GEORGE BROWN PRESS
JOURNALS, BOOKS & PROCEEDINGS

Economics and Management Innovation

Article

Study on the Spatial Spillover Effect of Agricultural Carbon Emissions in Beibu Gulf City Cluster and Its Influencing Factors

Yue Liu [1,*], Ling Zhang [1], Xi Wu [1] and Rizhen Liang [1]

[1] Guangxi Normal University, Guilin, Guangxi Zhuang Autonomous Region, China
* Correspondence: Yue Liu, Guangxi Normal University, Guilin, Guangxi Zhuang Autonomous Region, China

Abstract: Analyzing the spatial spillover effect of agricultural carbon emissions in the Beibu Gulf urban agglomeration reveals the transmission pathways and key factors influencing agricultural carbon emissions across various regions. This, in turn, provides targeted policy recommendations for government bodies and relevant decision-makers. Using panel data from the Beibu Gulf urban agglomeration between 2012 and 2021, this paper conducts spatial correlation tests to quantitatively analyze the spatial spillover effect of agricultural carbon emissions, exploring their distribution patterns and the factors that influence them. The results are as follows: (1) The cities with the highest total average agricultural carbon emissions do not necessarily align with those having the highest average agricultural carbon emission intensity; a high carbon consumption does not directly correlate with a simultaneous rise in agricultural output. (2) A significant positive spatial correlation exists in agricultural carbon emissions within the Beibu Gulf urban agglomeration, indicating a spatial clustering effect. (3) Agricultural carbon emissions in most cities in the Beibu Gulf exhibit two clustering trends: "low-low" and "high-high." Understanding these effects and their determinants can serve as a valuable reference for agricultural carbon reduction strategies and targeted policies, not only within the Beibu Gulf urban agglomeration but also across the entire country.

Keywords: agricultural carbon emissions; Beibu Gulf city cluster; spatial spillover effects

Received: 15 February 2025
Revised: 20 February 2025
Accepted: 06 March 2025
Published: 11 March 2025

1. Introduction

As the effects of global climate change become more pronounced, the issue of greenhouse gas emissions has gained significant global attention. By the close of 2023, agricultural activities in China accounted for 6.1% of the nation's total greenhouse gas emissions, positioning it as the third-largest contributor. following energy and industrial activities. Therefore, advancing agricultural emission reduction, carbon sequestration, and low-carbon agricultural development is crucial for achieving China's "dual-carbon" targets. In response to national directives, Guangxi has fully executed the strategic directives set forth by the Central Committee of the Communist Party of China and the State Council regarding carbon peaking and carbon neutrality. The region has also released the "Implementation Plan for Carbon Peaking in Guangxi Zhuang Autonomous Region," offering guidance for promoting industrial green development. With rapid urbanization and regional integration, urban agglomerations have become central to economic growth. The Beibu Gulf urban agglomeration, a crucial region for China's cooperation with ASEAN, holds a vital position in the national development strategy. Its agricultural production benefits from unique geographical and resource advantages, making it essential for ensuring regional food security and stable agricultural supplies. However, factors such as accelerated urbanization, agricultural modernization, and population growth have increasingly connected the economies of cities within the Beibu Gulf urban agglomeration, leading to mutual influences in agricultural activities. This interconnectedness may trigger a spatial spillover effect in agricultural carbon emissions, meaning the changes in emissions in one region not only depend on local factors but could also affect neighboring regions either positively or negatively. Based on this, this paper first examines the spatial distribution characteristics of agricultural carbon emissions in the Beibu Gulf urban agglomeration, constructs a spatial spillover model, and explores the mutual effects of emissions across cities. It then calculates the spatial autocorrelation coefficient and builds a spatial econometric model to reveal the spillover mechanisms and transmission pathways of agricultural carbon emissions. Additionally, the paper analyzes the impact of factors such as agricultural industrial structure, energy efficiency, and agricultural technology on emissions, and offers targeted strategies for emission reduction. This research aims to support the green transformation and sustainable agricultural development in the Beibu Gulf urban agglomeration, improve the regional ecological environment, contribute to achieving the "dual-carbon" goals, and provide valuable theoretical and practical insights for promoting high-quality development of agriculture in China.

2. Literature Review

Carbon emissions, a key area of contemporary academic research, have seen significant advancements in recent years. Among these, agricultural carbon emissions have attracted considerable attention due to their complexity and practical significance. Both domestic and international scholars have extensively studied the construction of carbon emission measurement systems. Regarding the sources of agricultural carbon emissions, it is widely acknowledged that fertilizers, pesticides, agricultural films, irrigation, land tillage, straw burning, and livestock and poultry breeding are the primary contributors [1-5], with fertilizers being the leading source of emissions. As research deepens, some scholars have expanded the range of factors included in agricultural carbon emission measurement systems. For instance, agricultural diesel fuel was incorporated [1], while the role of methane emissions from rice cultivation in contributing to carbon emissions was highlighted [6].

Current academic approaches to accounting for agricultural carbon emissions include methods such as field measurement [7], the emission factor method (also known as the emission coefficient method) [8-10], the Gini coefficient method [2,11], and the life cycle method [12-14]. Kernel density estimation and the Markov chain method [15], based on the Gini coefficient approach, were used to analyze the distribution and movement of regional agricultural carbon emissions. China was divided into three regions and eight sub-regions, and the Terrell index and log-mean of variance were used to systematically analyze the structural characteristics and spatial-temporal differences in agricultural carbon emissions across the country [2].

In addition, there has been a growing focus on the spatial distribution and evolution of agricultural carbon emissions. Studies have shown that the spatial distribution of agricultural carbon emissions in China closely aligns with the major grain-producing areas, following a pattern of central > eastern > western regions [3,16]. Some researchers have examined the spatial evolution of these emissions, noting a general decline in emissions in China's primary grain-producing areas in recent years, although inter-provincial disparities have widened [17,18]. Wei Qin et al. observed that the gap between agricultural carbon emissions in northern and southern China is gradually narrowing [19]. Economic development has been identified as the most significant factor driving the spatial correlation of agricultural carbon emissions, with agricultural production efficiency and labor migration also playing roles in influencing the spatial distribution of these emissions. [20-22].

As a major contributor to global greenhouse gas emissions, agricultural carbon emissions are critical to regional development. The SBM-Undesirable model was used to explore the significant reduction in arable land utilization in Henan, Heilongjiang, and

Jiangxi, considering carbon emissions. It has also been argued that the varying impacts of carbon taxes on agricultural carbon emissions across regions could exacerbate regional development imbalances [23,24]. In conclusion, both domestic and international literature offers a wide array of perspectives and extensive theoretical discussions, providing substantial theoretical and empirical support for the study of agricultural carbon emissions. This body of work serves as a valuable reference for understanding the drivers, spatial distribution, and underlying mechanisms of agricultural carbon emissions, offering guidance for the formulation and implementation of emission reduction policies. However, in terms of research focus, few studies have conducted in-depth analysis on the agricultural carbon emissions in the Beibu Gulf Economic Belt, despite its significance as a major agricultural production region in China. This paper aims to address this gap by focusing on the Beibu Gulf economic belt urban agglomeration, contributing to the development of research on agricultural carbon emissions in the southeastern region of China. Moreover, the effectiveness and depth of existing agricultural carbon emission measurement systems still require improvement. This paper enhances the scope by incorporating additional indicators, including variables such as agricultural product trade and environmental regulation levels, and introduces innovative spatial geographic and spatial econometric models for the modeling framework.

3. Research Methodology, Selection of Indicators and Data Sources

3.1. Research Methods

3.1.1. Measurement of agricultural carbon emission intensity

Based on previous studies, this paper identifies the primary carbon sources as fertilizer application, total agricultural machinery power, mechanized farming area, crop sown area, and irrigated farmland area [4,25]. The corresponding emission coefficients are 0.8956kg/kg, 0.18kg/kW, 16.47kg/hm², 312.6kg/km², and 19.8575kg/hm², respectively. The agricultural carbon emissions are calculated using the following formula:

$$E = \sum E_i \times T_i \tag{1}$$

In equation (1), E represents the total agricultural carbon emissions, E_i denotes the carbon emission coefficient for a specific category i of carbon source, and T_i refers to the total consumption of that carbon source.

At present, most scholars use the carbon emissions per unit of agricultural output value to measure the intensity of agricultural carbon emissions, and the calculation formula is:

$$AEI = E/AGDP \tag{2}$$

In equation (2), AEI is the intensity of agricultural carbon emissions; E is the total amount of agricultural carbon emissions; and $AGDP$ is the total agricultural output value.

3.1.2. Spatial Correlation Test

Global Moran's I (Global Moran's Index) is used to test whether there is spatial correlation between agricultural carbon emissions in the Beibu Gulf urban agglomeration, and the calculation formula is:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij(x_i-\bar{x})}}{S^2\sum_{n=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{3}$$

Meanwhile, Local Moran's I (LMI) was used to analyze the agglomeration pattern of agricultural carbon emissions in adjacent areas, calculated as:

$$I_i = \frac{(x_i-\bar{x})}{S^2}\sum_{j=1}^{n} w_{ij}\,(x_i-\bar{x}) \tag{4}$$

In Eqs. (3) and (4), x_i is the agricultural carbon emission in region i; $\bar{x}$ is the sample mean; S^2 is the sample variance; and w_{ij} is the element of row i and column j in the spatial matrix. Where $I \in [-1, 1]$. The three spatial matrices constructed are: adjacency spatial matrix: $w_{01} = \begin{cases} 1, & i \text{ and } j \text{ are adjacent} \\ 0, & i \text{ and } j \text{ are not adjacent} \end{cases}$; geographic distance matrix: $w_{ij} =$

$\begin{cases} \frac{1}{d^2}, i \neq j \\ 0, i = j \end{cases}$; and economic distance matrix: $w_{ij} = \begin{cases} \frac{1}{|\overline{y_i} - \overline{y_j}|}, i \neq j \\ 0, i = j \end{cases}$. d is the distance between the two distances between regions; $w_{ij} = \begin{cases} \frac{1}{|\overline{y_i} - \overline{y_j}|}, i \neq j \\ 0, i = j \end{cases}$ denotes the per capita GDP of Region i.

3.2. Selection of Indicators

Drawing on existing literature, this paper identifies three key factors:

1) Industrial structure, which indicates the degree of agricultural resource utilization and production efficiency, and thus plays a direct or indirect role in the low-carbon transition of agriculture. This is measured by the proportion of agricultural output value to the total output value of agriculture, forestry, animal husbandry, and fishery.
2) Urbanization rate, which reflects the level of technological support for agriculture through industrialization. As urbanization progresses, there is a growing demand for clean, non-polluting, and high-quality agricultural products, encouraging farmers to adopt more sustainable production technologies, leading to reduced carbon consumption. This is measured by the proportion of the urban population to the total population.
3) Scale of agricultural cultivation, where the economic advantages of large-scale cultivation are well-documented in previous studies, as it enhances agricultural efficiency and reduces carbon consumption. This paper measures it using the ratio of crop cultivation area to rural population.

3.3. Data Sources

The data used in this paper are primarily sourced from the Guangdong Rural Statistical Yearbook, Hainan Statistical Yearbook, China Urban Statistical Yearbook, Guangdong Statistical Yearbook, and Guangxi Statistical Yearbook. Detailed statistical results for each variable are presented in Table 1.

Table 1. Descriptive statistics of variables.

Variable name	Observed value	Mean value	Standard deviation	Minimum value	Maximum value
Agricultural carbon emissions	150	167,790.74	136,278.64	25,593.67	516,019.81
Industrial structure	150	0.448	0.168	0.148	0.822
Urbanization level	150	0.506	0.109	0.329	0.826
Cultivated area per capita	150	5.389	6.648	0.418	28.184

4. Research Results and Analysis

4.1. Distribution Characteristics of Agricultural Carbon Emissions in the Beibu Gulf City Cluster

The figure illustrates the spatial distribution of total agricultural carbon emissions across different prefecture-level cities. From 2012 to 2021, cities in the Beibu Bay region, such as Zhanjiang, Maoming, and Nanning, exhibited higher average total agricultural carbon emissions, while cities like Dongfang, Danzhou, and Haikou had lower emissions. Figure 2 further shows that areas with higher average carbon intensity within the Beibu Bay cities are primarily concentrated in Chengmai County, Changjiang Lizu Autonomous County, and Chongzuo City, whereas cities like Yangjiang, Zhanjiang, Maoming, and Beihai have lower agricultural carbon intensity. This comparison reveals that cities with high total agricultural carbon emissions do not necessarily overlap with those showing high carbon intensity. A higher carbon intensity does not imply that the agricultural economy is growing at the same pace. Cities such as Chongzuo and Chengmai, which have both high total agricultural carbon emissions and high agricultural carbon intensity, are pivotal for the development of low-carbon agricultural strategies.

4.2. Spatial Correlation Test

Overall, the Moran's I index values are all greater than 0, with the Moran's I index for China's agricultural carbon emissions in 2012, 2013, 2014, 2015, 2016, 2017, and 2019 passing at least the 5% significance test (Table 2). This suggests a significant positive spatial correlation in agricultural carbon emissions within the Beibu Gulf urban agglomeration, indicating a spatial clustering effect. (Table 2).

Table 2. Moran's I index under the spatial weight matrix of geographic distance, 2012-2021.

year	i	E(i)	sd(i)	z	p-value
2012	0.208	-0.071	0.139	2.012	0.044
2013	0.216	-0.071	0.139	2.076	0.038
2014	0.215	-0.071	0.138	2.067	0.039
2015	0.210	-0.071	0.138	2.046	0.041
2016	0.210	-0.071	0.137	2.052	0.040
2017	0.194	-0.071	0.135	1.965	0.049
2018	0.188	-0.071	0.135	1.929	0.054
2019	0.200	-0.071	0.137	1.977	0.048
2020	0.194	-0.071	0.137	1.934	0.053
2021	0.172	-0.071	0.133	1.830	0.067

4.3. Local Spatial Correlation

The Moran's I scatter plot helps characterize the local spatial correlation. Cities in the first quadrant indicate relatively high agricultural carbon emissions that form a cluster, while cities in the third quadrant represent relatively low agricultural carbon emissions that also form a cluster. Cities in Quadrants 2 and 4 either have low agricultural carbon emissions surrounded by high emissions or vice versa. The following Moran's I scatter plots for agricultural carbon emissions in the Beibu Gulf city cluster for 2013, 2017, and 2021 are presented. The figures reveal that most cities' agricultural carbon emissions are clustered in the first and third quadrants, forming "low-low" and "high-high" clustering patterns.

5. Conclusion

Based on empirical analysis, this paper explores the spatial spillover effect of agricultural carbon emissions in the Beibu Gulf city cluster and the factors influencing them, drawing the following conclusions:

The total agricultural carbon emissions in the Beibu Gulf city cluster have generally declined over time, with a corresponding decrease in emission intensity. This trend is largely attributed to the government's increasing focus on ecological development and promotion of low-carbon growth. In response, the Beibu Gulf city cluster has made efforts to reduce both total emissions and their intensity.

There are notable regional disparities in agricultural carbon emission intensity within the Beibu Gulf city cluster. Cities with higher economic development, particularly inland areas, tend to have higher emission intensity, while coastal cities typically exhibit lower intensity. For instance, Nanning, the central city of the region, shows higher carbon intensity, while coastal cities like Qinzhou and Beihai have lower emissions.

The spatial panel econometric model confirms a significant spatial spillover effect, highlighting the strong correlation and interconnectedness of agricultural carbon emissions across different regions.

To further reduce emissions, the agricultural industrial structure needs to transition towards a greener, low-carbon model. Currently, the traditional structure is primarily focused on planting, with limited attention to forestry and fisheries. The Beibu Gulf cities should leverage their local agricultural advantages, introduce new elements, and adjust their industrial structure to promote sustainable, green agriculture. Moreover, reducing pesticide, fertilizer, and diesel fuel use, while advancing low-carbon agriculture, is crucial for achieving energy savings and emission reductions, ensuring agriculture's long-term sustainability.

Government policy and technological innovation are essential for further reducing agricultural carbon emissions. Local governments should attract scientific talent and modern technology to improve agricultural production efficiency. Incorporating advanced technologies with local methods can reduce costs and enhance mechanization. Additionally, government policies should support agricultural producers in adopting modern production techniques, ensuring both increased efficiency and lower carbon intensity in the agricultural process.

Finally, inter-regional cooperation should be strengthened to promote coordinated development. Regions in the Beibu Gulf should share their experiences in carbon emission management, creating demonstration bases and developing strategies to reduce emission intensity. Through collaboration, regions can complement each other’s strengths, learn from best practices, and work together to reduce agricultural carbon emissions.

References

1. Y. Tian, J. Zhang, and Y. He, "Research on spatial-temporal characteristics and driving factor of agricultural carbon emissions in China," *J. Integr. Agric.*, vol. 13, no. 6, pp. 1393-1403, 2014, doi: 10.1016/S2095-3119(13)60624-3.
2. S. Wen, Y. Hu, and H. Liu, "Measurement and spatial temporal characteristics of agricultural carbon emission in China: an internal structural perspective," *Agriculture*, vol. 12, no. 11, p. 1749, 2022, doi: 10.3390/agriculture12111749.
3. C. Hu, J. Fan, and J. Chen, "Spatial and temporal characteristics and drivers of agricultural carbon emissions in Jiangsu Province, China," *Int. J. Environ. Res. Public Health*, vol. 19, no. 19, p. 12463, 2022, doi: 10.3390/ijerph191912463.
4. W. Liu, R. Xu, Y. Deng, W. Lu, B. Zhou, and M. Zhao, "Dynamic relationships, regional differences, and driving mechanisms between economic development and carbon emissions from the farming industry: empirical evidence from rural China," *Int. J. Environ. Res. Public Health*, vol. 18, no. 5, p. 2257, 2021, doi: 10.3390/ijerph18052257.
5. Y. Liu, L. Zou, and Y. Wang, "Spatial-temporal characteristics and influencing factors of agricultural eco-efficiency in China in recent 40 years," *Land Use Policy*, vol. 97, p. 104794, 2020, doi: 10.1016/j.landusepol.2020.104794.
6. H. Guo, S. Xie, and C. Pan, "The impact of planting industry structural changes on carbon emissions in the three northeast provinces of China," *Int. J. Environ. Res. Public Health*, vol. 18, no. 2, p. 705, 2021, doi: 10.3390/ijerph18020705.
7. L. Xiong, M. Wang, J. Mao, and B. Huang, "A review of building carbon emission accounting methods under low-carbon building background," *Buildings*, vol. 14, no. 3, p. 777, 2024, doi: 10.3390/buildings14030777.
8. Y. Hu, K. Zhang, N. Hu, and L. Wu, "Review on measurement of agricultural carbon emission in China," *Chin. J. Eco-Agric.*, vol. 31, no. 2, pp. 163-176, 2023, doi: 10.12357/cjea.20220777.
9. R. Du, T. He, A. Khan, and M. Zhao, "Carbon emissions changes of animal husbandry in China: Trends, attributions, and solutions: A spatial shift-share analysis," *Sci. Total Environ.*, vol. 929, p. 172490, 2024, doi: 10.1016/j.scitotenv.2024.172490.
10. Z. Li, T. Cao, and Z. Sun, "Spatial-temporal pattern and driving factors of carbon emission intensity of main crops in Henan province," *Sustainability*, vol. 14, no. 24, p. 16569, 2022, doi: 10.3390/su142416569.
11. Y. Zhou, B. Li, and R. Zhang, "Spatiotemporal evolution and influencing factors of agricultural carbon emissions in Hebei Province at the county scale," *Chin. J. Eco-Agric.*, vol. 30, no. 4, pp. 570-581, 2022, doi: 10.12357/cjea.20210624.
12. M. Chen, Y. Cui, S. Jiang, and N. Forsell, "Toward carbon neutrality before 2060: Trajectory and technical mitigation potential of non-CO2 greenhouse gas emissions from Chinese agriculture," *J. Clean. Prod.*, vol. 368, p. 133186, 2022, doi: 10.1016/j.jclepro.2022.133186.
13. C. K. Chau, T. M. Leung, and W. Y. Ng, "A review on life cycle assessment, life cycle energy assessment and life cycle carbon emissions assessment on buildings," *Appl. Energy*, vol. 143, pp. 395-413, 2015, doi: 10.1016/j.apenergy.2015.01.023.
14. C. Lu and W. Li, "A comprehensive city-level GHGs inventory accounting quantitative estimation with an empirical case of Baoding," *Sci. Total Environ.*, vol. 651, pp. 601-613, 2019, doi: 10.1016/j.scitotenv.2018.09.223.

15. Y. Guo and M. Chen, "Re-measurement of agricultural carbon emission rates: Drivers, regional differences and dynamic evolution," *PLoS One*, vol. 19, no. 8, p. e0308496, 2024, doi: 10.1371/journal.pone.0308496.
16. K. C. Hen, Y. W. Wang, H. L. Liu, S. Z. Hang, and J. Jia, "Spatio-temporal characteristics, decoupling effect and its driving factors of carbon emissions from planting industry in Henan province," *Chin. J. Agrometeorol.*, vol. 45, no. 3, p. 219, 2024, doi: 10.3969/j.issn.1000-6362.2024.03.001.
17. S. Wen, Y. Hu, and H. Liu, "Measurement and spatial-temporal characteristics of agricultural carbon emission in China: an internal structural perspective," *Agriculture*, vol. 12, no. 11, p. 1749, 2022, doi: 10.3390/agriculture12111749.
18. J. Xu, J. Wang, T. Wang, and C. Li, "Impact of industrial agglomeration on carbon emissions from dairy farming-empirical analysis based on life cycle assessment method and spatial Durbin model," *J. Clean. Prod.*, vol. 406, p. 137081, 2023, doi: 10.1016/j.jclepro.2023.137081.
19. Q. Wei, J. S. Qu, J. Bai, H. J. Li, L. N. Liu, and L. Xu, "Influencing factors of agricultural carbon emission and regional differences between south and north in China," *J. Ecol. Rural Environ.*, vol. 34, no. 4, pp. 318-325, 2018, doi: 10.11934/j.issn.1673-4831.2018.04.004.
20. T. Shan, Y. Xia, C. Hu, S. Zhang, J. Zhang, Y. Xiao, and F. Dan, "Analysis of regional agricultural carbon emission efficiency and influencing factors: Case study of Hubei Province in China," *PLoS One*, vol. 17, no. 4, p. e0266172, 2022, doi: 10.1371/journal.pone.0266172.
21. P. Xiao, Y. Zhang, P. Qian, M. Lu, Z. Yu, J. Xu, and H. Qian, "Spatiotemporal characteristics, decoupling effect and driving factors of carbon emission from cultivated land utilization in Hubei Province," *Int. J. Environ. Res. Public Health*, vol. 19, no. 15, p. 9326, 2022, doi: 10.3390/ijerph19159326.
22. Y. He, R. Chen, H. Wu, J. Xu, and Y. Song, "Spatial dynamics of agricultural carbon emissions in China and the related driving factors," *Chin. J. Eco-Agriculture*, vol. 26, no. 9, pp. 1269-1282, 2018, doi: 10.13930/j.cnki.cjea.171097.
23. H. Xie, Y. Zhang, and Y. Choi, "Measuring the cultivated land use efficiency of the main grain-producing areas in China under the constraints of carbon emissions and agricultural nonpoint source pollution," *Sustainability*, vol. 10, no. 6, p. 1932, 2018, doi: 10.3390/su10061932.
24. Z. Zhang and Y. Li, "The impact of carbon tax on economic growth in China," *Energy Procedia*, vol. 5, pp. 1757-1761, 2011, doi: 10.1016/j.egypro.2011.03.299.
25. L. Su, Y. Wang, and F. Yu, "Analysis of regional differences and spatial spillover effects of agricultural carbon emissions in China," *Heliyon*, vol. 9, no. 6, 2023, doi: 10.1016/j.heliyon.2023.e16752.