take adaptive measures to meet the challenge and reduce the vulnerability of the agricultural sector. At the same time, climate change may also change the pattern of agricultural carbon emissions (Xiao, 2019). The agricultural production mode and practice adopt organic agriculture and optimize agricultural management in Shanxi Province. Among them, organic dryland farming, as a new mode of agricultural production, helps to actively promote agricultural carbon emission reduction in Shanxi Province. The high-quality development of agriculture is one of the important contents of rural revitalization (Zakaria,2019; Kumawat, 2023). By strengthening the quality supervision of agricultural products and the construction of inspection and detection system, the quality of agricultural products and the level of food safety are continuously improved. At the same time, Shanxi Province also actively promotes the brand construction of agricultural products. By cultivating well-known brands, it can improve the market competitiveness and reputation of Shanxi agricultural products (Liu, 2023; Chen, 2019). By strengthening exchanges and cooperation with international agricultural organizations, and introducing advanced technology and management experience, agriculture in Shanxi will be brought into line with international standards (Liu, 2020). It also actively organized and participated in various agricultural products exhibitions and trade fairs to display characteristic agricultural products in Shanxi Province and expand sales channels.

2. LITERATURE REVIEW

At present, there are many domestic research results focusing on the measurement and characteristic analysis of agricultural carbon emissions. From the perspective of research scope, the literature mainly focuses on the national and provincial levels. Existing literatures have found that agricultural carbon emissions are on the decline in China, while the regional differences are obvious (Liu, 2021; Koondhar, 2021). And the polarization phenomenon is gradually weakening. The regional pattern of carbon emissions is high in the Middle and in the East, and low in the West. The traditional agricultural provinces located in the high-value area of agricultural carbon emissions in China (Cui, 2019). From the provincial level, some scholars discussed the spatial differences and influencing factors of carbon emissions in provinces, such as Shandong, Henan, Shanxi, Hubei, and Anhui (Cui, 2020). At the same time, parts of existing literatures focus on the sources of agricultural carbon emissions and measurement of carbon emissions (Shan, 2020). Among them, the carbon emission sources of planting industry mainly focus on agricultural inputs and farmland management, such as chemical fertilizers, pesticides, agricultural film, agricultural diesel, irrigation, tillage, straw burning and so on (Chen, 2022; Li, 2022). The carbon emission sources of animal husbandry are concentrated in the intestinal fermentation of livestock and poultry, fecal management and other links (Bai, 2023; Chen, 2019). Many studies have shown that animal intestinal fermentation, farming land and rice planting accounted for more than 80% of agricultural carbon emission (Fan, 2022; Wang, 2020).

Literatures rarely have in-depth discussion on the spatial characteristics of agricultural carbon emissions at county level in Shanxi Province. Agriculture occupies an important position in its economic structure in Shanxi province (Wang, 2021; Ugbogu, 2019). In 2022, the total agricultural production value was 224.25 billion yuan in Shanxi Province, of which planting and animal husbandry accounted for 86.73%. From the county level, the top ten counties in terms of agricultural GDP are mainly in Yuncheng City and Jinzhong City. The industrial structure of Shanxi Province is single, and the energy and heavy chemical industry accounts for a large proportion. The agricultural structure also needs to be adjusted and optimized to improve the quality of agricultural products and food safety (Deng, 2021). At the same time, the irrational use of chemical fertilizers and pesticides in the process of agricultural production has also brought certain negative effects on the environment, increasing the concentration of pollutants such as particulate matter and ozone in the atmosphere, which has a negative impact on human health and ecosystem (Chen, 2020).

To sum up, this study focuses on the sources of carbon emissions from different aspects of agricultural activities, scientifically calculates the carbon emission quantity and carbon emission intensity at county level, systematically analyzes the temporal and spatial characteristics, and improves the research on agricultural carbon emissions in Shanxi Province, so as to provide reference to formulate differentiated reduction policies of agricultural carbon emission and achieve the goals of carbon peaking and carbon neutralization for Shanxi Province.

3. RESEARCH METHOD AND DATA SOURCE

3.1 Calculation of Agricultural Carbon Emission Quantity and Intensity

3.1.1 Calculation of Agricultural Carbon Emission Quantity

This study focuses on county-level agricultural carbon emissions in Shanxi Province, and defines the accounting scope as the greenhouse gases directly or indirectly emitted in the agricultural production system (Dongying, 2023). According to the definition of agricultural greenhouse gases in the guidelines for national greenhouse gas inventories (2006) organized by IPCC (Intergovernmental Panel on climate change), the agricultural greenhouse gases accounted for are mainly carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O) (Hou, 2022). Based on the current situation of county agriculture in Shanxi Province and the availability of data, the calculation model is as follows by using the carbon emission coefficient method:

$$C = \sum C_j = \sum E_j \times F_j$$

Where, C is agricultural carbon emission quantity, and C_j is the carbon emission of the jth carbon source, E_j is the jth carbon source activity, F_j is the emission coefficient of the jth carbon source (see Table 1). In this paper, CH_4 and N_2O is converted into carbon emissions. According to the results of IPCC's sixth assessment report, the global warming potential (GWP) of CH_4 and N_2O is respectively 20 and 273 times of CO_2 within a 100-year time frame.

Table 1: Agricultural Carbon Sources and Emission Coefficients of Greenhouse Gas

Emission source			Emission coefficient	Coefficient source
Planting sector	Agricultural inputs (in C)/(kg·kg^{-1})	fertilizer	0.8956	Oak Ridge National Laboratory（ORNL）
		pesticide	4.9341	
		Agricultural film	5.18	Institute of Resources and Ecological Environment for Agriculture, Nanjing Agricultural University(IREEA)
	Farmland management /(kg·hm^{-2})	Irrigation	19.8575	
		Agricultural diesel	0.5987	Intergovernmental Panel on climate change (IPCC)
		Cropland tillage	3.126	
Husbandry sector	Enteric fermentation (CH_4)/(kg·(head·a)$^{-1}$)	Cattle	51	Guidelines for the Preparation of Provincial Greenhouse Gas Inventory (Trial)
		Sheep	5	
		Hog	1	
		Poultry	-	
	Fecal management (CH4, NO2)/(kg·(head·a)$^{-1}$)	Cattle	1.5, 1.29	Guidelines for the Preparation of Provincial Greenhouse Gas Inventory (Trial)
		Sheep	0.16, 0.227	
		Hog	3.12, 0.093	
		Poultry	0.02, 0.007	

Note: The average lifespan of pigs and poultry is 200 days and 55 days, respectively

3.1.2 Calculation of Agricultural Carbon Emission Intensity

Based on the connotation of agricultural carbon emission intensity (Datta, 2022), the calculation model is determined as follows:

$$\mathrm{T} = C/A_{GDP}$$

Where, T is the intensity of agricultural carbon emissions (in t/10000 yuan); C is the agricultural carbon emission quantity (in t); A_{GDP} is the total agricultural output value (in 10000 yuan).

3.2 Spatial Auto Correlation Model

Spatial Auto Correlation is an analytical method that tests whether there is a correlation between the observed values of a certain point in space and the values of its adjacent points. If the value of a variable is high in a certain location and the value of the variable is also high in its nearby location, it is a positive spatial autocorrelation; otherwise, it is a negative spatial autocorrelation. The measuring indicators mainly include the Global Moran's Index and the Local Moran's Index (LISA Moran's I).

3.2.1 Global Moran's Index

This indicator can indicate that the distribution of a certain attribute value in a region belongs to a clustered, discrete, or random distribution pattern. The range of Moran's index is [-1,1], with a value of -1 indicating completely negative correlation, a value of 1 indicating completely positive correlation, and a value of 0 indicating no correlation (Liming, 2022). The formula is as follows:

$$\mathrm{I} = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}\,(x_i - \overline{x})\left(x_j - \overline{x}\right)}{\sum_{i=1}^{n}(x_i - \overline{x})^2}$$

where, n is the number of spatial units in the study area, x_i and x_j represent the observed values of space units i and j respectively, $\overline{x}$ represents the mean of the observed values, $w_{i,j}$ is the spatial weight matrix.

For the Global Moran's Index, the presence of spatial autocorrelation in n regions can be tested by standardizing the Z-value of the statistical measure. The formula is as follows:

$$\mathrm{Z} = \frac{Moran's\ I - E(I)}{\sqrt{VAR(I)}}$$

$VAR(I)$ is the theoretical variance of the Moran Index, and E(I)=-1/(n-1) is its theoretical expectation.

The relationship between Z-value, p-value, and confidence is shown in Table 2. This article uses a Z-value with a confidence level of 95% and a p-value less than 0.05 as the standard threshold for testing whether there is spatial autocorrelation between regions.

Table 2: Relationship among Z-value, P-value and Confidence

Z-value(standard deviation)	P-value(possibility)	Confidence
< -1．65 or > +1．65	< 0．10	90%
< -1．96 or > +1．96	< 0．05	95%
< -2．58 or > +2．58	< 0．01	99%

Data source: http://resources.arcgis.com/zh-cn/help/main/10.1/index.html

3.2.2 Local Moran′s Index

The Local Moran's Index is the decomposition form of Global Moran's Index. The local Moran's Index can be used to reveal the heterogeneity of attributes between different spatial units in the study area (Scuderi, 2021; Tao, 2021; Liao; 2020). A high value of the local Moran's index indicates that area units with similar values of the variable are clustered in space, while a low value indicates that area units with dissimilar values of the variable are clustered in space. The formula is as follows:

$$\mathrm{I} = \frac{n^2}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}} \frac{(x_i - \overline{x})\sum_{j=1}^{n} w_{i,j}\left(x_j - \overline{x}\right)}{\sum_{j=1}^{n}\left(x_j - \overline{x}\right)}$$

3.3 Data Source

The basic data used in this article, including agricultural fertilizers, pesticides, agricultural films, crop sowing area and effective irrigation area, as well as total agricultural output value, are all sourced from the Shanxi Provincial Statistical Yearbook published by the Shanxi Provincial Bureau of Statistics over the years. Among them, the amount of compound fertilizer is converted into the pure amount of contained nitrogen, phosphorus, or potassium. County-level agricultural diesel is calculated based on the proportion in total power of agricultural machinery in Shanxi Province.

4. RESEARCH RESULTS

4.1 Trend of Agricultural Carbon Emissions

4.1.1 Trend of Agricultural Carbon Emission Quantity

Agricultural carbon emissions overall increased for 64.10% of 117 counties in Shanxi Province (shown in Figure 1). Agricultural carbon emissions decreased only in 42 counties, and 13 of them decreased by less than 1% annually. From the perspective of sector segmentation, the carbon emission reduction rate is not optimistic for planting and animal husbandry in most counties. The carbon emission quantity decreased in 64 counties for planting sector, only by 3.76% of an average annual changing rate. Even more, the decline of carbon emissions is more sluggish in animal husbandry sector. The carbon emission in 36 counties decreased slightly for animal husbandry sector, which was only accounting 30% in total 117 counties, and the decrease was less than 1% in 10 counties. However, there are as many as 19 counties with an average annual growth rate of more than 10%.

According to the average annual change rate of agricultural carbon emissions at the county level, the natural breakpoints are set at -10%, -1%, 0, 1% and 10%. The 117 counties in Shanxi Province are divided into six categories, namely, extremely rapid descent type, rapid descent type, slow descent type, slow growth type, fast growth type and extremely fast growth type.

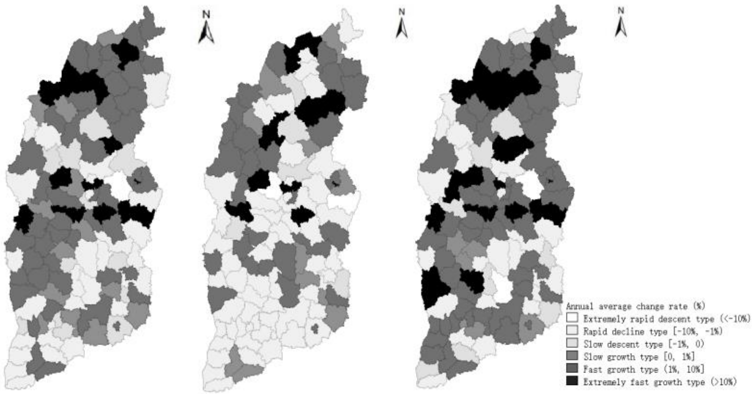

Figure 1: Trend of Carbon Emission Quantity for Agriculture, Planting and Animal Husbandry at County Level in Shanxi Province from 2018 to 2022

4.1.2 Trend of Agricultural Carbon Emission Intensity

The reduction of county-level agricultural carbon emission intensity is quite small, and the compression space is large (shown in Figure 2). From 2018 to 2022, the agricultural carbon emission intensity showed a downward trend for 89 counties in Shanxi Province, with an average decrease of 6.46%. The decline was different in each county. The top five counties with the decline were Taigu District, Zuoquan County, Zhongyang County, Linxian county and Wenxi County, with an average annual rate of -16.00%, -13.99%, -13.51%, -13.01% and -12.52%, respectively. There are 8 counties with a decline rate of less than 1%. The intensity of agricultural carbon emissions increased in other counties, with an average increase rate of 15.67%, much higher than the decline rate. The counties with an increase of more than 10% are Heshun County, Xiaodian District, Jinyuan District, Xinghualing district and Jiancaoping district. It shows that it is necessary to further reduce the intensity of suburban agricultural carbon emissions.

From the perspective of carbon emission intensity in planting sector, the decline is obvious in most counties. Carbon emissions reduced by an average rate of 8.01% in 93 counties. The top five counties with the decline were Zhongyang County, Linxian County, Liulin County, Gujiao City and Xixian county from top to bottom. The average growth rate reached 15.92% in 24 other counties. The counties with an average annual increase rate of more than 10% in carbon emission intensity of planting industry are Jinyuan District, Loufan County, Chengqu 14, Jiancaoping District, Taigu District, Heshun county and Xiaodian District.

Compared with planting sector, the reduction of carbon emission intensity is limited in animal husbandry sector, and the compression space is much larger for carbon emission. The intensity declined in 74 counties, with an average decline rate of 5.92%. Among them, the decline rate is very small in 10 counties less than 1%. The average growth rate was 4.90% in other counties. Yungang District, Yunzhou District, Xiaoyi City and Jinyuan District have an average annual growth rate of more than 10%.

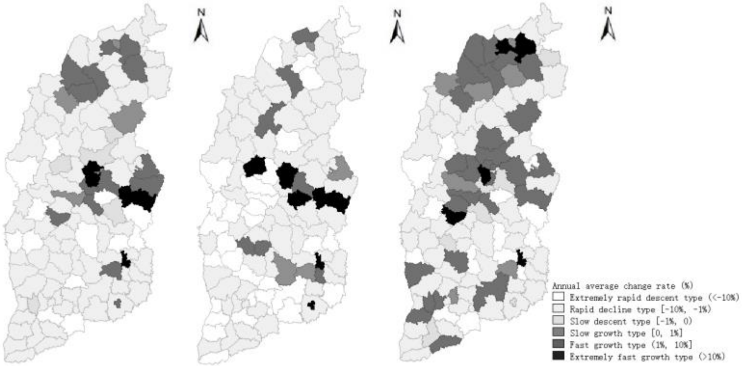

Figure 2: Trend of Carbon Emission Intensity for Agriculture, Planting and Animal Husbandry at County Level in Shanxi Province from 2018 to 2022

4.1.3 Trend of Agricultural Carbon Emission Structure

According to the sources of carbon emissions, agricultural carbon emissions mainly come from agricultural inputs, farmland management, animal intestinal fermentation, and fecal management. Among them, animal intestinal fermentation is the primary source of carbon emissions in county-level agriculture. In 2018, the average proportions of these four sources were 21.78%, 4.50%, 46.83%, and 26.90%, respectively. In 2022, the proportions reached to 19.76%, 5.86%, 47.39%, and 26.99%, respectively. The fertilizer usage is the primary source of carbon emissions in agricultural inputs. The diesel usage is the primary source of carbon emissions in agricultural management. Cattle and sheep are the two main sources of carbon emissions in animal husbandry.

4.2 Spatial Evolution of Agricultural Carbon Emissions

4.2.1 Spatial Evolution of Agricultural Carbon Emission Quantity

Spatial Characteristics of Agricultural Carbon Emission Quantity

By sorting the carbon emissions of agriculture, planting, and animal husbandry in a descending order for 117 counties in Shanxi Province in 2022 respectively, it sets the top 20%, 50%, and 80% as three nodes, and divides all counties into four categories, high carbon, relatively high carbon, medium carbon, and low carbon emission areas. The carbon emissions of counties are relatively high in the north and middle of Shanxi Province, while the carbon emissions of counties are relatively low in the southern areas. More counties are located in low-carbon emission areas (shown in Figure 3).

From the perspective of planting sector, the northern and central counties in Shanxi are also high carbon emission areas, and show regional homogeneity. This is mainly because planting is a common agricultural activity in these regional counties. Planting sector has become the main source of local agricultural carbon emissions. It has a large area of grain planting and a large amount of agricultural inputs in these regions, but the planting income is low, resulting in large agricultural carbon emissions and high intensity.

From the perspective of animal husbandry, the carbon emission quantity of the northern and central counties is generally higher compared with that of the southern counties in Shanxi Province. This is closely related to the fact that the northern part of Shanxi Province is a traditional agricultural and pastoral area. The number of livestock and poultry breeding is mainly guided by government regulation and environmental protection policies, and the carbon emissions of animal husbandry are in a small growth state. With the improvement of consumer’s living standards, the demand for meat, egg and milk products has gradually increased. Livestock breeding has also become another important source of local carbon emissions.

To sum up, areas are superimposed with high carbon emissions both from planting and animal husbandry. The counties in northern Shanxi Province have formed a situation of high carbon emissions.

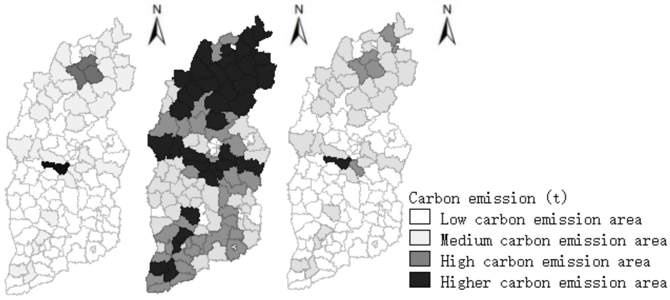

Figure 3: County-level Spatial Distribution of Carbon Emission Quantity for Agriculture, Planting and Animal Husbandry in Shanxi Province in 2022

Spatial Autocorrelation Analysis

The samples in 2018 and 2022 were selected for analysis. Referring to the local Moran index, Moran scatter diagram and Lisa cluster map of county-level agricultural carbon emissions in Shanxi Province were drawn respectively. Moran's I is the global Moran index in the scatter diagram. The first and third quadrants in the Moran scatter diagram respectively represent the characteristics of high-high and low-low agglomeration, and the second and fourth quadrants respectively represent the characteristics of low-high and high-low agglomeration. If the sample points are located in the first or third quadrant, it indicates that there is a positive correlation in the spatial distribution of agricultural carbon emissions for the sample points. If located in the second or fourth quadrant, there is a negative correlation for the sample points.

In 2018, the Moran index was 0.4322 for agricultural carbon emissions at county level in Shanxi (shown in Figure 4). In 2022, the Moran index rose to 0.4918. These Moran indexes passed the bilateral threshold test under 5% significant level. This shows that there is a spatial autocorrelation of agricultural carbon emissions in Shanxi Province at the county level. The dispersion of sample points is large in high- high agglomeration area, which indicates that the difference among high value of carbon emissions is in a quite big range. However, the differences are small among low-low, high-low and low-high agglomeration areas. It is noteworthy that the degree of dispersion decreases most significantly in the low-low agglomeration regions. This shows that low-carbon counties tend to be more homogeneous in space. Most of the counties in Shanxi Province are located in the first or third quadrant, indicating that the counties are in a homogeneous agglomeration state located in the high carbon emission area and the low carbon emission area. In 2018, 33 and 52 counties were distributed in the high-high or low-low agglomeration areas respectively, while the number were 31 and 63 in 2022. This shows that the spatial homogeneity of county-level agricultural carbon emissions has been enhanced in the study period. From the evolution track of the four quadrants, the number of counties in low-low agglomeration areas increased significantly from 2018 to 2022, mainly due to the transformation of the original high-low agglomerated counties. In 2018, 15 counties were high-high clustered among the 32 counties with significant agglomeration, mainly distributed in Yunzhou district and Guangling County of Datong City and Shanyin County and Ying County of Shuozhou City in northern Shanxi Province (shown in Figure 5). The 14 counties are low-low clustered, mainly scattered in Shilou County and Zhongyang County of Lvliang City in the west of Shanxi Province, Yangqu County, Jinyuan District and Xinghualing District of Taiyuan City in the middle, Huguan County and Pingshun County of Changzhi City in the south, and Daning County and Yonghe County of Linfen City in the South. There are two counties with low-high agglomeration, which are close to the counties with high-high agglomeration. There is only one county with high-low agglomeration. In 2022, the spatial homogeneity of agricultural carbon emissions increased slightly at the county level. And the spatial distribution pattern is relatively stable. 36 counties are significantly clustered. Among them, the number of high-high agglomerated counties decreased to 14, and the number of counties with low-low agglomeration increased to 19. Shouyang County with originally high-low agglomeration, Yangqu County, the suburbs of Yangquan City and Yangqu County with nonsignificant agglomeration, moved into low-low significant agglomeration area. The number of counties with low-high agglomeration decreased to 3. Spatial heterogeneity decreased slightly.

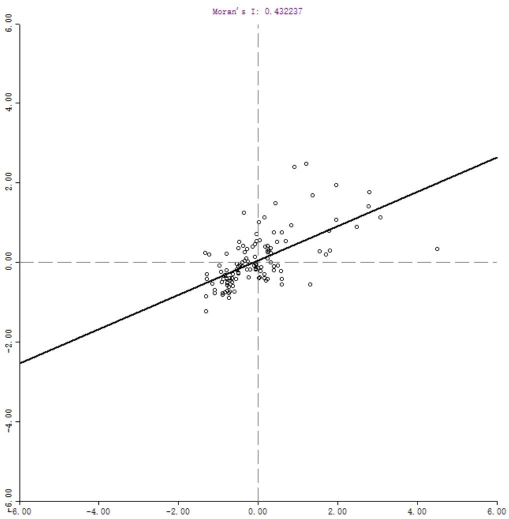

Figure 4: Moran Scatter Diagram of County-Level Agricultural Carbon Emission Quantity in Shanxi Province in 2018 and 2022

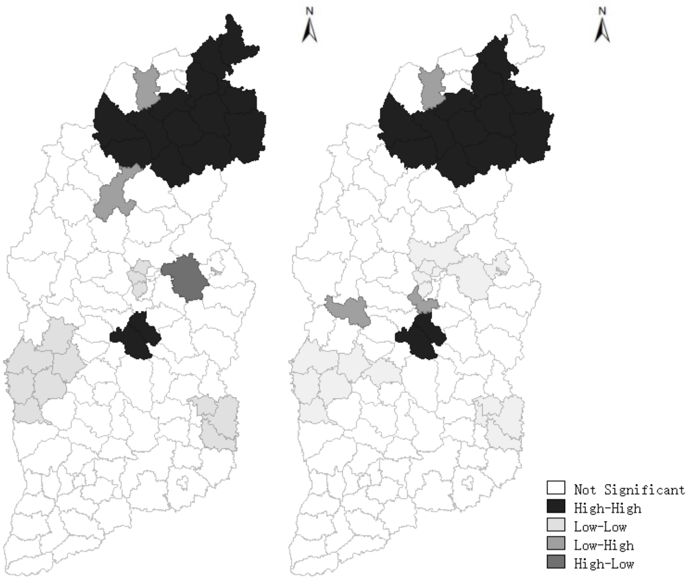

Figure 5: LISA Cluster Map of County-level Agricultural Carbon Emission Quantity in Shanxi Province in 2018 and 2022

4.2.2 Spatial Evolution of Agricultural Carbon Emission Intensity

Spatial Characteristics of Agricultural Carbon Emission Intensity

By sorting the carbon emission intensity of agriculture, planting, and animal husbandry in a descending order for 117 counties in Shanxi Province in 2022 respectively, it sets the top 20%, 50%, and 80% as three nodes, and divides 117 counties into four categories, high carbon, relatively high carbon, medium carbon, and low carbon emission intensity areas. More than half counties are located in low or medium carbon emission intensity areas (shown in Figure 6). The counties with high carbon emission intensity are mainly distributed in the north and west of Shanxi Province. This is the result of the high superposition of carbon emission intensity of planting and animal husbandry in the northern and western counties. The carbon emission intensity is relatively low in southern counties. The sown area of crops in this area is large, and the proportion of cash crops is high. Compared with the increase of agricultural carbon emission quantity, the increase in agricultural output value is much higher.

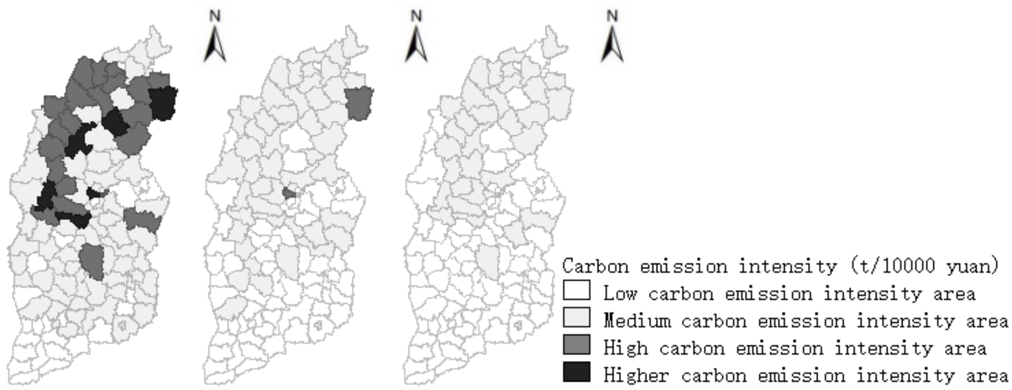

Figure 6: Spatial Distribution of County-level Carbon Emission Intensity of Agriculture, Planting and Animal Husbandry in Shanxi Province in 2022

Spatial Autocorrelation Analysis

In the study period, there is a spatial autocorrelation for the intensity of agricultural carbon emissions at the county level. In 2018, the Moran index of county-level agricultural carbon emission intensity was 0.4525. In 2022, the index rose to 0.4933 (shown in Figure 7). Also these Moran indexes passed the bilateral threshold test under 5% significant level. Most of the counties in Shanxi Province are located in the first or third quadrant, indicating that the counties present a homogeneous agglomeration state in the areas with high carbon emission intensity or low carbon emission intensity. In 2018, the number of counties in the high and low quadrants was 36 and 52 respectively, while the number increased to 39 and 54 in 2022. The spatial distribution of counties with significant agglomeration of carbon emission intensity is relatively stable, and the scope is slightly expanded. During the survey period, the number of counties with significant agglomeration increased from 43 to 48. This is mainly due to the increase in the number of counties with high-high and low-low significant agglomeration. This also led to the county spatial homogeneity of agricultural carbon emission intensity increased. Counties with high-high agglomeration are mainly distributed in Guangling County, Lingqiu County, Hunyuan County, Shanyin County and Ying County of Datong City in the north, Jiaocheng County, Linxian County, Xingxian County, Lan County, Fangshan County and Lishi District of LVliang City in the west, and Wutai County, Fanshi County, Jingle County, Shenchi County, Wuzhai County and Kelan County of Xinzhou City. Counties with low-low agglomeration are mainly scattered in Yanhu District, Linyi County, Wanrong County, Wenxi County, Yuanqu County, Xia County, Pinglu County, Ruicheng County, Yongji City, Shangdang District and Changzi County of Changzhi City and Qinshui County, Lingchuan County and Gaoping City of Jincheng City in the south of Shanxi Province (shown in Figure 8).

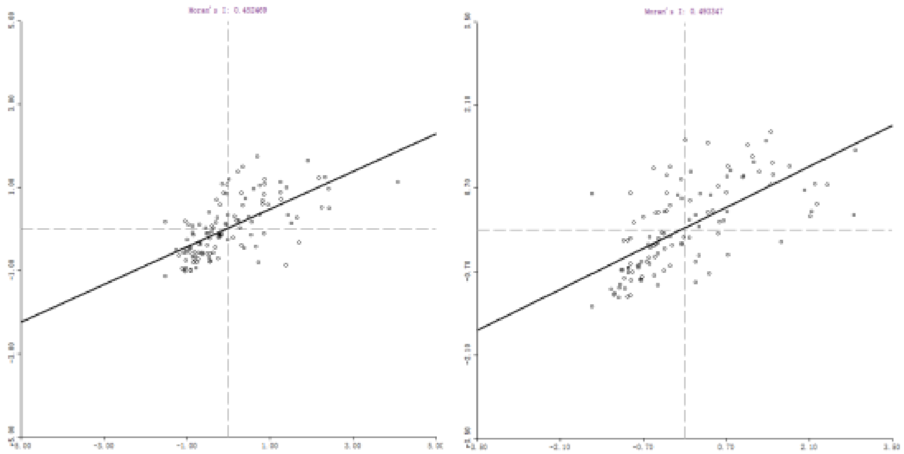

Figure 7: Moran Scatter Diagram of County-level Agricultural Carbon Emission Intensity in Shanxi Province in 2018 and 2022

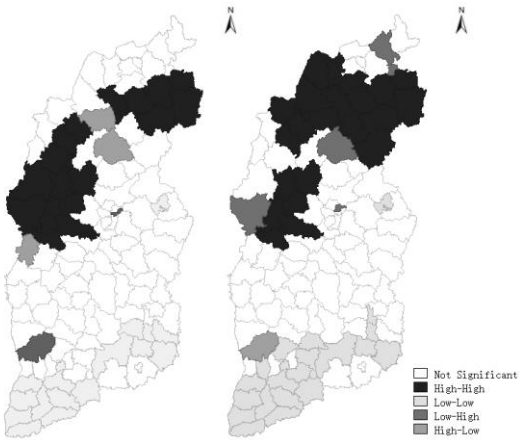

Figure 8: LISA Cluster Map of County-level Agricultural Carbon Emission Intensity in Shanxi Province in 2018 and 2022

5. CONCLUSIONS AND SUGGESTIONS

5.1 Conclusions

Based on the above analysis, agricultural carbon emissions show an increase for 64.10% in total counties from the perspective of changing trend. Agricultural carbon emissions declined in only 42 counties. It is quite limited for the reduction of carbon emission intensity on county-level agriculture, and the potential compression space is large. The agricultural carbon emission intensity of 89 counties in Shanxi Province showed a downward trend, with an average decline of 6.46%. From the perspective of sector segmentation, the decline of carbon emissions is not optimistic from planting and animal husbandry in most counties. On the whole, the intensity of agricultural carbon emissions in the county decreased slightly, and the compression space was large. Animal intestinal fermentation became the primary source of agricultural carbon emissions in the county during the study period. From the perspective of spatial distribution, agricultural carbon emissions are relatively high in the northern and western counties of Shanxi Province. The counties with high carbon emission intensity are mainly distributed in the north and west of Shanxi Province. The carbon emission intensity of southern counties is relatively low. In 2022, the Moran indexes were 0.4918 and 0.4933 for quantity and intensity of county-level agricultural carbon emission respectively. This shows that there is a positive spatial autocorrelation for the indicators. The spatial distribution pattern is relatively stable for agricultural carbon emissions at county level. The number of counties with low-low agglomeration increased more significantly than other types of agglomeration. The spatial distributions scale was slightly expanded for carbon emission intensity in significantly agglomerated counties, and the spatial homogeneity was slightly enhanced.

5.2 Suggestions

5.2.1 Treat Livestock Manure Scientifically and Develop Biogas Resources Effectively

It should reduce livestock breeding with high energy consumption and high emissions, and increase agricultural activities with low energy consumption and low emissions, such as organic agriculture and ecological agriculture (Yerli, 2022). Promote the use of clean energy such as biogas and biomass energy to reduce dependence on fossil fuels. Strengthen the management and treatment of livestock waste, promote the harmless treatment and resource utilization of livestock and poultry manure, and convert the waste into biogas, organic fertilizer and other resources through anaerobic fermentation, so as to realize the resource reuse of manure. Strengthen the promotion and application of recycling agricultural technology, convert waste into fertilizer, feed and other resources, realize resource recycling, and reduce energy consumption and greenhouse gas emissions. Formulate relevant policies and regulations, encourage enterprises and farmers to adopt low-carbon and clean production methods, and promote the realization of agricultural carbon emission reduction (Proto, 2021; Li, 2019). Strengthen the publicity and education on carbon emission reduction for farmers and relevant management personnel, improve their environmental awareness and carbon reduction skills, promote the scientific treatment of livestock manure, and reasonably develop biogas resources.

5.2.2 Improve the Technical Level and Management Efficiency of Agricultural Carbon Emission Reduction

Agricultural carbon emission reduction technical standards and management norms are the basis for ensuring the realization of agricultural carbon emission control goals. Around the key areas and links of agricultural emission reduction and carbon sequestration, relevant technical standards and management norms are formulated to standardize agricultural production, operation, management and service behavior (A, 2020; Ramírez, 2020). Establish a sound carbon emission monitoring and management system to achieve dynamic and precise control of agricultural carbon emissions. Establish a professional management organization and research platform for agricultural carbon emission reduction, strengthen the systematic research on the theory, methods, technologies and policies of agricultural carbon peaking and carbon neutralization, and improve the management level of agricultural carbon emission reduction technology. We will strengthen research on key and core technologies of soil carbon sequestration, rationally distribute and grow crops, and improve farmland management measures such as fertilization technology, farming technology, and irrigation technology. More and more farmers are aware of the impact of climate change on agricultural production, and actively seek and apply carbon emission reduction technologies. At the same time, the government and social organizations are also actively carrying out publicity and training activities to improve farmers' awareness and application ability of carbon emission reduction technologies. Strengthen the scientific and technological innovation of agricultural carbon emission reduction and the application and transformation of achievements (Sun, 2023). Promote advanced agricultural carbon emission reduction technologies and management methods, encourage farmers to adopt low-carbon, environmental friendly and energy-saving green planting and breeding production methods, layout ecological agriculture, optimize and upgrade the agricultural industrial structure, and improve agricultural production efficiency and resource utilization efficiency. Establish an incentive mechanism for agricultural carbon emission reduction to generate a broader demonstration and driving effect of carbon emission reduction.

5.2.3 Give Full Play to the Guiding Role of Fiscal and Taxation Policies in Carbon Emission Reduction

By establishing a carbon emissions trading market, the government encourages agricultural enterprises to reduce carbon emissions and provides economic incentives to provide economic return mechanisms for farmers (Ai, 2021). The government provides tax incentives, supports agricultural enterprises' application of low-carbon agricultural technologies and practices such as water-saving irrigation and precision fertilization, guides scientific planting and development of efficiency enhancing agriculture and other measures, realizes the sustainability of agricultural production mode, and encourages and supports the development and application of agricultural carbon emission reduction technologies. The government has set up a special agricultural carbon emission reduction fund to support agricultural enterprises to carry out technology research and development, demonstration projects and training related to carbon emission reduction, promote innovation and technology upgrading of agricultural enterprises, and improve the ability of farmers to understand low-carbon agriculture. Actively explore market-oriented incentive mechanism and establish carbon emission trading system to promote enterprises and farmers to actively participate in carbon emission reduction actions (Yang, 2019). The government formulates strict agricultural carbon emission standards to ensure that agricultural enterprises comply with emission reduction requirements through monitoring and inspection. For enterprises that fail to meet the standards, corresponding punishment measures shall be taken, and enterprises that meet the standards shall be rewarded and recognized. The government should strengthen the popularization of carbon emission reduction knowledge of farmers and agricultural enterprises and improve the awareness of environmental protection (Gessesse, 2020). At the same time, establish an information disclosure platform for agricultural carbon emission reduction, disclose the progress and achievements of agricultural carbon emission reduction to the public, encourage the participation of all sectors of society, and promote the transformation of the agricultural industry to the direction of low-carbon, environmental protection and sustainable development.

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