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Spatial Differentiation and Dynamic Evolution of Agricultural Carbon Emissions in Fujian Province of China

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ABSTRACT

The previous literatures have insufficient content on spatial dependence and heterogeneity of agricultural carbon emissions (ACEs), which is inconsistent with the actual situation, weakening the practical significance of research conclusions. To fill this knowledge gap, this study attempts to explore the spatial evolution pattern of ACEs at the city-scale in the Fujian Province of China from spatio-temporal latitudes and adopts the exploratory spatial data analysis method (ESDA) to analyze the spatial correlation effects of ACEs. The findings revealed that ACEs in Fujian show a downtrend as a whole. From the perspective of carbon sources of ACEs, agricultural materials and livestock breeding caused the largest emissions, accounting for 73.82% of the total ACEs, while rice growth led to the smallest carbon emissions, accounting for 26.18% of the total ACEs. We also found that there is obvious non-equilibrium in the spatial distribution of ACEs and their intensity, showing a strong spatial correlation; and although a relatively obvious clustering area has been formed, the spatial autocorrelation of most regions is not significant. Accordingly, we suggest that exploring the "carbon compensation mechanism", is conducive to stimulating the low-carbon agricultural production behavior with positive externalities, to reduce agricultural carbon emissions.

INTRODUCTION

As a semi-artificial-semi-natural composite ecosystem, however, the agricultural ecosystem is one of the important sources of carbon emissions from human activities. Data displayed that 10-14% of global greenhouse gas emissions are directly emitted by agricultural production (Paustian et al. 2016). Existing research results exhibited that China's greenhouse gas (GHG) emissions from agricultural sources account for about 17% of the country's total GHG emissions, among which CH_4 and NO_2 from the agricultural sector account for 50% and 92% of the total emissions, respectively (Rebolledo-Leiva et al. 2017). At present, China is advancing the process of agricultural modernization, which will likely emit more carbon emissions during its realization; meanwhile, in the context of climate change, agricultural production activities have become very sensitive and fragile, which is the most vulnerable to climate change. Therefore, study on agricultural carbon emissions (ACEs) has gradually become one of the hotspots in the research field of climate change and carbon emissions.

In view of the important contribution of ACEs to global GHG emissions, scholars have done a lot of research work on agricultural low-carbon development and put forward many enlightening viewpoints and conclusions around ACEs. For example, Adewale et al. (2019) found that only by clarifying the factors behind the difference in total carbon emissions can the agricultural sector effectively reduce GHG emissions. Balsalobre-Lorente et al. (2019) investigated EKC (Environment Kuznets Curve) hypothesis for BRICS, and the empirical results verified an inverted U-shaped relationship between ACEs and economic growth. On the other hand, Chinese scholars have conducted a large number of empirical discussions on the aspects of ACEs measurement and agricultural carbon emissions intensity (Huang et al. 2019, Pang et al. 2020), influencing factor decomposition and regional differences (Wang et al. 2020, Xiong et al. 2020), agricultural carbon footprint (Li et al. 2021), agricultural ecological compensation from a low-carbon perspective (Chen & Jiang 2018a, 2018b), ACEs performance (Wang et al. 2019) and carbon productivity (Xu et al. 2019). However, most of the above studies regarded the study area as independent homogeneous units, and seldom consider the spatial dependence and heterogeneity of ACEs, which is inconsistent with the actual situation, weakening the practical significance of the research conclusions. Furthermore, scholars often choose an adjacency weight matrix to represent spatial attributes when constructing spatial econometric models, which not only ignore the possible interaction of spatial non-adjacent units but also can not reflect the effect difference caused by geographical distance.

There is a large gap between the endowment of agricultural natural resources and the level of agricultural economic development, it is necessary to conduct more empirical analysis in different regions of China to better reveal the regional differences in agricultural carbon emissions. Since “the Belt and Road” (B&R) initiative was put forward, the areas along the route have gradually become the target of research areas related to carbon emissions (Fan et al. 2019, Muhammad et al. 2020). However, studies focusing on ACEs and their carbon effects in the core area of “B&R” have not yet been found. Fujian Province has been designated as the “core area of the 21st-Century Maritime Silk Road”, and as “a demonstration area of China’s ecological civilization”, its agricultural production must be combined with its regional advantages to achieve low-carbon agricultural development. The greenhouse effect caused by carbon emissions has led to a decline in the capacity of agro-ecosystem services in Fujian Province (Su et al. 2020). Based on this, it is necessary to explore agricultural carbon emissions and their spatial evolution in the core area, to provide a reference basis for the sustainable development of the agricultural sector.

Accordingly, to fill this knowledge gap, this study tried to expand the existing research from the following two aspects based on previous studies. Firstly, by discussing the spatial-temporal distribution characteristics of ACEs, this study was conducive to a more comprehensive grasp of the law of ACEs. Secondly, ESDA was used to capture the spatial dependence effect caused by the interaction between regions, and to discuss the spatial correlation and agglomeration of regional carbon emissions. This study attempted to combine the characteristics of spatial-temporal distribution with spatial dependence, which is helpful to understand the inherent logical relationship of ACEs. This is rarely mentioned in previous studies on the spatial-temporal distribution of ACEs. Therefore, based on the calculated data of ACEs in Fujian Province of China from 2005 to 2019, this study applied the ESDA method to capture the correlation effect between ACEs in cities to accurately grasp the evolution law of ACEs. The results of this study can not only provide a reference basis for measures to reduce regional agricultural carbon emissions, but also provide research ideas for related research in other regions/countries.

MATERIALS AND METHODS

Study Area Overview

Fujian Province is located on the southeast coast of the Chinese mainland (between 115°50’~ 120 °40’ E and 23°18’- 28°22’ N), with a total land area of 121,400 square kilometers. Its geographical features are that 90% of the land area is mountainous and hilly while the rest is arable land (Su et al. 2020). It belongs to the subtropical marine monsoon climate; the annual temperature and the annual precipitation are 17°C to 21°C and 1,351 to 2,645 millimeters, respectively.

Additionally, Fujian was also one of the earliest provinces in China to carry out the policy of reform and opening-up, which has a GDP of 4.24 trillion CNY in 2019, an increase of 7.6% (FPBS, 2020). And, the resident population of Fujian Province was 39.73 million, and the per capita GDP was 107139 CNY, an increase of 6.7% over the previous year. Moreover, its sown areas of farm crops reached 164.8×10^4 hectares, of which 82.2×10^4 hectares were grain crops (FPBS 2020). As the “core area of the 21st-Century Maritime Silk Road”, and a demonstration area of China’s ecological civilization, its agricultural production must be combined with its regional advantages to achieve low-carbon agricultural development.

Calculation of Agricultural Carbon Emissions (ACEs)

The calculation of ACEs in this study mainly considers the carbon emissions generated in the process of agricultural production, which are specifically calculated from the following three aspects. That is carbon emissions caused by the input of agricultural materials, CH_4 emissions from paddy fields, CH_4 and N_2O emissions produced by the manure management system, and enteric fermentation in the process of livestock breeding. The calculation equation of ACEs is as follows.

$$ACEs = E_a + E_b + E_c + E_d + E_e + E_f + E_g + E_h + E_j + E_k \quad \ldots(1)$$

where, $ACEs$ are agricultural carbon emissions($\times10^4$ t); E_a, E_b, E_c, E_d, E_e, and E_f denote carbon emissions caused by the use of chemical fertilizers, pesticides, agricultural film, agricultural machinery, agricultural diesel, and agricultural irrigation, respectively; E_g represents CH_4 emissions from paddy fields; E_h represents CH_4 emissions produced by enteric fermentation in the process of livestock breeding; E_j and E_k denote CH_4 and N_2O emissions produced by the manure management system in the process of livestock breeding, respectively.

$$E_a = \left(Q_{a1}\times A_1 + Q_{a2}\times A_2 + Q_{a3}\times A_3 + Q_{a4}\times A_4\right)\times10^{-7} \quad \ldots(2)$$

$$E_b = Q_b \times B \times 10^{-7} \quad \ldots(3)$$

$$E_c = Q_c \times C \times 10^{-7} \quad \ldots(4)$$

$$E_d=\left[\left(S_d\times D\right)+\left(W_d\times F\right)\right]\times 10^{-7} \quad \ldots(5)$$

$$E_e=Q_e\times G\times 10^{-7} \quad \ldots(6)$$

$$E_f=S_f\times H\times 10^{-7} \quad \ldots(7)$$

$$E_g=\sum\left(EF_i\times AD_i\right)\times 10^{-7} \quad \ldots(8)$$

$$E_h=\sum\left(EF_{CH_4,enteric,i}\times AP_i\right)\times 10^{-7} \quad \ldots(9)$$

$$E_j=\sum\left(EF_{CH_4,manure,i}\times AP_i\right)\times 10^{-7} \quad \ldots(10)$$

$$E_k=\sum\left(EF_{N_2O,manure,i}\times AP_i\right)\times 10^{-7} \quad \ldots(11)$$

The meanings of the symbols in the above equations and the carbon emissions coefficient values of each carbon source are shown in Table 1.

For ease of analysis, we convert CH_4 and N_2O into CO_{2e}, and calculate equations as follows:

$$E_{convert}=\left[\left(E_h+E_j\right)\times 28+E_k\times 265\right]\Big/\tfrac{44}{12} \quad \ldots(12)$$

where $E_{convert}$ represents the total amount of CH_4 and N_2O converted into carbon equivalent ($\times 10^4$t). 28 and 265 denote the global warming potentials (GWP) values of CH_4 and N_2O for a 100-year time horizon, respectively (Pachauri et al. 2014).

Table 1: Carbon emissions coefficient of ACEs sources.

Symbols	Carbon sources	Symbols	Coefficient	Data sources
Q_{a1}	Nitrogenous Fertilizer (kg)	A_1	1.74000 kg/kg	(Lu et al. 2008)
Q_{a2}	Phosphate Fertilizer (kg)	A_2	0.16509 kg/kg	(West & Marland 2002)
Q_{a3}	Potash Fertilizer (kg)	A_3	0.12028 kg/kg	(West & Marland 2002)
Q_{a4}	Compound Fertilizer (kg)	A_4	0.38097 kg/kg	(Tian et al. 2015)
Q_b	Pesticide (kg)	B	4.93410 kg/kg	(West & Marland 2002)
Q_c	Agricultural film (kg)	C	5.18000 kg/kg	(Tian et al. 2015)
S_d	Farmland tillage (hm^2)	D	16.47 kg/hm^2	(Wang et al. 2016)
W_e	Farm machinery (kw)	F	0.18 kg/kw	
Q_e	Agricultural diesel	G	0.5927 kg/kg	(West & Marland 2002)
S_f	Agricultural irrigation	H	266.48 kg/hm^2	
EF_i	Single-cropping rice (hm^2)	AD_i	215.5 kg/hm^2	(NCSC n.d.)
	Double-cropping early rice (hm^2)		211.4 kg/hm^2	
	Double-cropping late rice (hm^2)		224.5 kg/hm^2	
$EF_{CH4,\ enteric,\ i}$	Cow (head/a)	AP_i	76.1 kg/head/a	(NCSC n.d.)
	Sheep (head/a)		8.8 kg/head/a	
	Pig (head/a)		1 kg/head/a	
$EF_{CH4,\ manure,\ i}$	Cow (head/a)	AP_i	5.73 kg/head/a	(NCSC n.d.)
	Sheep (head/a)		0.27 kg/head/a	
	Pig (head/a)		5.08 kg/head/a	
	Poultry (head/a)		0.02 kg/head/a	
	Rabbit (head/a)		0.08 kg/head/a	
$EF_{N2O,\ manure,\ i}$	Cow (head/a)	AP_i	1.261 kg/head/a	(NCSC n.d.)
	Sheep (head/a)		0.113 kg/head/a	
	Pig (head/a)		0.175 kg/head/a	
	Poultry (head/a)		0.007 kg/head/a	
	Rabbit (head/a)		0.007 kg/head/a	

Calculation of Agricultural Carbon Emissions Intensity (ACEI)

ACEI discussed in this study mainly refers to carbon emissions produced by economic benefit per unit of the agricultural sector, based on the total agricultural economic output value (*AGDP*) and agricultural carbon emissions of each city, ACEI can be expressed as:

$$ACEI = {ACE}/{AGDP} \quad \ldots(13)$$

Exploratory Spatial Data Analysis (ESDA)

The commonly used spatial correlation indexes include Global Moran's *I* and Local Moran's *I*. Global Moran's *I* is used to measure the spatial correlation of variable attribute values between neighboring regions in the whole region. But Global Moran's *I* measure the spatial correlation characteristics of variable attribute values as a whole, but it cannot measure the specific types of spatial correlation of variable attribute values in different provinces. This requires the use of Local Moran's *I*. For details of the expression of Global Moran's *I* and Local Moran's *I*, please see reference (Su & Lee 2021).

Data Acquisition and Processing

The data of chemical fertilizers, pesticides, agricultural film, the total power of agricultural machinery, crop area and livestock number, etc., used in this study were all from the Statistical Yearbook of Fujian Province (2006-2020) and the statistical yearbooks of 9 prefecture-level cities (2006-2020). In addition, to eliminate the impact of price fluctuations, the actual agricultural GDP was recalculated based on the constant price in 2005, and then the agricultural carbon emissions intensity was calculated.

RESULTS AND DISCUSSION

Temporal Evolution Characteristics of ACEs and ACEI

According to equations (1-12), agricultural carbon emissions caused by each carbon source in Fujian Province from 2005 to 2019 were as shown in Fig. 1.

As can be seen from Fig. 1, ACEs in Fujian Province displayed an overall downward trend from 2005 to 2019. It dropped from 549.3×10^4t in 2005 to 393.9×10^4t in 2019, a decrease of 28.28%, with an average annual decline of 1.89%. The change in agricultural carbon emissions in Fujian Province can be roughly divided into three stages. 2005-2007 was the first stage, ACEs continue to reduce, and the rate of decline continues to decline. Then, 2007-2013 is the second stage, ACEs are relatively stable. It is worth noting that since 2013, ACEs in Fujian Province have dropped sharply, and in these six years, the total carbon emissions have dropped from 507.0×10^4t (2014) to 393.9×10^4t (2019), with an average annual growth rate of -3.72%. The negative growth rate of carbon emissions may be due to the decline of carbon emissions caused by the reduction of livestock-breeding scale and adjustment of

Fig. 1: Total ACEs and ACEI in Fujian Province during 2005-2019.

breeding structure; on the other hand, due to the decline of agricultural income, the agricultural labor force has been transferred to non-agricultural industries, resulting in a decline in agricultural production activities. In general, the fluctuation trend of ACEs in Fujian Province in the whole sample range in the past 15 years showed the evolution characteristics of three stages, i.e., "fluctuation decline - maintaining stability - rapid decline". This demonstrated that Fujian Province has a certain degree of control over carbon emissions in the process of agricultural development, and the meaning of the development of ecological agriculture has been strengthened. Additionally, the average agricultural carbon emissions intensity (ACEI) in Fujian Province has generally shown a downward trend since 2005, from 0.778 t/10^4 CNY in 2005 to 0.364 t/10^4 CNY in 2019, with an average annual decline of 4.24%. The entire sample has fluctuated and the amplitude is also quite different. The largest drop in 2018 reached 10.97%, followed by the largest drop of 7.87% in 2019, and the third one was the drop of 7.03% in 2016. The smallest drop was in 2006, it was only 1.98%. It can be seen that the various characteristics of ACEI are consistent with the variation trend of ACEs.

From the perspective of specific carbon source classification, carbon emissions caused by rice growth, livestock-breeding, and agricultural materials decreased from 164.1×10^4t, 159.3×10^4t, and 225.9×10^4t in 2005 to 99.6×10^4t, 81.0×10^4t, and 213.3×10^4t in 2019, with a decrease of 39.28%, 49.14%, and 5.58%, respectively. Among them, the proportion of carbon emissions brought by carbon emissions from agricultural materials has been maintained at about 42.4% and is showing an upward trend year by year. This is directly related to the extensive use of agricultural materials (chemical fertilizers, pesticides, agricultural film, agricultural diesel, etc.). Moreover, the carbon emissions caused by rice paddy account for 23.3% and exhibited a downward trend year by year. This may be directly related to the abandonment of a large amount of agricultural land in Fujian Province and the decline of rice planting area year by year. It can be seen that ACEs caused by agricultural materials and livestock-breeding account for about 65.8% of total emissions, which is the most important factor for ACEs in Fujian Province.

The above analysis is only from the perspective of total carbon emissions in Fujian Province. Due to the different agricultural resource endowments and economic development of each region, the characteristics of carbon emissions are different. Therefore, it is necessary to analyze the structural differences between ACEs in different cities (Table 2).

It can be seen from Table 2 that Zhangzhou City had the largest total ACEs, reaching 77.86×10^4t, which was 12.71 times that of Xiamen City(6.13×10^4t); followed by Nanping (64.52×10^4t), Longyan(54.96×10^4t), Sanming (54.22×10^4t), Fuzhou (45.34×10^4t), Quanzhou (43.36×10^4t), Ningde (33.81×10^4t), and Putian (18.38×10^4t) from highest to lowest; the last one is Xiamen, which has the least ACEs in 2019. The results of the above agricultural carbon emissions structure displayed that the main sources of ACEs in 9 cities of Fujian Province are agricultural materials and livestock breeding, accounting for an average of about 65.8%, while the proportion of carbon emissions caused by rice growth is the smallest, only 23.3%. It is worth noting that Zhangzhou City, Nanping City, and Longyan City have the largest carbon emissions of agricultural materials, rice growth, and livestock breeding, reaching 59.59×10^4t, 24.68×10^4t, and 18.33×10^4t in 2019, respectively.

Spatial Differentiation Characteristics of ACEs and ACEI

To further reveal the spatial evolution characteristics of ACEs and ACEI in each city in Fujian Province, this study used ArcGIS10.8 to classify ACEs and ACEI to get their spatial distribution Figs (Fig. 2 and Fig. 3) based on the classification principle of the natural breaks method.

According to Fig. 2, the changing pattern of ACEs in the coastal areas (Ningde, Fuzhou, Putian, Quanzhou, Xiamen, and Zhangzhou) of Fujian Province is relatively stable compared with the inland areas (Nanping, Sanming, and Longyan). Among them, the ACEs of Zhangzhou have always been a high emission area. The reason is that Zhangzhou is a big agricultural city, which is the main grain-producing area in Fujian Province. This makes more input in agricultural materials lead to increased carbon emissions. In addition, it is worth pointing out that Xiamen is a special economic zone of China, which has always been a low-emission area of ACEs in Fujian Province. This is because Xiamen's agricultural development model mainly uses agricultural landscape resources and agricultural production conditions to develop a leisure agricultural development model that integrates sightseeing, leisure, and tourism. As a result, its ACEs have been at a low level.

Since carbon emissions intensity considers the impact of total resources on the distribution, it can more accurately reflect the extent of regional ACEs. From the perspective of ACEI (Fig. 3), the spatial distribution of ACEs intensity in different cities of Fujian Province is uneven, and there are obvious differences. ACEI of Nanping City, Ningde City, and Longyan City have been in high-intensity areas. The degree of agricultural modernization in these cities still lags, the development model of agriculture is still "high input and high output", the development model of the agricultural industry

Table 2: Total and components of ACEs for 9 cities in Fujian Province, 2005-2019. ($\times 10^4$t).

City	Year	Rice	Livestock	Agricultural materials	Total
Fuzhou	2005	18.51	19.07	29.90	67.48
	2019	6.46	9.93	28.95	45.34
Xiamen	2005	1.27	6.35	4.38	12.00
	2019	0.31	1.56	4.26	6.13
Ningde	2005	16.69	6.10	15.23	38.03
	2019	9.67	4.31	19.83	33.81
Putian	2005	7.52	10.30	11.22	29.04
	2019	2.98	2.20	13.20	18.38
Quanzhou	2005	17.41	21.17	27.14	65.71
	2019	9.37	10.38	23.61	43.36
Zhangzhou	2005	18.36	26.21	66.63	111.20
	2019	7.79	10.48	59.59	77.86
Sanming	2005	26.98	18.48	22.25	67.71
	2019	19.73	9.66	24.83	54.22
Longyan	2005	24.86	30.17	19.17	74.19
	2019	18.64	18.33	17.99	54.96
Nanping	2005	32.48	21.46	28.55	82.48
	2019	24.68	14.16	25.69	64.52

is relatively single, and the total agricultural output mainly depends on agricultural materials input. As a result, the ACEI of these cities is at a high level.

Spatial Correlation Analysis of ACEs and ACEI

This study used ArcGIS10.8 to conduct spatial autocorrelation analysis on ACEs data of 9 cities in Fujian Province of China from 2005 to 2019. The variation curves of Moran's *I* index and *P*-value for each year were shown in Fig. 4.

As can be seen from Fig. 4, the Moran's *I* index from 2005 to 2019 is positive and all passed the significance test at the level of 5%, indicating that the spatial distribution of ACEs and ACEI at the city-scale in Fujian Province is not completely random, but has significant spatial dependence characteristics. From the Moran's *I* index, it showed a downward trend as a whole, which indicates that the spatial correlation between ACEs and ACEI is weakening.

The global Moran's *I* index can only explain the overall spatial dependence of ACEs for each city in Fujian Province, however, it cannot represent the specific structure and spatial correlation of spatial dependence of ACEI. Hence, to better grasp the local spatial pattern of ACEI, the LISA clustering map of 2005 and 2019 was drawn by using ArcGIS 10.8, according to the spatial and temporal distribution characteristics of different cities (Fig. 5).

As shown in Fig. 5, at a significant level of 5%, the local spatial dependence of agricultural carbon emissions for each city in Fujian Province is relatively obvious. From the LISA agglomeration map in 2005, it can be seen that ACEI in Fujian Province has formed high-high agglomeration areas (Sanming) and low-low agglomeration areas (Putian). According to the LISA agglomeration map in 2019, the high-low agglomeration area expanded (Quanzhou and Ningde). It can be seen that although a certain agglomeration area has been formed, the spatial autocorrelation in most areas is not significant, and the agglomeration effect is very limited. In particular, the diffusion effect and demonstration effect of the low-low agglomeration region have not yet played a significant role, and the area of the high-low agglomeration area has expanded.

CONCLUSION

Considering the deficiency of past literature studies on spatial heterogeneity of factors affecting agricultural carbon emissions (ACEs), this study first constructed a system for measuring ACEs, and calculated ACEs and agricultural carbon emissions intensity (ACEI) at the city-scale of 'The Belt

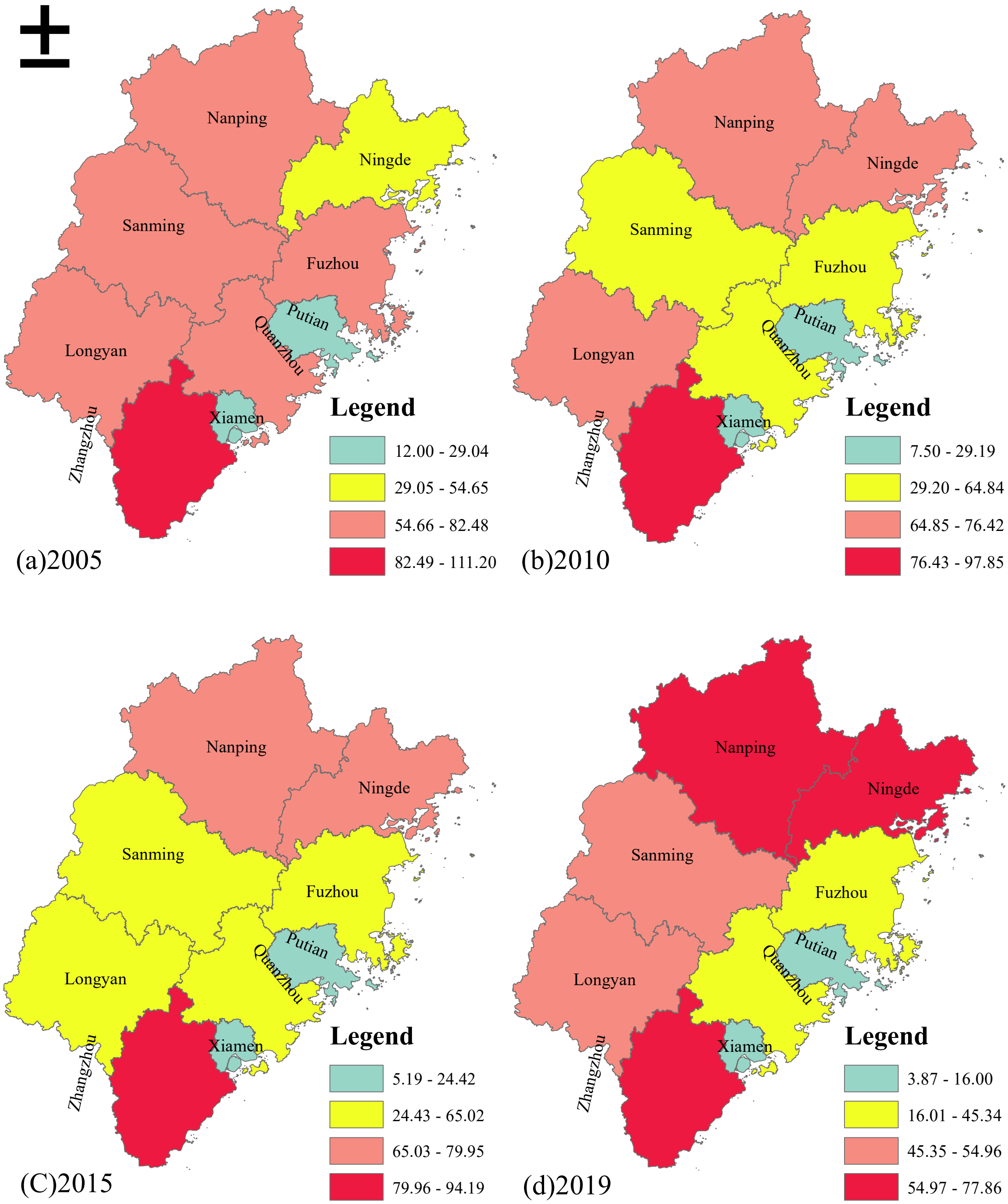

Fig. 2: Spatial distribution of ACEs in Fujian Province during 2005-2019 (10^4t).

and Road' Core Area (Fujian Province) in China from 2005 to 2019. Then, the evolution characteristics of agricultural carbon emissions, intensity, and structure in Fujian Province were discussed from spatio-temporal latitudes. Finally, ESDA was applied to analyze the spatial correlation of ACEI and to explore the spatial agglomeration area of ACEI. Accordingly, the main conclusions and corresponding optimization measures of this study are summarized as follows.

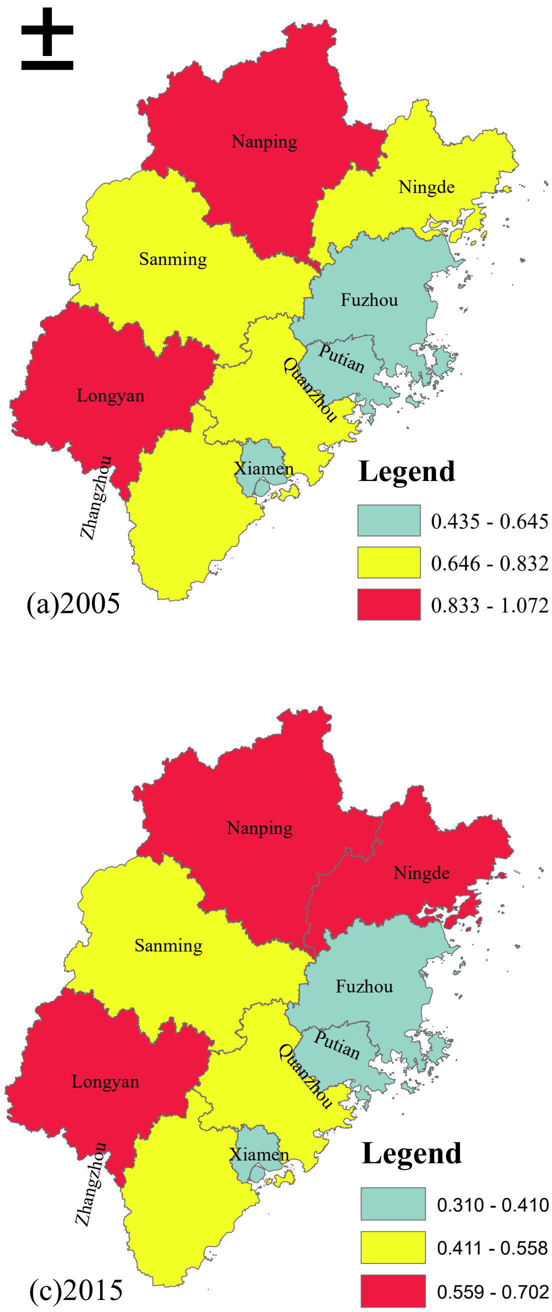

Fig. 3: Spatial distribution of ACEI at the city-scale in Fujian Province from 2005-2019 (10^4t).

(1) In this study, more sources of carbon emissions, especially methane and N_2O, were considered when constructing the measurement system of ACEs. This makes our result reveals a relatively more accurate estimation of ACEs for this study area compared with those from the other studies (e.g. Zhang & Zhang 2020). ACEs in Fujian Province demonstrated a downward trend as a whole during 2005-2019. Results exhibited that ACEs in Fujian Province decreased from 549.3×10^4t in 2005 to 393.9 ×10^4t in 2019, with an average annual decline of 1.89%. In terms of carbon sources of ACEs, agricultural materials cause the largest emissions, with an average annual emission of 233.0×10^4t, accounting for 47.59% of the total ACEs, while rice growth leads to the smallest carbon emissions, with an average annual emission

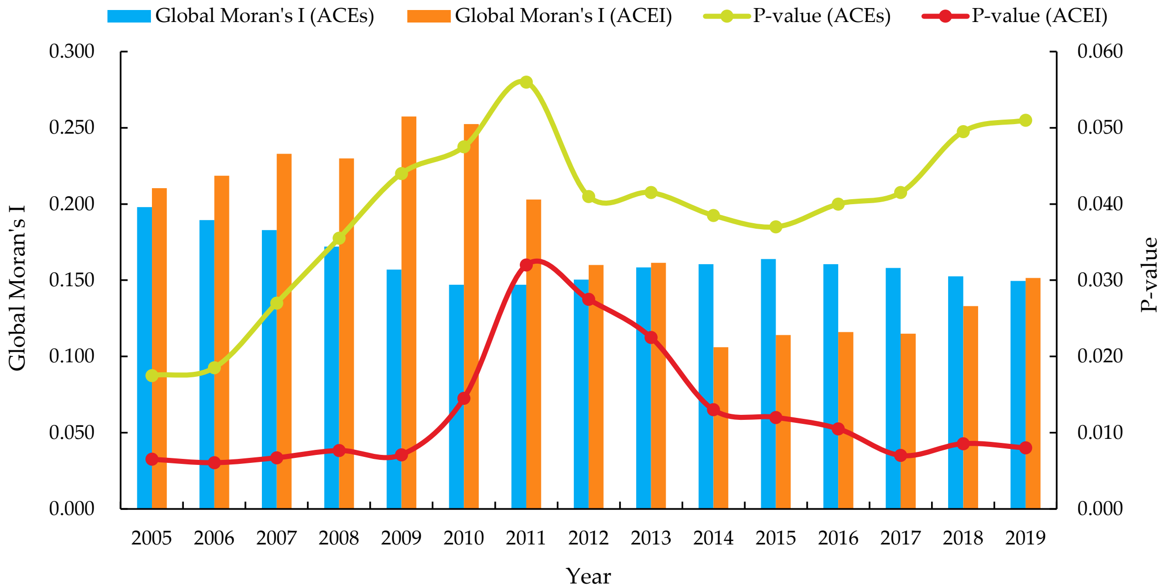

Fig. 4: Global Moran's *I* index of ACEs and ACEI for each city in Fujian Province from 2005-2019.

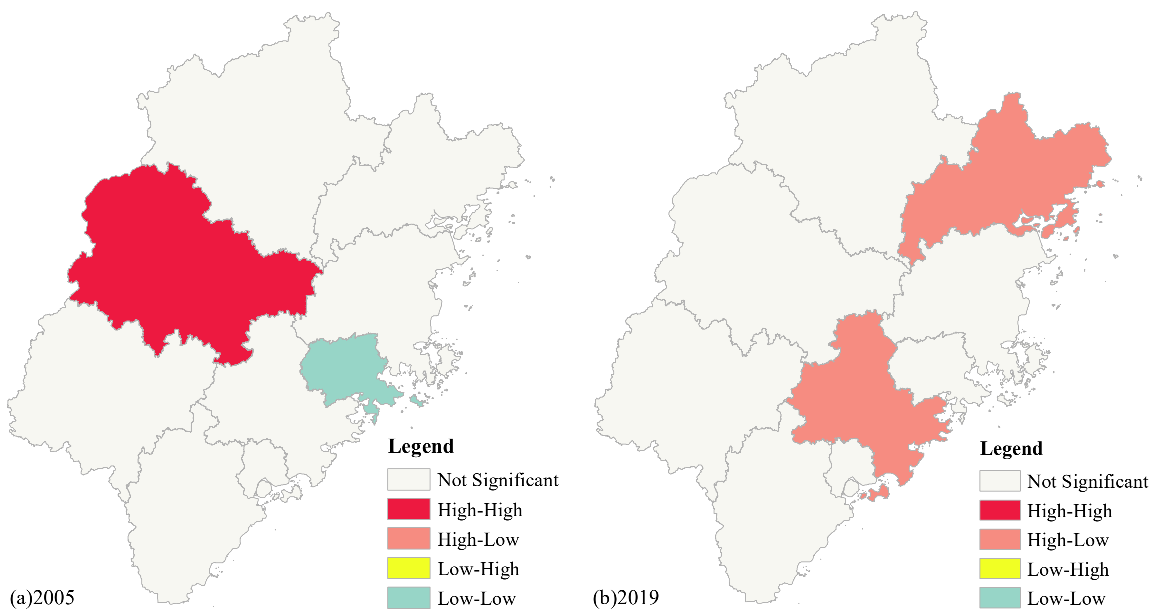

Fig. 5: LISA clustering map of ACEI in Fujian Province.

of 128.2×10^4t, accounting for 26.18% of the total ACEs. In addition, ACEI displayed a downward trend as a whole, with a decline rate of 63.56%, and an average annual decrease of 4.24%. There are fluctuations and differences in ACEs of Fujian Province from 2005 to 2019. Therefore, we suggest that the government should formulate differentiated policies on agricultural carbon reduction. This is because each city's agricultural natural resource endowment and technological level are different, so the evolution of its ACEs has its characteristics, and there are differences in the sources of carbon emissions. Only in this way can we improve the effectiveness of agricultural carbon reduction.

(2) The spatial distribution of ACEs and ACEI in Fujian Province is different. Except for Xiamen and Putian, ACEs of other cities all exceeded 50×10^4t, accounting for 95.05% of the province's total emissions. Among them, the top three regions in terms of carbon emissions are Zhangzhou City, Nanping City, and Longyan City. These areas are the main rice-growing areas in Fujian Province, with a large input of agricultural materials and relatively developed animal husbandry, which make a greater contribution to the total carbon emissions. So, the government should further guide consumers/farmers to choose agricultural products with green and low-carbon scientifically and reasonably to form a low-carbon consumption pattern of agricultural products. Moreover, the results showed that methane emission from paddy fields is also the main source of ACEs. Thus, in addition to formulating differential policies, the government should also choose reasonable management measures to cultivate new agricultural varieties. For instance, Some scholars have found a kind of low methane and high starch rice (SUSIBA2) (Su et al. 2015), which opened up a new idea for the breeding of new varieties in the later stage.

(3) There exists an obvious spatial correlation of ACEs for each city in Fujian Province. From 2005 to 2019, the Moran's *I* index values were positive and passed the significance test, indicating that ACEs and ACEI in Fujian Province showed obvious spatial dependence. According to LISA's clustering map and significance map, although a relatively obvious clustering area has been formed, the spatial autocorrelation of most regions is not significant. Therefore, it is necessary to further strengthen regional cooperation and jointly control the key carbon sources. Meanwhile, we believe that the government and scholars should further explore the seamless integration of ecological compensation mechanism and carbon trading system, namely, "carbon compensation mechanism". Previous studies have shown that ecological compensation plays an important role in the green and low-carbon development of the agricultural sector (Cui et al. 2021, Xiong et al. 2019). Through this compensation mechanism, low-carbon agricultural production behavior with positive externalities can be stimulated, and carbon emissions can be reduced. For example, the behavior of using environmentally friendly technologies (such as organic application, ecological control of diseases and insect pests) and livestock and poultry farming manure treatment (biogas treatment), etc.

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