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Original Research

Sustainable Agricultural Development in China: An Analysis on Spatiotemporal Evolution and Driving Forces

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Abstract

Environmental issues worldwide are growing increasingly severe, leading to concerns about sustainable food systems. Therefore, it is significant to research sustainable agricultural development (SAD). This study focuses on China as a research area since it is one of the largest agricultural countries globally. A key objective of this research is the development of a novel evaluation framework for Sustainable Agricultural Development (SAD), alongside the analysis of the spatiotemporal differentiation and evolution of China's SAD levels, and the exploration of the heterogeneity in its driving factors. The goal is to facilitate relevant departments in formulating differentiated regional agricultural sustainable development strategies. SAD levels across various Chinese provinces are evaluated through the development of an index-based assessment system, with a focus on three key aspects: Resource Conservation, Environmental Friendliness, and Production Efficiency. Additionally, spatiotemporal differentiation and evolution are analyzed using Kernel Density Estimation and Spatial Autocorrelation models. We explore the spatiotemporal heterogeneity of driving factors for SAD through the Geographical and Temporal Weighted Regression (GTWR) model. Findings indicate a steady rise in SAD levels across China from 2013 to 2021, with notable regional variations. The southeast coastal region exhibits high SAD levels, while the western inland and northeastern regions show lower levels. There is a strong positive correlation in SAD levels amongst these selected Chinese provinces, with increasing agglomeration effects over time. Low-low agglomeration zones are primarily concentrated in the west, while high-high agglomeration zones are more prevalent in the east. Based on the outcomes, the factors exhibit spatial and temporal heterogeneity. Economic Development Level, R&D Investment, and Agricultural Socialized Services positively influence SAD. However, a positive shift to a negative shift in the impact of Human Capital Education and Openness Level on SAD over time indicates the areas China's government should focus on in order to revitalize a path towards great SAD.

Keywords: sustainable agricultural development, spatiotemporal evolution, driving forces, GTWR

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Introduction

Sustainable development aims to achieve ecological health, social responsibility, and economic prosperity [1]. Given that agriculture forms the foundation of environmental, social, and economic well-being [2], it is crucial to explore sustainable agricultural practices. The United Nations made the 2030 Agenda Declaration for Sustainable Development, providing a shared framework for global peace and prosperity. The 17 Sustainable Development Goals form the core of this agenda, functioning as a global call to action for all nations, irrespective of their stage of development.

Currently, academic research is focused on defining "agricultural sustainable development", quantitatively evaluating its progress, and identifying key influencing factors. The concept of sustainable agriculture is multifaceted, with varying interpretations among scholars [3, 4]. An instance is that of Roy and Chen defining sustainable agriculture, as the practices that satisfy essential criteria while maintaining ecological stability, economic viability, and social equity [5]. Cao and Solangi considered sustainable agriculture to boost agricultural prolificacy, distribute yield impartially, and conserve natural resources [6]. Diverse definitions and metrics of sustainable agriculture underscore its interdisciplinary nature and the necessity for comprehensive monitoring approaches. Researchers have identified indicators such as resource conservation [7], social economy [8], and environmental friendliness [9] to assess agricultural sustainability. By constructing a comprehensive evaluation index system for sustainable agriculture [10–13], researchers have measured and evaluated the SAD level in specific areas and researched the influence of factors such as the digital economy and environmental regulations on SAD by using intermediary effects models; threshold panel mod els; structural equation models and others [14–21].

Overall, the theoretical foundation and research methods in the existing studies on SAD are robust. However, the previous research on the evolution of SAD levels in China is insufficient, especially on the regional agglomeration effect and the spatiotemporal heterogeneity of driving factors. Therefore, this paper uses a variety of spatial econometric models to research the above problems. The main contribution of this paper lies in: (1) An innovative comprehensive index system constructed to measure SAD level, which introduces industry integration indicators; (2) Using Kernel Density Estimation to analyze the spatiotemporal differentiation and evolution of SAD; (3) The Spatial Autocorrelation model is used to explore the regional agglomeration effect of SAD; (4) Based on the GTWR model, this paper innovatively explores the spatiotemporal heterogeneity of driving factors of SAD, providing new insights for the implementation path towards sustainable agriculture development.

The rest of the paper is arranged as follows: Section 2 outlines the methodological framework and processes underpinning the model construction, along with a detailed account of the data sources utilized in this study. Section 3 expounds on the empirical results and analysis. Section 4 is devoted to the conclusions. Section 5 presents the discussion.

Material and Methods

Construction of an Indicator System to Assess SAD Level

Building on the theoretical foundations of Sustainable Agricultural Development (SAD), this article develops an indicator system that assesses SAD levels in terms of Resource Conservation, Environmental Friendliness, and Production Efficiency. Resource Conservation is reflected in the protection and rational utilization of all kinds of resources in the process of agricultural production, improving resource utilization efficiency to reduce natural resource consumption. Four specific indicators are chosen, namely the water-saving irrigation rate, the cropland replanting rate, the intensity of agricultural electricity consumption, and the level of fiscal support for agriculture. Environmental Friendliness refers to reducing pollution levels in agricultural production for the ecological environment (including greenhouse gas emissions from agricultural production). Select six specific indicators, including fertilization intensity, pesticide usage, agricultural membrane usage, agricultural Chemical Oxygen Demand (COD) emissions, agricultural ammonia nitrogen emissions, and the crop disaster rate. Production Efficiency refers to the comprehensive improvement of economic, ecological, and social benefits. Six specific indicators are identified, encompassing unit grain sowing area yield, unit agricultural machinery power output value, labor productivity, land output rate, the structural composition of the agricultural industry, and the degree of industry integration.

Using the Panel Entropy Weighting Method to Weight the Indicators

The Shannon Entropy Weighting method is an objective technique used to assign weights to indicators based on the magnitude of their information entropy. In addition, panel data can offer additional insights into the dynamic behavior of the samples. When exploring the development of SAD, it is also crucial to investigate how SAD has evolved over time in response to various factors in different provinces. Consequently, the panel entropy method is used in this article as a weight indicator.

Table 1 shows various indicators and weights. The indicator attribute "positive" means the value increases with the indicator data; "negative" means the value decreases with the indicator data. According to the weights and values of indicators, the evaluation value y of SAD in the 31 provinces (excluding Hong Kong, Taiwan, and Macao) from 2013 to 2021 can be calculated.

Table 1. Index system for sustainable development level of agriculture.

Guideline	Index	Calculation method	Attribute	Weight %
Resource conservation	Water-saving irrigation rate	Water-saving irrigation area/actual total irrigation area	positive	12.14
	Cropland replanting rate	Crop sowing area/cultivated land area	Negative	4.46
	Agricultural electricity intensity	Electricity consumption/total output value of agriculture, forestry, animal husbandry, and fishery	Negative	1.02
	Fiscal support for agriculture	Expenditure on agricultural, forestry, and water affairs/ general public budget expenditure of local finance	Negative	4.91
Environment Friendliness	Fertilizer intensity	Fertilizer application rate/crop sowing area	Negative	3.63
	Pesticide usage	Pesticide application rate/crop sowing area	Negative	1.50
	Agricultural membrane usage	Usage of agricultural membrane /planting area of crops	Negative	1.90
	Agricultural COD emission intensity	Agricultural COD emission intensity	Negative	0.25
	Agricultural ammonia nitrogen emission	Agricultural ammonia nitrogen emission intensity	Negative	1.23
	Crop disaster rate	Affected area of crops/Sowing area of crops	Negative	1.40
Production Efficiency	Unit grain sowing area yield	Total grain yield/grain sowing area	positive	6.77
	Unit agricultural machinery power output value	Total agricultural output value/total power of agricultural machinery	positive	7.91
	Labor productivity	Total output value of agriculture, forestry, animal husbandry and fishery/primary industry employees	positive	11.29
	Land output rate	Planting output value/cultivated land area	positive	15.73
	The structural form of agricultural industry	Value added of professional and auxiliary activities in agriculture, forestry, animal husbandry and fishery/ total output value of agriculture, forestry, animal husbandry and fishery	positive	8.25
	Industrial integration level	Operating income from large-scale agricultural product processing industry/total output value of agriculture, forestry, animal husbandry, and fishery	positive	17.65

Using Kernel Density Estimation (KDE) to Explore the Evolution of SAD

We used the KDE method to fit the level of SAD in the 31 provinces from 2013 to 2021 to further explore its temporal evolution [25]. KDE is a non-parametric data distribution detection model that fits the distribution properties of the data [26]. As a statistical inference method based on data samples, Kernel Density Estimation does not need to make too many assumptions about the population distribution, so it can better reflect the actual situation of the data. The model form is as follows

$$\widehat{f(y)} = \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{y-y_i}{h}\right), i = 1,2,3,\ldots\ldots,31, \quad (1)$$

where $N = 31$ is the sample size, y_i is the level of SAD in the i-th province, $K(\cdot)$ is kernel function, h is density estimation bandwidth. Given that the Epanechnikov Kernel is optimal in terms of minimizing mean square error when determining the optimal bandwidth, and considering its minimal efficiency loss, this study selects the Epanechnikov Kernel as the kernel function, as outlined below.

$$K(y_i) = \begin{cases} \frac{3}{4}(1-{y_i}^2), \text{if } |y_i| \leq 1 \\ 0, \quad \text{Otherwise} \end{cases}, i = 1,2,3,\ldots\ldots,31. \quad (2)$$

Exploring the Agglomeration Effect of the Spatial Autocorrelation Model

Spatial Autocorrelation analysis enables the identification of spatial correlation patterns in the Sustainable Agricultural Development (SAD) levels across the 31 provinces examined in this study. The Global Moran's I is employed to assess the presence of spatial clustering phenomena, and its calculation formula is provided below.

$$I = \frac{N}{W}\frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(y_i-\bar{y})(y_j-\bar{y})}{\sum_{i=1}^{N}(y_i-\bar{y})^2}, i = 1,2,3,\ldots\ldots 31, \quad (3)$$

$$W = \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij}, i = 1,2,3, \dots \dots 31, \quad (4)$$

where w_{ij} is the adjacency weight of the i-th and j-th provinces. If the i-th and j-th provinces are adjacent, then $w_{ij} = 1$, otherwise $w_{ij} = 0$. To meet the needs of the model, Hainan and Guangdong are defined as adjacent and specifies $w_{ij} = 0$, if $i = j$.

The null hypothesis can be rejected, as the significant p-value suggests that the feature is not randomly distributed in the study area. At this stage, Local Moran's I can be applied to identify the location, extent, and significance of agglomeration, and its calculation formula is provided below.

$$I_i = \frac{(y_i - \bar{y}) \sum_{j=1}^{N} w_{ij}(y_i - \bar{y})}{\sum_{i=1}^{N}(y_i - \bar{y})^2}, i = 1,2,3, \dots \dots 31. \quad (5)$$

If $I_i > 0$, represents the spatial pattern of high-level provinces gathering to form a high-high agglomeration zone or low-level provinces gathering to form a low-low agglomeration zone; Conversely, $I_i < 0$ reflects the formation of high-low or low-high patterns, where high-level and low-level provinces interact.

Constructing a GTWR Model to Explore the Driving Factors of Agricultural Sustainability

The degree of SAD varies amongst provinces due to variations in their natural environments, geographic locations, and socioeconomic developments. This paper begins by examining the relationship between humans and the environment and selects five indicators, including Economic Development Level, R&D Investment, Human Capital Education, Agricultural Socialized Services, and Openness Levels. Table 2 shows driving factors and selected indicators. The specific instructions are outlined below.

(1) Economic Development Level.

Areas with high levels of economic development have a relatively high input-output ratio for agricultural production, which is strong in favor of promoting SAD.

(2) R&D Investment.

Technological advancements are pivotal in driving agricultural progress, with R&D investment fostering innovation in agricultural technologies and promoting the sustainability of agricultural development [28].

(3) Human Capital Education.

Human Capital Education has been shown to increase the innovation and flexibility of agricultural producers [29], leading to improvements in the efficiency and quality of agricultural production. This also enhances the competitiveness and resilience of the agricultural sector.

(4) Agricultural Socialized Services.

By providing professional,scientific and efficient services, agricultural socialized service organizations play a crucial role in enhancing various aspects of agricultural supply,including guarantee capabilities, technological innovation capabilities, sustainable development capabilities and international competitiveness. These services facilitate the adoption of sustainable agricultural technologies by smallholders, thereby transitioning conventional agriculture towards sustainable practices [30].

(5) Openness Level.

Advancing the comprehensive internationalization of agricultural practices is crucial for mitigating domestic resource shortages, alleviating resource and environmental pressures, and fostering a conducive environment for Sustainable Agricultural Development (SAD)[31].

This paper uses the GTWR model to explore the impact of these driving factors on SAD. The GTWR model is a regression linear model that periphrastically reflects the spatiotemporal heterogeneity characteristics of the study data by calculating the trends for changes in parameters with time and space [32, 33]. Currently, this method is predominantly applied in analyzing the scale and intensity of carbon emissions, rural settlement patterns, urban planning, and the spread of epidemics. It is less applied to the field of influencing factors in agricultural development, especially the driving factors of sustainable agricultural development. This paper uses the spatiotemporal and geographical weighted regression model to analyze the influence of various

Table 2. The driving factors of China's sustainable agricultural development level.

Driving factors	Select indicators
Economic Development Level	Regional per person GDP
R&D Investment	Agricultural R&D investment funds/Regional GDP
Human Capital Education	The proportion of people with a high school education and above
Agricultural Socialized Services	Agricultural professional and auxiliary activity output value/regional GDP
Openness Level	Actual utilization of foreign direct investment/regional GDP

factors on agricultural sustainable development from the perspective of time and space and provides theoretical support and empirical experience for formulating relevant policies to promote agricultural sustainable development. The model is structured as follows.

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^{m} \beta_k(u_i, v_i, t_i)x_{ik} + \varepsilon_i, \quad (6)$$

$$i = 1,2,3, \dots \dots 31,$$

where y_i is the SAD level of the i-th province, x_{ik} is the observed value of the k-th driving factor in the i-th province, (u_i, v_i) is the spatial position coordinate of the i-th province, t_i represents the corresponding time dimension, $\beta_k(u_i, v_i, t_i)$ is the regression coefficient of the k-th driving factor in the i-th province, $\beta_0(u_i, v_i, t_i)$ is the spatiotemporal intercept of the i-th province, and ε_i represents the random error. If $\beta_k > 0$, then there is a positive correlation between the SAD and driving factors; otherwise, it is a negative correlation. The weighted least square method (WLS) is used to calibrate the GTWR model. The matrix expression of the estimated coefficients of the i-th province can be given as shown in formula (7).

$$\widehat{\beta_k}(u_i, v_i) = [X^T W^T W X]^{-1} X^T W^T W Y, \quad (7)$$

Using the method of Huang et al. [33], the weight matrix is constructed based on adaptive bandwidth, Gaussian kernel function, and Euclidean distance.

Data Source and Processing

The data used in this study mainly comes from the China Statistical Yearbook, the China Statistical Yearbook on Environment, the China Agricultural Products Processing Yearbook, and the statistical yearbooks of provinces. Any missing data was completed using an interpolation method.

Results and Analysis

The Measurement Results of the SAD Level

This article used the panel Entropy Weight method to measure the evaluation index system of SAD [34] mentioned above and obtain the level values in 31 provinces in China from 2013 to 2021. Table 3 displays the results.

From a national perspective, the average level of SAD has been increasing year by year, from 0.326 in 2013 to 0.422 in 2021, with an average annual growth rate of 3.28%. This demonstrates China's SAD is accelerating, and agriculture is transforming and upgrading. In addition, as can be seen from the measurement results, the level

Table 3. The level of sustainable agricultural development in 31 provinces of China.

Region	2013	Ranking	2015	Ranking	2017	Ranking	2019	Ranking	2021	Ranking
Anhui	0.280	24	0.302	24	0.321	23	0.320	23	0.349	24
Beijing	0.454	2	0.466	3	0.513	2	0.548	2	0.608	3
Fujian	0.391	7	0.420	6	0.449	6	0.535	3	0.614	2
Gansu	0.265	27	0.273	28	0.273	28	0.282	29	0.295	29
Guangdong	0.338	10	0.364	10	0.395	8	0.464	7	0.526	6
Guangxi	0.295	20	0.309	21	0.334	21	0.353	20	0.396	18
Guizhou	0.230	30	0.281	26	0.320	24	0.328	22	0.385	21
Hainan	0.282	23	0.325	19	0.355	17	0.438	8	0.506	8
Hebei	0.324	12	0.327	16	0.357	15	0.375	14	0.425	13
Henan	0.295	21	0.333	13	0.390	11	0.374	15	0.401	16
Heilongjiang	0.311	16	0.308	22	0.334	22	0.308	26	0.345	25
Hubei	0.314	14	0.344	12	0.359	14	0.385	13	0.426	12
Hunan	0.305	17	0.327	18	0.350	18	0.361	19	0.404	15
Jilin	0.378	8	0.373	8	0.368	12	0.312	24	0.326	27
Jiangsu	0.408	5	0.451	4	0.481	4	0.494	4	0.531	5
Jiangxi	0.298	19	0.331	15	0.349	19	0.364	17	0.388	20
Liaoning	0.420	4	0.387	7	0.380	9	0.398	10	0.419	14

Region	2013	Ranking	2015	Ranking	2017	Ranking	2019	Ranking	2021	Ranking
Inner Mongolia	0.303	18	0.300	25	0.292	27	0.299	27	0.321	28
Ningxia	0.268	26	0.306	23	0.317	25	0.335	21	0.359	22
Qinghai	0.234	28	0.248	29	0.232	31	0.247	30	0.287	30
Shandong	0.403	6	0.421	5	0.454	5	0.438	9	0.467	9
Shanxi	0.275	25	0.281	27	0.305	26	0.309	25	0.350	23
Shaanxi	0.316	13	0.331	14	0.362	13	0.392	11	0.428	11
Shanghai	0.513	1	0.498	1	0.515	1	0.562	1	0.638	1
Sichuan	0.312	15	0.327	17	0.356	16	0.370	16	0.395	19
Tianjin	0.445	3	0.479	2	0.492	3	0.477	5	0.548	4
Xizang	0.229	31	0.226	31	0.242	30	0.232	31	0.251	31
Xinjiang	0.358	9	0.365	9	0.378	10	0.387	12	0.441	10
Yunnan	0.231	29	0.243	30	0.265	29	0.287	28	0.330	26
Zhejiang	0.331	11	0.361	11	0.402	7	0.472	6	0.520	7
Chongqing	0.292	22	0.320	20	0.341	20	0.363	18	0.398	17

of SAD in China's provinces from 2013 to 2021 showed significant spatial heterogeneity changes.

Based on a comparative analysis across provinces, Shanghai (0.546), Beijing (0.516), and Tianjin (0.487) rank highest amongst the provinces in terms of average sustainable agricultural development from 2013 to 2021. These three provinces have strong capacities for innovation in agricultural technology, high levels of economic development, and conditional advantages in SAD. The bottom three provinces are Xizang (0.234), Qinghai (0.251), and Yunnan (0.270). These three areas face limitations in terms of local agricultural resources and technological advancements, resulting in a relatively underdeveloped state of SAD.

The top three provinces are Hainan (7.776%), Guizhou (6.766%), and Zhejiang (5.86%) in terms of the growth rate of SAD levels; Jilin (-1.55%), Liaoning (0.04%), and Inner Mongolia (0.77%) are the lowest three provinces.

The Spatiotemporal Evolution of SAD

During the period of 2013 to 2021, the kernel density curves for SAD in different provinces, including the eastern, central, and western regions, all moved towards the right. This suggests that the level of SAD has progressively improved over time. There was a notable improvement in the degree of SAD in the eastern and western regions, as evidenced by the comparatively large changes observed in these regions, whereas the central region experienced relatively small changes (Fig. 1). The distribution pattern indicates that the primary peak of kernel density in the eastern region remains relatively stable, with an overall rightward shift in the estimated curve, indicating minimal internal variations within this region. However, in the central and western regions, there has been a consistent decrease in the main peak value of kernel density estimation each year, accompanied by an increase in bandwidth width. This suggests a widening gap in the levels of sustainable agricultural development among provinces in these regions. The maximum level of sustainable agricultural development at the national level experiences a rise followed by a decline, with the range of variation gradually expanding. The distribution shape indicates a "weak double peak" on the 2021 curve in the eastern region, but the difference in peak values is not statistically significant. Furthermore, the country's overall curve displays a single peak and a gradually elongating right tail, suggesting that high-level provinces of SAD are emerging and the overall level of SAD is continuously improving.

Spatial Differentiation and Agglomeration Effect of SAD Level

Each province's sustainable agricultural development level is categorized into four stages based on the maximum, minimum, and average levels of China's SAD for each year: low level, medium-low level, medium-high level, and high level. A general improvement phenomenon of SAD was observed in different Chinese provinces between 2013 and 2021 (Fig. 2), and there was a significant overall spatial distribution heterogeneity, indicating a high level of development in the eastern coastal region and a low level in the western inland and northeastern regions. From the perspective of regional evolution types of SAD level, from 2013 to 2021, the proportion of low and medium-low level development cities gradually decreased from 38.71%

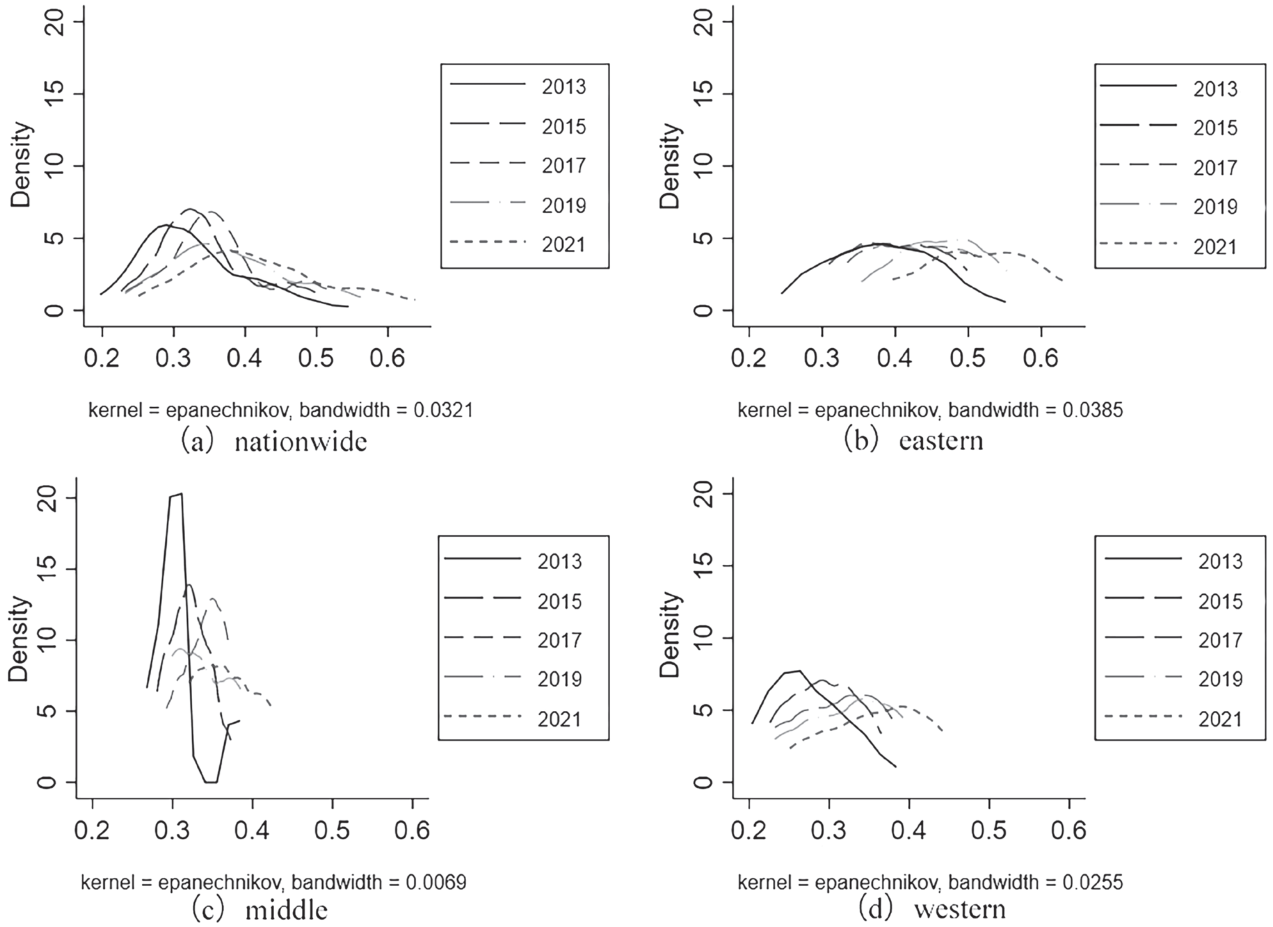


Fig. 1. The spatiotemporal evolution of China's sustainable agricultural development level.

in 2013 to 9.68% in 2021, and SAD in coastal provinces gradually entered a high level.

Using Stata17 software to calculate the Global Moran's I index from 2013 to 2021. The results are shown in Table 4.

The Moran index exhibited a p value below 0.05 across all years, indicating statistical significance. The results indicate a significant positive relationship between the level of SAD across various provinces in China. Moreover, the global Moran index has shown a consistent increase each year, indicating a strengthening agglomeration effect of these trends within each province over time. This shows that the nation has advocated ecological construction and sustainable development since the 12th Five Year Plan, and several provinces have stepped up their efforts to enhance SAD. The agglomeration effect has been strengthened by neighboring provinces' experience with and borrowing from sustainable agricultural development initiatives.

Draw Local Moran's I scatter plots for 2013, 2017, and 2021 (Fig. 3), with the four quadrants corresponding to four types in turn: high-high agglomeration zone, low-high agglomeration zone, low-low agglomeration zone, and high-low agglomeration zone. A high-high agglomeration zone refers to a region where both the province itself and its neighboring provinces exhibit high levels of sustainable agricultural development (SAD). Similar interpretations apply to other agglomeration patterns in different regions.

High-high agglomeration zones are primarily found in China's eastern regions, which include Beijing, Tianjin, Jiangsu, Shanghai, and Zhejiang, as Fig. 3 illustrates. Guangdong and Hainan also displayed a high-high agglomeration situation in 2021. In the meantime, the high-high agglomeration zones progressively moved from the northeast to the southeast over time. Western China is the primary location for low-low agglomeration zones. These regions include Yunnan, Xizang, Ningxia, Gansu, Qinghai, Guizhou, and Shanxi. It's evident that there is an obvious spatial agglomeration in SAD across different provinces, which is constrained by things like the natural geographic setting and the economic climate.

Analysis of Driving Factors for SAD

Analysis of Basic Regression Results

Based on the global linear regression model, using R4.2.2 software (RStudio) to estimate the coefficients. Table 5 demonstrates that the Economic Development Level, R&D Investment, Human Capital Education, Agricultural

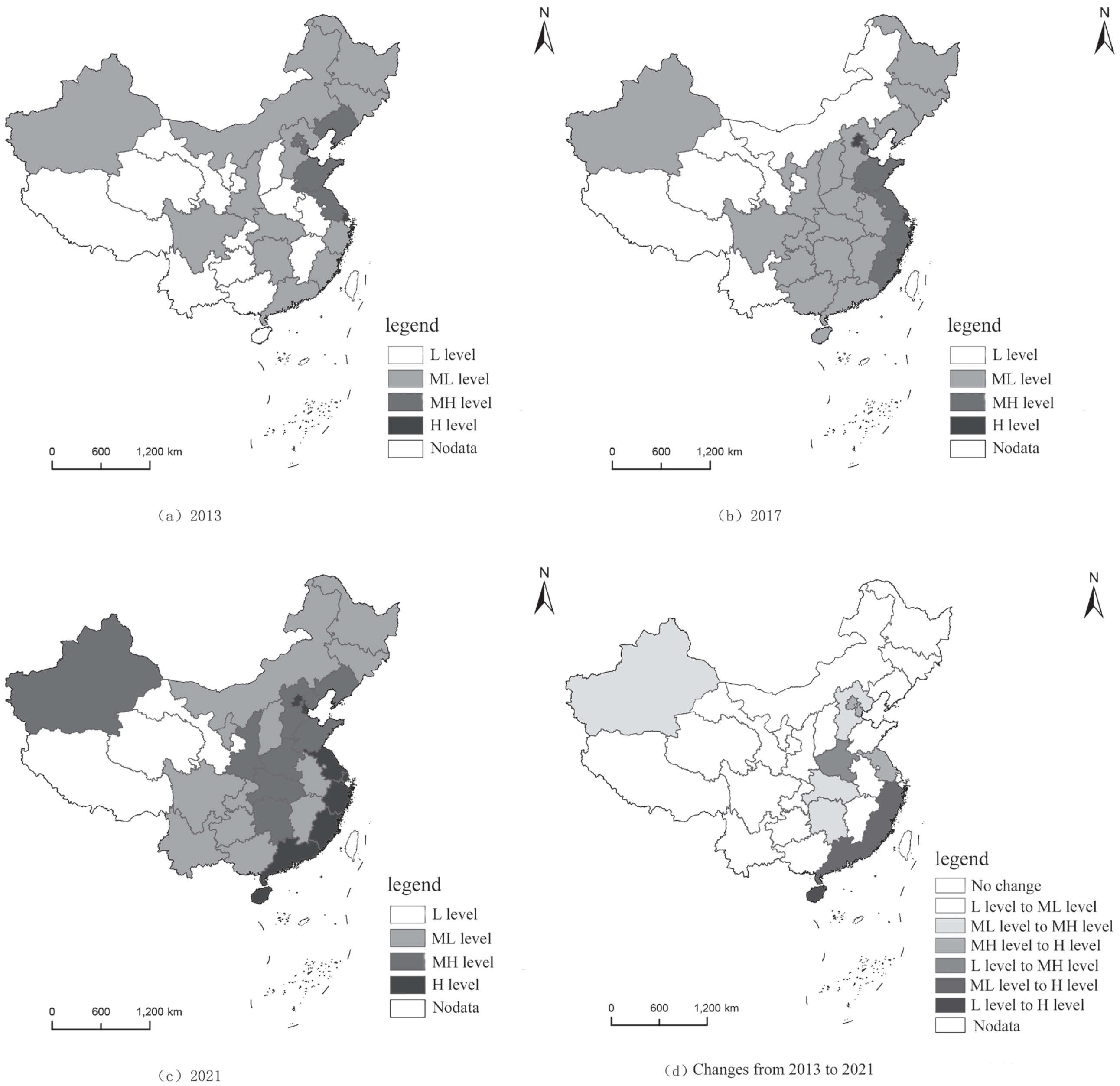


Fig. 2. The level and changes of sustainable agricultural development in various provinces of China in 2013, 2017, and 2021.

Table 4. Global Moran's I index of the level of sustainable development in agriculture.

Year	2013	2014	2015	2016	2017	2018	2019	2020	2021
Moran's I	0.341***	0.376***	0.392***	0.429***	0.436***	0.452***	0.478***	0.475***	0.483***
Z	3.179	3.475	3.589	3.905	3.959	4.111	4.288	4.298	4.337
P-value	0.002	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Socialized Services, and Openness Level exhibit a positive impact on SAD, aligning with the anticipated findings. Furthermore, all statistical tests conducted met the criteria for statistical significance at a 5% level. From the diagnostic information of the global regression model, if the variance inflation factor (VIF) of each explanatory variable is less than 7.5, it can be considered that there is no significant multicollinearity between the explanatory variables. At the same time, it was found that the determinability coefficient of the model was relatively high ($R^2 = 0.8172$),

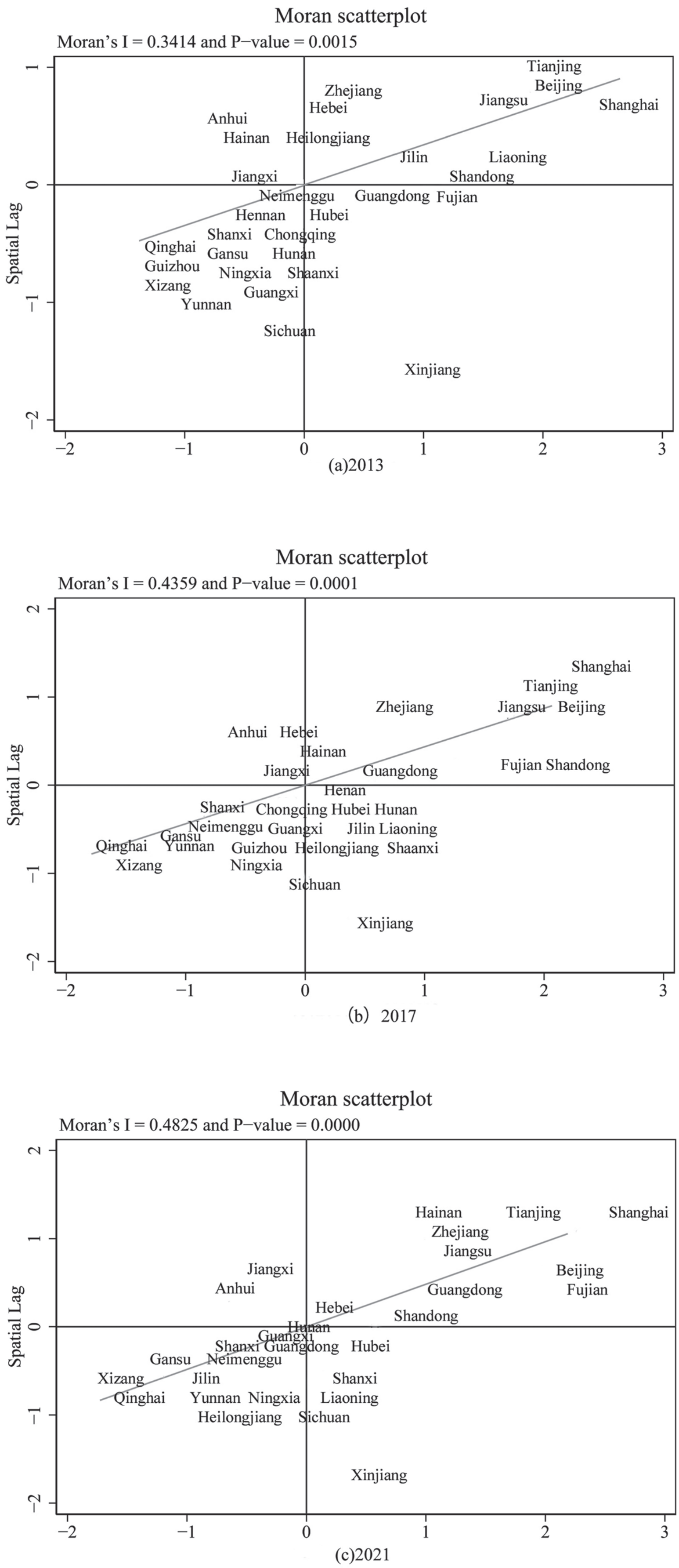
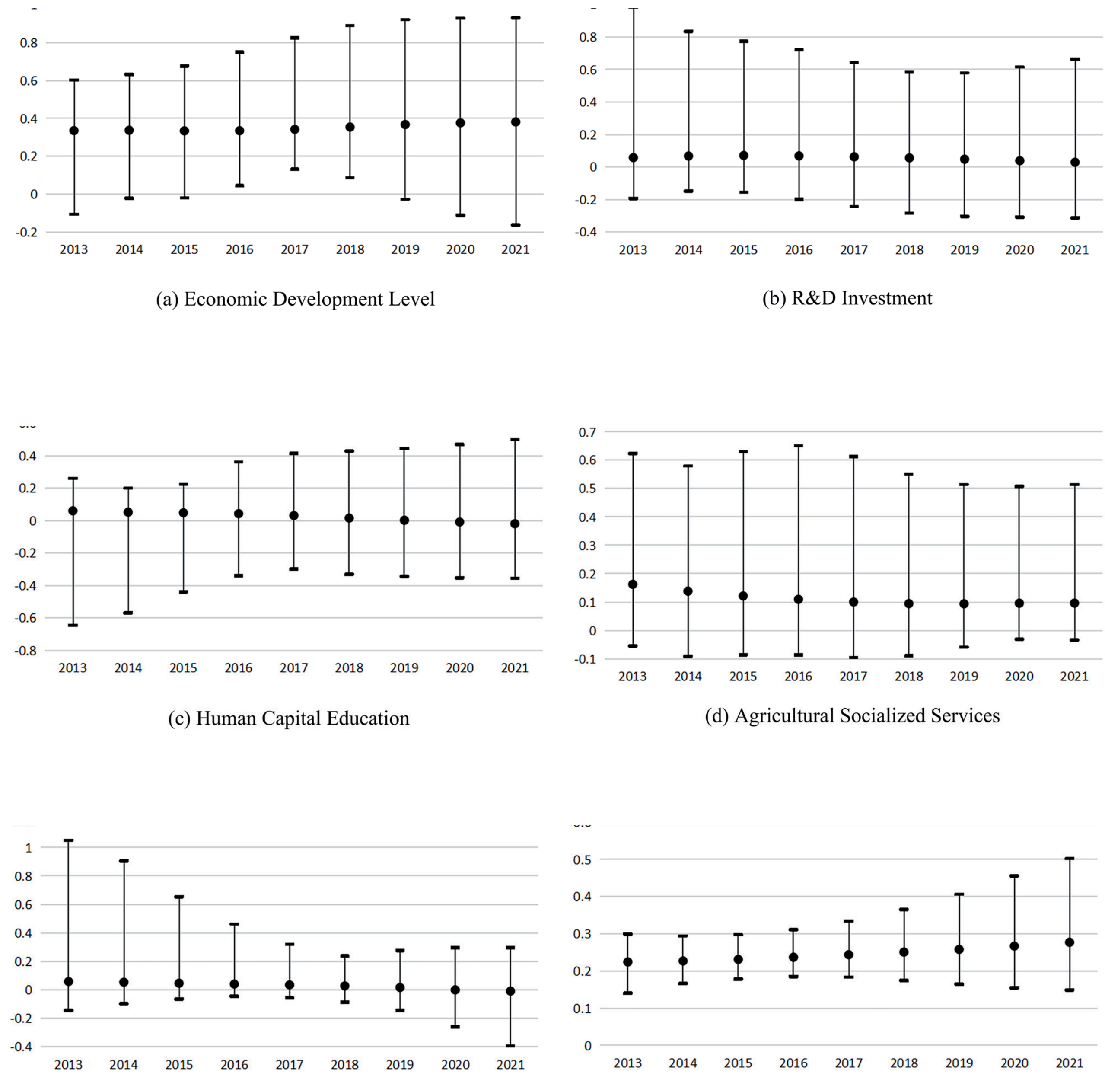


Fig. 3. Scatter plot of the Moran Index for the overall level of sustainable agricultural development in various provinces across China in 2013, 2017, and 2021.



(a) Economic Development Level (b) R&D Investment

(c) Human Capital Education (d) Agricultural Socialized Services

(e) Openness Level (f) interception

Fig. 4. Time variation of GTWR regression coefficient from 2013 to 2021.

Table 5. Basic linear regression results.

Factors	Estimate	Std. Error	t value	Pr(>|t|)	VIF
(Intercept)	0.237	0.005	46.701	< 2e-16 ***	—
Economic Development Level	0.335	0.016	21.265	< 2e-16 ***	1.671
R&D Investment	0.037	0.016	2.254	0.025 *	2.179
Human Capital Education	0.048	0.012	3.905	0.000 ***	1.488
Agricultural Socialized Services	0.084	0.013	6.232	1.74e-09 ***	1.387
Openness Level	0.056	0.018	3.041	0.003 **	1.536

indicating a good fit of the global regression model and a strong explanatory power of the model.

Analysis of GTWR Model Results

As mentioned above, the data is multicollinearity-free and passed the Moran test, satisfying the prerequisites for the GTWR model. Based on the GTWR module in ArcGIS 10.8 software, we conducted a regression on the driving factors of SAD in various provinces of China from 2013 to 2021. To further verify the spatiotemporal heterogeneity of driving factors in various provinces, this paper compared the fitting effects of different models. Compare the calculation results of Time Weighted Regression (TWR), Geographically Weighted Regression (GWR), and Geographically and Temporally weighted regression (GTWR) models. The result shows that the AICc of TWR is -1054.99, $R^2 = 0.819$ and adjusted $R^2 = 0.816$; the AICc of GWR is -1184.04, which $R^2 = 0.907$ and adjusted $R^2 = 0.906$; and the AICc of GTWR is -1395.39, $R^2 = 0.970$ and adjusted $R^2 = 0.969$. The fitting results of GTWR are significantly better than those of TWR and GWR.

The Influence of Driving Factors Presents Temporal Heterogeneity

Unlike OLS, GTWR gives the coefficients of each independent variable at different times and locations. If the coefficient is positive, it indicates that the driving factor has a positive effect on the dependent variable. On the other hand, if the coefficient is negative, the driving factor has an inhibitory effect on the dependent variable. The greater the absolute value of the coefficient, the stronger the effect. In general, the Economic Development Level, R&D Investment, and Agricultural Socialized Services work to support the SAD. The influence of Human Capital Education and Openness Level on SAD has gradually changed from being supportive to inhibitive (Fig. 4). Additionally, each explanatory variable's influence shows time heterogeneity behavior.

According to Fig. 4 (a), the average regression coefficient of the Economic Development Level fluctuated from 0.335 (2013) to 0.381 (2021). This is because the nation first proposed the goal of "overall improvement of ecological environment quality" during the 13th Five Year Plan period, which forced provinces to deepen measures about SAD. Simultaneously, the establishment of the initial set of National Sustainable Agricultural Development Demonstration Zones, completed towards the close of 2017, additionally bolstered the stimulating influence of economic development on SAD.

Fig. 4(b) presents an inverted U-shaped feature where the average regression coefficient of R&D Investment gradually increased from 0.058 (2013) to 0.070 (2015) and then decreased to 0.029 (2021). This suggests that as time goes on, agricultural technology research and development has become more mature, while the factors driving the level of sustainable agricultural development are gradually diminishing.

The average Human Capital Education regression coefficient dropped from 0.061 (2013) to -0.019 (2021), as shown in Fig. 4(c). In contrast to technological investment, the current human capital aggregation resulting from SAD is predominantly low-level. Although it encourages economic growth in the short term, it also creates obstacles for the later stages of regional agriculture's upgrading and transformation, which limits the advancement of SAD.

As shown in Fig. 4(d), the average regression coefficient of Agricultural Socialized Services decreased gradually from 0.162 (2013) to 0.0961 (2021). This is a result of the three industries' ongoing promotion of rural integration, which raises the standard of Agricultural Socialized Services across different areas. The impact of Agricultural Socialized Services on Sustainable Agricultural Development (SAD) has progressively diminished in recent years compared to the early stages of development. This decline is attributed to the continuous advancements and improvements in various aspects of agricultural development, including material supply, technical services, information services, financial services, production services, insurance services, and agricultural product sales.

The average regression coefficient of the Openness Level has gradually dropped from 0.058 (2013) to -0.008 (2021), as shown in Fig. 4(e). This is due to the increasing caution in opening agricultural products to the international market, driven by the current complex global landscape and the need to safeguard national security. Consequently, the influence of openness on Sustainable Agricultural Development (SAD) has progressively diminished.

The Influence of Driving Factors Presents Spatial Heterogeneity

This study visualizes the regression coefficient intervals of each driving factor and investigates their spatial heterogeneity to intuitively describe the impact of various driving factors on SAD in various provinces. Using the natural breakpoint principle, we found the mean of the regression coefficients for each driving factor from 2013 to 2021, as indicated in Fig. 5.

The regression coefficient of the Economic Development Level from Fig. 5(a) demonstrates a trend of increasing from north to south. Economic Development in Guangdong, Guangxi, and Hainan provinces has a significant impact on SAD. This is attributed to the higher level of economic development in the southern region, where agricultural development initiated the green transformation earlier, providing substantial momentum for the sustainable development of agriculture. The northern and western regions are experiencing a slight slowdown in economic development, and there is little to no impact of this on SAD.

From Fig. 5(b), (c), and (d), we can observe that the regression coefficients for R&D Investment, Human Capital Education, and Agricultural Socialized Services all exhibit a consistent upward trend from the southeast to the northwest. This is due to the higher levels of R&D Investment, Human Capital Education, and Agricultural Socialized Services in the southeast, leading to a maturing

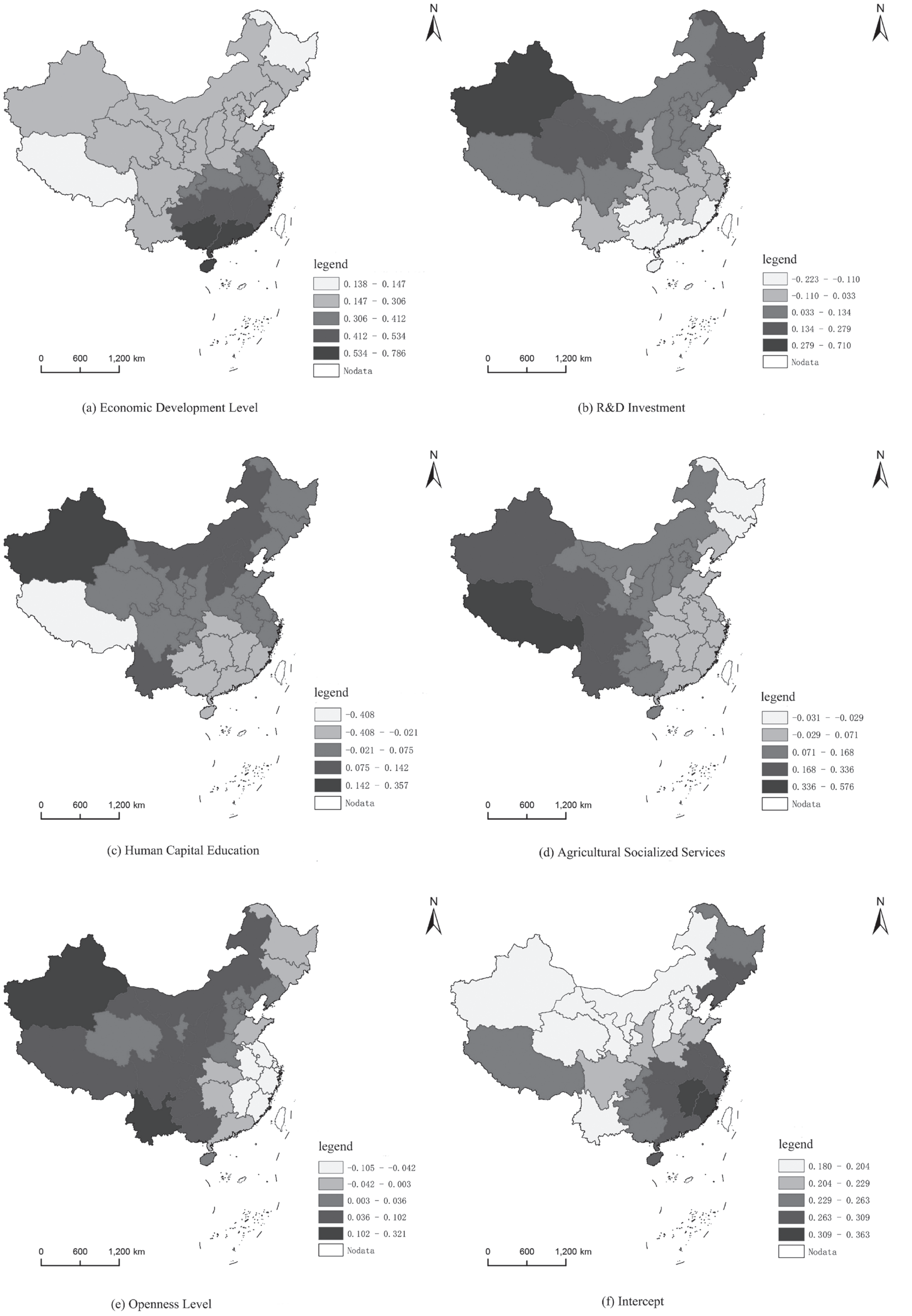


Fig. 5. Regression coefficients of various driving factors from 2013 to 2021.

and stabilizing impact on SAD. In contrast, the northwest is experiencing rapid growth in technology, human capital, and agricultural services for sustainable development in agriculture, resulting in a greater overall impact.

From Fig. 5(e), the regression coefficient of Openness Level shows an increasing trend from the eastern coastal areas to the western inland areas, indicating that Openness Level in the eastern coastal areas is relatively high. As the level of Sustainable Agricultural Development (SAD) continues to improve, its impact has gradually diminished. However, in recent years, with the persistent advancement of international trade initiatives such as the Belt and Road Initiative, the openness level of the western inland regions has progressively increased, resulting in a greater influence on SAD.

From the above analysis, the impact of various driving factors on the level of SAD shows spatial heterogeneity.

Conclusions

This article uses various econometric methods such as panel Entropy Weight method, Kernel Density Estimation, Spatial Autocorrelation analysis, and GTWR model to comprehensively measure the level of SAD in 31 provinces in China from 2013 to 2021 and analyze their spatiotemporal evolution and driving factors. The main conclusions are as follows.

Between 2013 and 2021, the level of SAD in China's provinces increased annually. It exhibits significant spatial heterogeneity. The southeastern coastal areas had high levels of SAD, while the western inland areas and northeastern regions had low levels of the same development.

The level of Sustainable Agricultural Development (SAD) across Chinese provinces from 2013 to 2021 demonstrates a strong positive correlation, with the agglomeration effect in individual provinces intensifying over time. The majority of the high-high agglomeration zones are found in China's eastern provinces, including Beijing, Tianjin, Jiangsu, Shanghai, and Zhejiang. Low-low agglomeration zones are mostly found in western China, primarily in the provinces of Yunnan, Xizang, Ningxia, Gansu, Qinghai, Guizhou, and Shanxi. Over time, the high-high agglomeration zones progressively move from the northeast to the southeast.

Overall, the Economic Development Level, R&D Investment, and Agricultural Socialized Services have a positive promoting effect on SAD. The impact of Human Capital Education and the Openness Level on SAD has gradually shifted from positive promotion to negative inhibition. The influence of each explanatory variable exhibits temporal and spatial heterogeneity.

Discussion

For the establishment of the indicator system for SAD, some scholars have examined the entire life cycle of agricultural production by integrating the developmental process from input, through production to output [35, 36]. Several scholars have measured Sustainable Agricultural Development (SAD) across three dimensions, namely the economy, society, and environment [37, 38]. Building upon these three levels — Resource Conservation, Environmental Protection, and Efficient Production — this study introduces two additional indicators, the Structural Form of Agricultural Industry and the Level of Industrial Integration. The rationale for this inclusion is that the advancement of industrial integration supports environmental conservation and ecological sustainability [39, 40]. For example, ecological agriculture combines the principles of traditional farming with modern agricultural technologies and auxiliary activities. This not only optimizes the efficient use of agricultural resources, but also emphasizes the scientific preservation and restoration of agricultural ecosystems [41]. On the other hand, industrial integration can promote rural and social sustainable development [42]. The government will also introduce various favorable policies and measures to attract the young and middle-aged labor force, college students, and others to return to their hometowns for entrepreneurship or employment, fully utilize various rural resources, and stimulate new vitality in SAD.

To enhance the SAD in China, it is imperative to address the disparity in levels of development between the southeastern and western inland regions and the northeastern regions. Each province and region should leverage its distinct resources to strategically develop and utilize a range of natural resources. Furthermore, they should leverage their strengths to foster the growth of environmentally friendly and sustainable agricultural practices and harness agglomeration effects to facilitate the inter-regional exchange of capital, technology, and resources.

There are still some shortcomings in this paper that need further refinement in subsequent research. In future studies, the possible interaction between various factors and indirect effects can be further considered. For example, environmental regulation [43], digital construction [44], and energy security [45] may affect economic growth and then influence sustainable agricultural development levels. Besides, considering that some data were missing due to inconsistent implementation of agricultural development policies in various provinces, we did not include policy factors in the driving factors, which may affect the accuracy of the model. We will continue to pay attention to the policy effect and incorporate it into the model as a possible driving factor after data becomes available in the future.

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Conflict of Interest

The authors declare no conflict of interest.

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