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Multi-level factor analysis-supported agricultural sustainability assessment and policy optimization pathways

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Abstract To address the challenges of multi-dimensional evaluation in agricultural sustainable development, this study integrates the composite evaluation method with multi-level factor analysis to construct an integrated model comprising "indicator dimension reduction-weight assignment-spatial validation." First, principal component analysis (PCA) and entropy methods are combined, and after passing the Spearman consistency test ($\rho < 0.05$), the fuzzy Borda model is used to synthesize the evaluation results. Subsequently, factor analysis is used for dimension reduction. The KMO value of 0.892 (Bartlett's test P=0.000) supports the extraction of three principal components. After rotation, the cumulative contribution rate reaches 85.766%. Four indicators with loadings <0.4 are excluded, ultimately establishing 18 core indicators across three categories: resource environment (9 indicators), production economy (9 indicators), and population and society (4 indicators). Empirical analysis of data from Region A from 2020 to 2024 indicates that resource pressure has intensified, with per capita arable land (C1) decreasing by 14.3% to 0.12 hm^2/person. However, ecological governance has achieved significant results, with the proportion of soil erosion (C6) decreasing by 20.0%. The economic dimension dominated the comprehensive evaluation (AHP weight of 62.8%), with agricultural total output value (C9) having the highest weight of 0.118. Regional evaluation results showed that all 20 regions scored an average of 13.26 (Grade II, good), but the range was as high as 11.95 points (Region k scored 17.19 points while Region l scored 5.24 points), indicating significant spatial differentiation. The Moran's I scatter plot reveals the expansion of high-value clusters (HH) from 25% to 40% between 2020 and 2024, while low-value zones (LL) shrink, reflecting policy coordination driving regional balanced development.

Index Terms multi-level factor analysis, agricultural sustainable development, composite evaluation method, AHP model

I. Introduction

The concept of "sustainable development" was first proposed in the 1987 Brundtland Report and has since gained widespread recognition [1]. As the theory of sustainable development has evolved and its application areas have expanded, the issue of sustainable agricultural development has become a common concern in contemporary society. The sustainable development system comprises five subsystems: population, resources, environment, economy, and society. Agriculture, as a foundational industry that directly utilizes natural resources for production, is closely intertwined with all subsystems of sustainable development [2], [3]. Whether agriculture can achieve sustainable development will impact the sustainable development levels of nations and regions, and is crucial to the realization of humanity's sustainable development goals [4], [5]. In 1991, the United Nations Food and Agriculture Organization defined sustainable agricultural development as the management and protection of natural resources, coupled with technological and institutional reforms, to ensure that the needs of both present and future generations are met in a sustainable manner [6]. This form of sustainable development (including agriculture, forestry, and fisheries) preserves land, water, and genetic resources of plants and animals. It is environmentally non-degrading, technologically appropriate, economically viable, and socially acceptable [7], [8].

Subsequently, various countries conducted further research based on their national circumstances and adopted different agricultural development approaches, such as the United States' sustainable agriculture focused on environmental protection, Japan's environmentally conservation-oriented agriculture, and China's intensive and efficient agriculture and ecological agriculture [9]-[11]. Additionally, various corporate groups have conducted related research. A notable example is Unilever, which views it as a feasible, economically beneficial, environmentally friendly, and community-appropriate agricultural practice that aligns with development needs [12], [13].

Currently, global agriculture faces three prominent challenges: severe degradation of global arable land, population growth that, though slowing, will inevitably threaten human survival due to land degradation, with an estimated 9.7 billion people requiring food by 2050 while degraded land approaches 2 billion hectares; agricultural production accounting for 23% of global greenhouse gas emissions, impacting climate and the environment; Smallholder farming accounts for over 80% of global agricultural production, but its actual scale efficiency is not significant [14]-[17]. In this context, conducting sustainable agricultural development evaluations, guiding sustainable agricultural development, optimizing policies, and achieving food security and environmental protection are of great significance. The multi-level factor analysis method combines the analytic hierarchy process (AHP) and factor analysis to address multi-level issues in complex systems [18]. This method demonstrates better adaptability for evaluating multiple dimensions in agricultural assessments.

There are numerous methods for sustainability evaluation. Literature [19] applies the Euclidean distance method to evaluate agricultural sustainability in Zhenyuan County, Gansu Province, over a 12-year period, integrating models, indices, rankings, indicators, target systems, and zero systems for agricultural sustainability, as well as an evaluation function model incorporating indicator weights. Literature [20] constructed an algorithm for evaluating agricultural sustainability with the support of mathematical measurement and standardization methods. This algorithm can dynamically display different ratings, providing an intuitive understanding of development levels and rankings. Literature [21] used an evaluation method based on the entropy value-TOPSIS model to assess indicators across multiple dimensions of agricultural sustainability, including economic, social, environmental, ecological, and resource aspects. It also combined an obstacle diagnosis model and a Tobit regression model to analyze and validate influencing factors. Literature [22] utilized dissipative structure theory and entropy weighting to evaluate the sustainable development of agriculture in Chengdu across five dimensions: economic, social, environmental, educational, and demographic. The trend showed annual growth from 2003 to 2017, maintaining a dynamic equilibrium. Literature [23] uses the entropy value method and the analytic hierarchy process to evaluate the sustainability of agriculture at the county level in Edessa Province, but the two methods yield inconsistent results in terms of indicator weighting. Literature [24] analyzes tools for assessing agricultural sustainability and finds that these tools differ in terms of background, objectives, and scope of application, and that they largely overlook the definition of social sustainability.

Additionally, the comparison of indicator importance is influenced by experts' interests and educational backgrounds, leading to low reliability in weighting results, which are often arbitrarily determined by researchers, even by authoritative evaluation institutions. A potential issue in comparing indicator importance is the scientific validity of such comparisons, such as the difficulty in assigning weights to social, economic, and ecological benefits, which are typically averaged or assigned similar weights. Furthermore, the importance of nitrogen, phosphorus, and potassium fertilizers may vary depending on factors such as region, crop, and human factors [25], [26]. Literature [27] points out that over the past 20 years, evaluations of agricultural sustainability have been conducted from economic, social, and environmental perspectives, using entropy weighting and analytic hierarchy process for indicator weighting. However, current research is not yet mature, and existing studies have not proposed relevant policy optimization recommendations based on evaluation results.

This study first integrates the results of two single models, principal component analysis (PCA) and entropy analysis, to fully utilize data information and enhance the robustness of the evaluation results. Second, to further explore the intrinsic structural relationships among evaluation indicators and construct a hierarchical evaluation framework, multi-level factor analysis is introduced. By analyzing the correlation coefficient matrix of the indicators, numerous original indicators are condensed into a few mutually independent common factors (principal components), effectively reducing the dimensionality and revealing the underlying structure of the data. Factor rotation is applied to enhance the interpretability of the factors, and factor scores are calculated for evaluation. Finally, to comprehensively rank the evaluation objects within a multi-level framework, the principal components extracted from factor analysis are used as criteria-level indicators, and the weights of each principal component are determined using the AHP model. This model constructs a hierarchical structure comprising a target layer, criterion layer, and scheme layer aimed at the comprehensive evaluation of agricultural sustainable development. By constructing a judgment matrix, calculating the relative weights of elements, and conducting rigorous consistency tests, the combined weights of each scheme layer object relative to the overall target are ultimately calculated, achieving a comprehensive evaluation based on a multi-level factor structure.

II. Establishment of an evaluation methodology system for sustainable agricultural development

II. A. Combined evaluation method

The composite evaluation method is based on the evaluation results obtained from two or more single evaluation models, emphasizing the full utilization of information to effectively enhance the scientific validity and authenticity of the evaluation results. The fuzzy Borda composite evaluation model takes into account the differences between scores and rankings, making it highly applicable. In this paper, the principal component analysis method and the entropy method are selected as single evaluation models for preliminary evaluation. After consistency is verified using the rank correlation method, a composite evaluation is conducted. The calculation process is as follows:

Step 1: Dimensionless processing of raw data

$$z_i = \frac{(x_i - \mu)}{\sigma} \tag{1}$$

(1) In the formula, x_i is the original value of a factor, μ is the mean, and σ is the standard deviation, which are used in principal component analysis. Since the Z-score method produces negative values in the processed data, the range standardization method is used to process the data in the entropy method:

$$z_{ij} = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})}\left(\text{Forward indicators}\right) \tag{2}$$

$$z_{ij} = \frac{\max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})}\left(\text{Reverse indicators}\right) \tag{3}$$

$$z'_{ij} = z_{ij} + A \tag{4}$$

In the above equation, A is the translation amplitude. In this paper, $A = 0.01$ is taken to make the standard data meaningful.

In the second step, the entropy method is used to calculate the indicator weight p_{ij}, entropy value e_j, difference coefficient d_j, and weight w_j for comprehensive evaluation.

$$p_{ij} = \frac{z'_{ij}}{\sum z'_{ij}} \tag{5}$$

$$e_j = -k\sum_{i=1}^{m} p_{ij} \ln p_{ij} \tag{6}$$

$$d_j = 1 - e_j \tag{7}$$

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{8}$$

$$F_{ij} = \sum_{j=1}^{n} w_j p_{ij} \tag{9}$$

In the above equation, $k = 1/\ln m$, where m is the number of prefectures and cities, and the smaller e_j is, the larger d_j is, indicating a significant difference between indicators and a larger weight.

Step 3: Calculate the principal factor score f_i and the comprehensive index of agricultural sustainable development F using principal component analysis.

$$f_i = \sum_{j=1}^{n} l_{ij} z_j, \left(i = 1, 2, \cdots, k\right) \tag{10}$$

$$F = \sum_{i=1}^{k} g_i f_j \tag{11}$$

In the above equation, g_i is the weight coefficient of the main factor score coefficient, and l_{ij} is the load value of the i th main factor on the j th indicator.

Step 4: Perform a pre-consistency test. Use the Spearman correlation coefficient test to test the evaluation results obtained by the principal component analysis method and the entropy value method to verify the reliability of the single evaluation model.

$$r = 1 - \frac{6\sum D_i^2}{n(n^2 - 1)} \tag{12}$$

In the formula (12), $D_i = X_i - Y_i$ is a measure of the deviation between the two evaluation results. The greater the deviation, the larger the value of $\sum D_i^2$.

Step 5: Calculate the membership degree

$$\mu_{ij} = \frac{-\min_i(F_{ij})}{\max_i(F_{ij}) - \min_i(F_{ij})} * 0.9 + 0.1 \tag{13}$$

In the formula (13), F_{ij} represents the score of the i th city under the j th evaluation method.

Step 6: Calculate the fuzzy frequency

$$\rho_{hi} = \sum_{j=1}^{2} \delta_{jh} \mu_{ij} \tag{14}$$

In the formula (14), when city i ranks h th in the j th evaluation method, δ_{jh} is 1; when city i does not rank h th in the j th evaluation method, δ_{jh} is 0.

Step 7: Calculate the fuzzy frequency and normalize the fuzzy frequency.

$$W_{hi} = \frac{\rho_{hi}}{\sum_{h=1}^{14} \rho_{hi}} \tag{15}$$

Step 8: Perform score conversion processing.

$$Q_h = (14-h)(14-h+1)/2 \tag{16}$$

In the formula (16), Q_h represents the score when the city ranks h th in the evaluation.

Step 9: Calculate the combined evaluation score.

$$FB_i = \sum_{j=1}^{2} W_{hi} Q_h \tag{17}$$

II. B.Multi-level factor analysis method

II. B. 1) Factor analysis model

Factor analysis is a statistical method that converts multiple indicators into a small number of mutually independent and unobservable random variables (i.e., factors) by studying the internal structure of the correlation coefficient matrix of the original data, thereby extracting most of the information contained in the original indicators. When the factor loading matrix structure is not sufficiently simplified, factor rotation can be used to give the factors more distinct practical significance. At the same time, factor score functions can be used to evaluate and rank the samples. The mathematical model of factor analysis is $\underset{(p\times 1)}{X} = \underset{(p\times m)}{A}\underset{(m\times 1)}{F} + \underset{(p\times 1)}{\varepsilon}$ and satisfies:

(1) $m \le p$;

(2) $Cov(F,\varepsilon)=0$, i.e., F and $\boldsymbol{\varepsilon}$ are uncorrelated;

(3) $D(\mathbf{F}) = \begin{pmatrix} I & 0 & \cdots & 0 \\ 0 & I & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & I \end{pmatrix} = I_m$, where $I = \begin{pmatrix} I & 0 & \cdots & 0 \\ 0 & I & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & I \end{pmatrix}_{p\times p}$

That is, $F_1,\ldots,F_m$ are uncorrelated and have variances of 1;

$D(\varepsilon) = \begin{pmatrix} \sigma_1^2 & 0 & \cdots & 0 \\ 0 & \sigma_2^2 & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & \sigma_p^2 \end{pmatrix}$ That is, are uncorrelated and have different var $\varepsilon_1,\ldots,\varepsilon_p$ iances.

where $X=\left(X_1,\ldots,X_p\right)'$ is a p -dimensional random vector composed of p observable indicators; $F=\left(F_1,\ldots,F_m\right)'$ is an unobservable vector, and F becomes the common factor of X; the matrix A is called the factor loading matrix; a_{ij} is called the factor loading, representing the loading of the i th variable on the j th common factor; $\boldsymbol{\varepsilon}$ is called the specific factor of X, representing the part of the variable that cannot be explained by the common factor. The specific factors are independent of each other and independent of the common factors.

II. B. 2) AHP model

This paper uses a multi-level analysis model for the AHP model, taking the five main components extracted as criteria-level measurement indicators and China's top ten high-tech zones as the solution level to conduct a comparative study of the overall satisfaction levels of scientific and technological workers in each high-tech zone. The basic steps of the multi-level analysis method are as follows:

(1) Calculate the hierarchical structure, as shown in Figure 1.

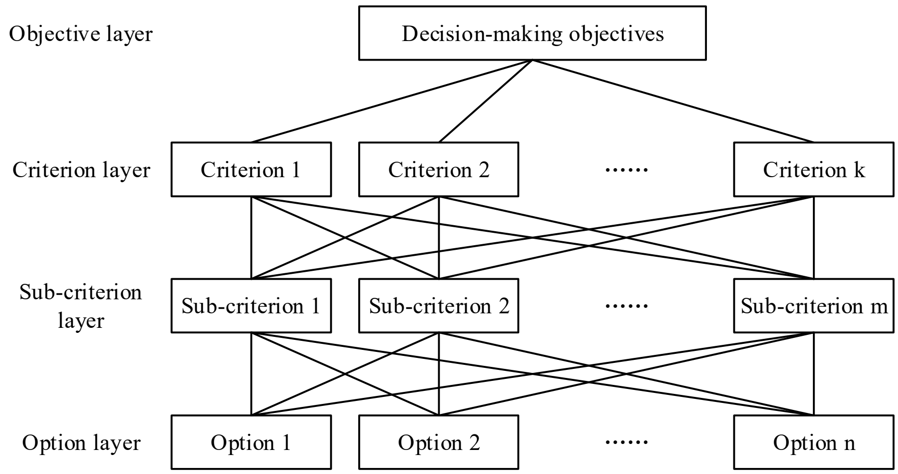

Figure 1: Hierarchical structure

(2) Calculating the relative importance of elements under a single criterion (single-level model)

In a single-level judgment matrix, when $a_{ij} = \frac{a_{ik}}{a_{jk}}$, the judgment matrix is called a consistency matrix; calculate the consistency index $CI_t = \frac{\lambda_{\max} - n}{n-1}$, n is the order of the judgment matrix; calculate the average random consistency index RI, RI is obtained by taking the arithmetic mean after repeatedly calculating the eigenvalues of the random judgment matrix; calculate the consistency ratio CR_t, $CR_t = CI_t / RI_t$, when $CR_t < 0.1$, it is generally considered that the consistency of the judgment matrix is acceptable.

(3) Calculate the combined weights of the elements at each level, and the method of calculating the combined weights is shown in Table 1.

Table 1: Method for calculating combined weights

Level B	A_1 a_1	A_2 a_2	......	A_n a_n	Weight of B-level element combinations
B_1	b_1^1	b_1^2	......	b_1^n	$b_1 = \sum_{i=1}^{n} a_i b_1^i$
B_2	b_2^1	b_2^2	......	b_2^n	$b_2 = \sum_{i=1}^{n} a_i b_2^i$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
B_n	b_n^1	b_n^2	......	b_n^n	$b_n = \sum_{i=1}^{n} a_i b_n^i$

(4) Consistency of the total ranking calculation results at each level

Let: CI be the consistency index of the overall ranking of levels, and RI be the random consistency index of the overall ranking of levels. Then, their formulas are as follows: $CI = \sum_{i=1}^{n} a_i CI_i$, where CI_i is the consistency index of the judgment matrix in level B corresponding to A_i; $\sum_{i=1}^{n} a_i RI_i$, where RI_i is the random consistency index of the judgment matrix at level B corresponding to A_i, and $CR = \frac{CI}{RI}$. When $CR \leq 0.10$, the results of the hierarchical total ranking are considered to have satisfactory consistency.

III. Agricultural sustainability evaluation model based on multi-level factor analysis

Using the "combined evaluation-multi-level factor analysis" methodology framework established in Chapter 2 (integrating PCA, entropy method, and AHP model), Chapter 3 will focus on the specific application of the evaluation model. First, based on the KMO test (0.892 > 0.5) and Bartlett's sphericity test (Sig. = 0.000), 22 initial indicators were selected. Through factor analysis, three principal components were extracted (cumulative contribution rate of 85.766%). Four indicators (B16, B17, B18, and B31) with loadings <0.4 were excluded, ultimately establishing 18 core indicators, providing a streamlined and efficient measurement tool for empirical evaluation.

Table 2: The initial evaluation indicators for sustainable agricultural development

Target layer	Criterion layer	Indicator layer	Calculation formula	Unit
Agricultural sustainable Development (A)	Sustainable Development of Agricultural Resources and Environment (B1)	B11: Per capita cultivated land area in rural areas	Cultivated land area/rural population	hm2/person
		B12: Per capita water resources	Total water resources/Total population	m2/person
		B13: Utilization rate of Water resources development	Regional water consumption/total water resources	%
		B14: Forest coverage rate	Collected according to statistical data	%
		B15: Per capita forest land area	Forest land area/total population	hm2/person
		B16: Proportion of effective irrigated area	Effective irrigated area/cultivated land area	%
		B17: Fertilizer application intensity	The amount of chemical fertilizer applied/the volume of cultivated land	kg/hm2
		B18: Agricultural film recovery rate	Collected according to statistical data	%
		B19: Proportion of soil erosion area	Soil erosion area/total land area	%
	Agricultural Production and Sustainable Economic Development (B2)	B21: Agricultural labor productivity	Total output value of agriculture, forestry, animal husbandry and fishery/Labor force of agriculture, forestry, animal husbandry and fishery	10,000 yuan/person
		B22: Agricultural land productivity	Total output value of agriculture, forestry, animal husbandry and fishery/Total land area	10,000 yuan/hm2
		B23: Gross Agricultural Product	Collected according to statistical data	100,000,000 yuan
		B24: Growth rate of agricultural output value	(Total agricultural output value of the current year - Total agricultural output value of the previous year)/ Total agricultural output value of the previous year	%
		B25: Per capita agricultural output value	Gross agricultural production value/Total population	yuan/person
		B26: Growth rate of per capita agricultural output value	(Per capita agricultural output value of this year - per capita agricultural output value of last year)/ Per capita agricultural output value of last year	%
		B27: Per capita grain output	Total grain output/total population	kg/person
		B28: Per capita meat production	Total meat production/total population	kg/person
		B29: Per capita aquatic product output	Total output of aquatic products/Total population	kg/person
	Agricultural Population and Social Sustainable Development (B3)	B31: Urbanization level	Urban population/total population	%
		B32: Population density	Total population/Land area	%
		B33: Population growth rate	(Population at the end of this year - Population at the end of last year)/ Population at the end of last year	%
		B34: The ratio of disposable income of rural residents to that of urban residents	Per capita disposable income of rural residents/per capita disposable income of urban residents	-

III. A. Determination of evaluation indicators

III. A. 1) Initial setting of evaluation indicators

This study starts from the connotation of sustainable agricultural development in China and, based on the principles of systematicity, scientificity, and availability of indicators, constructed an initial evaluation index system for sustainable agricultural development in China through multiple KMO tests and Bartlett tests, as shown in Table 2.

The three-tier agricultural sustainable development evaluation indicator system constructed in this paper comprises three criterion levels (resources and environment, production and economy, population and society) and 22 indicator levels. Among these, the resources and environment criterion level (B1) includes nine indicators such as arable land, water resources, forests, and pollution control, including per capita arable land and fertilizer application intensity, with a focus on ecological carrying capacity. Production and Economy (B2) includes nine economic efficiency indicators, such as agricultural labor productivity and agricultural output growth rate, reflecting output efficiency. Population and Society (B3) includes four social equity indicators, such as the urban-rural income ratio and population density, focusing on social balance.

III. A. 2) Questionnaire Survey

This survey was conducted from September to December 2024, with a total of 300 questionnaires distributed. Of these, 263 were valid, resulting in a validity rate of 87.67%. Following the conclusion of the survey, an analysis was conducted of the demographic and sociological characteristics of the respondents, as well as their basic travel characteristics. Table 3 provides an overview of the respondents' gender, age, education level, occupation, and other relevant information.

Table 3: Analysis of the demographic characteristics of the survey sample

Variable	Options	Number of people	Percentage
Gender	Male	143	54.37%
	Female	120	45.63%
Age	Under 20 years old	3	1.14%
	21 - 30 years old	12	4.56%
	31 - 40 years old	62	23.57%
	41 - 50 years old	138	52.47%
	Over 50 years old	48	18.25%
Educational qualifications	High school and below	3	1.14%
	Technical secondary school Junior College	10	3.80%
	Undergraduate degree	25	9.51%
	Master's degree or above	136	51.71%
	Government and public institution employees	89	33.84%
Occupation	Enterprise employees	68	25.86%
	Self-employed individuals Freelancer	85	32.32%
	Experts and scholars	21	7.98%
	Students in school Retired personnel	33	12.55%
	Other	13	4.94%
	Under 20 years old	16	6.08%
	21 - 30 years old	19	7.22%
	31 - 40 years old	8	3.04%

Table 3 presents the demographic characteristics of the respondents in this questionnaire survey, covering factors such as gender, age, educational attainment, and type of work. From a gender perspective, 54.37% of the respondents were male, while 45.63% were female. From an age perspective, the highest proportion of respondents was in the 41–50 age group, accounting for 52.47%. In terms of educational background, 14.45% of respondents had a high school diploma or lower, or a vocational or associate degree, 51.71% had a bachelor's degree, and 33.84% had a master's degree or higher. Among the respondents, 25.86% were from government agencies, 32.32% were from businesses, and individual merchants or self-employed entrepreneurs accounted for 7.98% and 12.55%, respectively. Most respondents indicated that they had participated multiple times in agricultural development and had a relatively in-depth understanding of the current status of sustainable agricultural development. The research findings have certain reference value and meet expectations.

III. A. 3) Significance testing

The primary purpose of the significance test is to determine whether factor analysis can be performed. This test method mainly involves calculating the KMO value and comparing it with 0.5. If the value is above 0.5, factor analysis can be performed; if it is below 0.5, factor analysis cannot be performed. The KMO values calculated in this paper are shown in Table 4.

Table 4: The KMO value and the Bartlett's sphericity test results

KMO sampling adequacy index Approximate Chi-square		0.892
Bartlett's sphericity test	Degree of freedom	1529.2932
	Significance	80
	KMO sampling adequacy index Approximate Chi-square	0.000

Table 4 shows that the KMO value calculated in this paper is 0.892, which is significantly higher than 0.5. Furthermore, the significance probability Sig. of Bartlett's sphericity test is 0.000, which is <0.05 and therefore significant, indicating a high level of significance. This means that the test has been passed and factor analysis can be performed.

III. B. Factor analysis

III. B. 1) Constructing factor variables

Eigenvalues can be used to measure whether a factor has sufficient influence. This paper selects factors based on the magnitude of their eigenvalues. Table 5 shows the total variance explained by each component factor. According to the data in Table 5, there are three principal component factors with eigenvalues greater than 1, and their cumulative contribution rate is 81.966%, indicating that the information from the 22 indicators is basically contained in the three principal component factors.

Table 5: The explained total variance of each component factor

Component	Initial eigenvalue			Extract the sum of squares and load			Rotate the sum of squares for loading		
	Total	Variance	Cumulative	Total	Variance	Cumulative	Total	Variance	Cumulative
B23	4.482	40.824	40.824	4.281	41.525	41.525	3.928	43.483	43.483
B25	3.394	28.583	69.407	3.071	30.532	72.057	2.171	29.349	72.832
B11	1.551	12.559	81.966	2.025	13.083	85.140	1.839	12.934	85.766
B12	0.931	4.741	86.707						
B24	0.897	3.649	90.356						
B26	0.834	2.246	92.602						
B22	0.765	1.945	94.547						
B27	0.753	1.503	96.05						
B21	0.697	1.215	97.265						
B28	0.641	1.077	98.342						
B33	0.618	0.562	98.904						
B32	0.547	0.197	99.101						
B29	0.421	0.127	99.228						
B34	0.354	0.159	99.387						
B13	0.253	0.128	99.515						
B15	0.226	0.137	99.652						
B19	0.175	0.144	99.796						
B14	0.128	0.069	99.865						
B16	0.094	0.053	99.918						
B17	0.068	0.037	99.955						
B31	0.028	0.032	99.987						
B18	0.014	0.009	99.996						

There are three factors with eigenvalues greater than 1, with initial eigenvalues of 4.482, 3.394, and 1.551, respectively. The first four factors account for 86.707%, but only the first three factors are retained (because their eigenvalues are greater than 1 and their cumulative contribution rate is 81.966%). Contribution rate optimization after extraction: After rotation, the cumulative contribution rate of the top three factors reached 85.766% (Component 1: 43.483%; Component 2: 29.349%; Component 3: 12.934%), indicating that the information content of the 22 indicators can be compressed into three principal components, meeting the dimensionality reduction requirement (>80% information retention).

III. B. 2) Establishing the factor loading matrix

The rotated component matrix is shown in Table 6.

Table 6: Explain the component matrix after rotation

Index	Component		
	1	2	3
B11	0.827		
B12	0.801		
B13	0.521		
B14	0.503		
B15	0.448		
B16	0.325		
B17	0.384		
B18	0.295		
B19	0.411		
B21		0.535	
B22		0.766	
B23		0.918	
B24		0.776	
B25		0.855	
B26		0.751	
B27		0.674	
B28		0.570	
B29		0.612	
B31			0.302
B32			0.619
B33			0.668
B34			0.513

As can be seen from the table above, the component load values of the four indicators—B16 effective irrigation, B17 fertilizer intensity, B18 agricultural film recovery rate, and B31 urbanization level—are less than 0.4, indicating a relatively weak correlation. Therefore, these indicators were removed. After removal, the existing indicators were renumbered and reanalyzed, with the specific results shown in Table 7.

Table 7: Explain the rotated component matrix (Deleting non-conforming indicators)

Indicator	Component		
	1	2	3
C1: Per capita cultivated land area in rural areas	0.915		
C2: Per capita water resources	0.863		
C3: Utilization rate of Water resources development	0.774		
C4: Forest coverage rate	0.784		
C5: Per capita forest land area	0.616		
C6: Proportion of soil erosion area	0.697		
C7: Agricultural labor productivity		0.735	
C8: Agricultural land productivity		0.825	
C9: Gross Agricultural Product		0.969	
C10: Growth rate of agricultural output value		0.842	
C11: Per capita agricultural output value		0.913	
C12: Growth rate of per capita agricultural output value		0.829	

C13: Per capita grain output		0.773	
C14: Per capita meat production		0.831	
C15: Per capita aquatic product output		0.702	
C16: Population density			0.812
C17: Population growth rate			0.726
C18: The ratio of disposable income of rural residents to that of urban residents			0.673

After excluding weak load indicators, the factor structure becomes clearer, and the load of Component 1 (resource environment) is comprehensively enhanced, such as per capita arable land (C1: 0.915), forest coverage (C4: 0.784), and new soil erosion ratio (C6: 0.697), highlighting ecological pressure indicators. The key indicators of Component 2 (Production and Economy) have seen a significant increase in loadings, such as land productivity (C8: 0.825), per capita agricultural output (C11: 0.913), and meat production (C14: 0.831), which have become new focal points. Component 3 (Population and Society) retains population density (C16: 0.812), growth rate (C17: 0.726), and urban-rural income ratio (C18: 0.673) exhibit a more compact structure after excluding urbanization levels.

All indicator loadings are >0.6, and the cumulative contribution rate of 85.766% has not significantly decreased, demonstrating that the streamlined indicator system is more efficient and the economic significance of the principal components is clearer.

IV. Research on the evaluation of sustainable agricultural development based on hierarchical analysis and factor analysis

Based on the 18-item indicator system optimized in Chapter 3, Chapter 4 uses Location A as an empirical object and collects panel data from 2020 to 2024. Through entropy standardization and AHP weighting, the dominant weight of the economic dimension is established, and then the comprehensive scores of 20 regions are calculated. Moran's dot plot is used to analyze spatial evolution characteristics.

IV. A. Data Acquisition and Processing

IV. A. 1) Data Acquisition

Through the aforementioned multi-level factor analysis, an evaluation index system for sustainable agricultural development in China was confirmed. Taking Area A as the research object, after on-site investigations and reviewing relevant materials, such as the Area A Statistical Yearbook and the Annual Report on Government Information Disclosure, the corresponding data for the 18 secondary indicators in Area A for 2020-2024 were calculated, as shown in Table 8.

Table 8: The corresponding data of secondary indicators in Area A from 2020 to 2024

Indicator	Unit	2020	2021	2022	2023	2024
C1: Per capita cultivated land area in rural areas	hm2/person	0.14	0.13	0.13	0.12	0.12
C2: Per capita water resources	m2/person	1825.36	1798.24	1763.15	1741.08	1720.59
C3: Utilization rate of Water resources development	%	38.25	39.17	41.03	42.86	44.12
C4: Forest coverage rate	%	23.18	23.75	24.32	24.91	25.47
C5: Per capita forest land area	hm2/person	0.21	0.22	0.22	0.23	0.23
C6: Proportion of soil erosion area	%	15.73	14.82	14.05	13.21	12.58
C7: Agricultural labor productivity	kg/hm2	3.85	4.12	4.06	4.33	4.57
C8: Agricultural land productivity	%	2.31	2.45	2.38	2.61	2.74
C9: Gross Agricultural Product	%	286.74	302.91	295.83	318.67	336.25
C10: Growth rate of agricultural output value	10,000 yuan/person	5.24	5.63	-2.34	7.72	5.51
C11: Per capita agricultural output value	10,000 yuan/hm2	8653.27	9128.45	8896.31	9574.62	10105.84
C12: Growth rate of per capita agricultural output value	100,000,000 yuan	4.87	5.49	-2.55	7.62	5.55
C13: Per capita grain output	%	482.36	496.75	467.28	503.14	518.92
C14: Per capita meat production	yuan/person	63.25	65.17	61.84	66.92	68.75
C15: Per capita aquatic product output	%	48.73	50.62	49.15	52.08	53.94
C16: Population density	kg/person	142.36	143.25	144.07	144.82	145.63
C17: Population growth rate	kg/person	0.32	0.28	0.25	0.22	0.19

C18: The ratio of disposable income of rural residents to that of urban residents	kg/person	2.65	2.59	2.53	2.48	2.43

As shown in Table 8, the trends in the 18 indicators of agricultural sustainable development in Area A from 2020 to 2024 exhibit the following characteristics: Resource pressure continues to increase, with the per capita arable land area in rural areas (C1) decreasing from 0.14 hm^2/person to 0.12 hm^2/person (-14.3%); per capita water resources (C2) decreased from 1,825.36 m^3/person to 1,720.59 m^3/person (-5.7%); water resource utilization rate (C3) increased from 38.25% to 44.12% (+15.4%), reflecting intensifying supply-demand contradictions; ecological governance achievements are significant, forest coverage rate (C4) increased from 23.18% to 25.47% (+9.9%); soil erosion ratio (C6) decreased from 15.73% to 12.58% (-20.0%).

Production and economic indicators generally declined in 2022 but rebounded strongly in 2023. Agricultural total output value (C9) decreased by 2.34% year-on-year in 2022 (from 295.83 billion yuan to 318.67 billion yuan) but rebounded by +7.72% in 2023; Per capita meat production (C14) dropped to 61.84 kg/person (-5.3%) in 2022 and rebounded to 66.92 kg/person in 2023; Agricultural labor productivity (C7) increased by 18.7% (from 38,500 to 45,700 yuan/person); Aquatic product production (C15) increased by 10.7% (from 48.73 to 53.94 kg per person).

At the same time, significant changes occurred in population structure: population density (C16) increased from 142.36 people per square kilometer to 145.63 people per square kilometer (+2.3%); The population growth rate (C17) decreased from 0.32% to 0.19% (-40.6%); The urban-rural gap continued to narrow, with the urban-rural income ratio (C18) decreasing from 2.65 to 2.43 (-8.3%).

IV. A. 2) Data Standardization Processing

To compare different data sets, it is necessary to standardize their usage.

The entropy method is a mathematical technique used to assess the dispersion of indicators. In information theory, a smaller entropy value indicates greater information content and lower uncertainty, while a larger entropy value signifies less information content and higher uncertainty. Based on the characteristics of entropy, using entropy values to assess the degree of dispersion of indicators, the greater the dispersion, the more the indicator will influence the comprehensive evaluation.

The data standardized using the entropy method is shown in Table 9.

Table 9: Standardized processed data

Indicator	2020	2021	2022	2023	2024
C1	1.000	0.500	0.500	0.000	0.000
C2	1.000	0.741	0.406	0.196	0.000
C3	1.000	0.844	0.527	0.215	0.000
C4	0.000	0.249	0.498	0.755	1.000
C5	0.000	0.500	0.500	1.000	1.000
C6	0.000	0.289	0.533	0.800	1.000
C7	0.000	0.375	0.292	0.667	1.000
C8	0.000	0.326	0.163	0.698	1.000
C9	0.000	0.326	0.184	0.645	1.000
C10	0.754	0.792	0.000	1.000	0.780
C11	0.000	0.327	0.167	0.634	1.000
C12	0.730	0.791	0.000	1.000	0.796
C13	0.292	0.571	0.000	0.694	1.000
C14	0.204	0.482	0.000	0.735	1.000
C15	0.000	0.363	0.081	0.643	1.000
C16	1.000	0.728	0.477	0.248	0.000
C17	0.000	0.308	0.538	0.769	1.000
C18	0.000	0.273	0.545	0.773	1.000

IV. B. Establishing indicator weights

When using the Analytic Hierarchy Process (AHP) for weight calculation, it is necessary to conduct a consistency analysis of the judgment matrix, specifically calculating the consistency ratio (CR) value (CR = CI/RI, where RI is obtained from a table based on the order of the judgment matrix). Generally, the smaller the CR value, the better the consistency of the judgment matrix. Typically, if the CR value is less than 0.1, the judgment matrix satisfies the consistency test.

In this study, the CI value for an 18-order judgment matrix was calculated to be 0.073, and the RI value was obtained from a table as 1.12. Therefore, the CR value was calculated to be 0.065 < 0.1, indicating that the judgment matrix in this study satisfies the consistency test, and the calculated weights are consistent.

The study established indicator weights using the AHP hierarchical analysis method, yielding the final first-level, second-level indicator weights, and comprehensive weights as shown in Table 10.

Table 10: The weights of indicators at all levels and the comprehensive weights

First-level indicator	Weight	Secondary indicators	Weight
Sustainable Development of Agricultural Resources and Environment (B1)	0.241	C1	0.081
		C2	0.077
		C3	0.029
		C4	0.011
		C5	0.022
		C6	0.021
Agricultural Production and Sustainable Economic Development (B2)	0.628	C7	0.061
		C8	0.068
		C9	0.118
		C10	0.072
		C11	0.082
		C12	0.070
		C13	0.068
		C14	0.051
		C15	0.038
Agricultural Population and Social Sustainable Development (B3)	0.131	C16	0.046
		C17	0.049
		C18	0.036

It can be seen that the economic dimension dominates: production and economic weighting accounts for 62.8%, reflecting that agricultural sustainable development is driven by economic efficiency; ecological foundations provide support, with resource and environmental weighting at 24.1%, highlighting the foundational role of ecological carrying capacity.

Among the secondary indicators, C9 (agricultural gross domestic product) has the highest weighting at 0.118. Among the top five weighting indicators, four belong to the economic dimension (with a combined weighting of 0.340). C1 (per capita arable land) ranks first among resource-related indicators with a weighting of 0.081, reflecting the strategic importance of arable land protection. Population density (C16) and urban-rural income ratio (C18) have similar weights (0.046 vs. 0.036), balancing spatial distribution and equity.

IV. C.Analysis of Evaluation Results

Based on the indicator weight values derived from Table 10, the comprehensive scores for the level of agricultural sustainable development in each region of Area A can be calculated. The total score is 18 points, divided into four grades: [15,18] is Grade I (Excellent), [12,15) is Grade II (Good), [9,12) is Grade III (Passing), and [0,9) is Grade IV (Failing). The evaluation results for the agricultural sustainable development of the 20 regions in Area A are shown in Table 11.

Table 11: Evaluation results of sustainable agricultural development in Area A

Region	Score	Ranking	Grade
a	15.09	6	I
b	6.03	19	IV
c	16.6	4	I
d	13.15	11	II
e	10.64	14	III
f	7.63	18	IV

g	17.12	2	Ⅰ
h	15.71	5	Ⅰ
i	14.15	9	Ⅱ
j	11.12	13	Ⅲ
k	17.19	1	Ⅰ
l	5.24	20	Ⅳ
m	13.78	10	Ⅱ
n	14.52	8	Ⅱ
o	8.79	17	Ⅳ
p	10.09	15	Ⅲ
q	16.94	3	Ⅰ
r	12.05	12	Ⅱ
s	9.41	16	Ⅲ
t	14.79	7	Ⅱ
A	13.26	-	Ⅱ

The comprehensive evaluation results for agricultural sustainable development across 20 regions in Area A exhibit significant spatial variation. Overall, the average score for the regions is 13.26 points (Grade II, Good), but there are substantial internal differences: the highest-scoring region k (17.19 points) is 3.3 times higher than the lowest-scoring region l (5.24 points), with a range of 11.95 points, revealing the underlying contradictions of uneven development.

Advanced regions cluster together: Six Grade I regions (30%) all scored ≥15.09 points, with regions k, g, and q occupying the top three spots (17.19–16.94 points), forming a high-quality development cluster. These regions generally excel in the economic dimension (B2), confirming the decisive influence of economic efficiency on the comprehensive score. The intermediate tier includes Level II (good) and Level III (passing) regions, accounting for 30% and 20% respectively, but there is a significant gap in development quality. Level II regions (e.g., Region T with 14.79 points and Region N with 14.52 points) often rely on a single advantage, such as Region T's forest coverage rate (C4) reaching 1.0 (optimal), but its labor productivity (C7) is only 0.667 (average); Grade III regions (e.g., P region with 10.09 points, S region with 9.41 points) generally exhibit the “wooden bucket effect,” such as S region's water resource utilization rate (C3) standardized value of 0 (over-exploitation), and population growth rate (C17) approaching 0, highlighting dual pressures from resources and population.

Geographical agglomeration is significant, with Grade I regions concentrated in alluvial plains (K, G, Q adjacent), benefiting from fertile farmland and intensive production; Grade IV regions are concentrated in hilly ecologically fragile zones (B, L located in soil erosion areas), with scarce farmland resources (C1 ≤ 0.12 hm^2/person) and weak risk-resistance capabilities. The score difference between the adjacent d region (13.15 points, Level II) and o region (8.79 points, Level IV) reaches 4.36 points, reflecting insufficient technological diffusion and policy coordination between regions.

IV. D.Local spatial autocorrelation analysis of sustainable agricultural development

The years 2020, 2022, and 2024 were selected as research time points for analyzing local spatial aggregation characteristics. The SPSSAU software was used to measure whether there were statistically significant aggregation distribution characteristics in the local spatial scale of agricultural sustainable development in Area A. Moran's dot plot and LISA aggregation maps were used to explore local spatial distribution characteristics.

Using tools such as SPSSAU and ArcGIS, Moran's dot plots and LISA aggregation maps were created for the three study time points. The four quadrants of the Moran's dot plot reflect four types of agricultural sustainable development in Area A: High-high aggregation zone: This indicates that both the region and its surrounding areas have characteristics above the average value, showing positive spatial correlation and minimal differences between regions. High-low aggregation zone: This indicates that the characteristic value of a region is higher than the average, while the surrounding regions are below the average, with a negative spatial correlation. Low-high aggregation zone: This indicates that the characteristic value of a region is lower than the average, while the surrounding regions are higher than the average, with a negative spatial correlation. Low-low aggregation zone: This indicates that both the region and its surrounding areas have characteristics below the average, with a positive spatial correlation and small differences between regions. The Moran scatter plots for agricultural sustainable development in Region A in 2020, 2022, and 2024 are shown in Figures 2, 3, and 4, respectively.

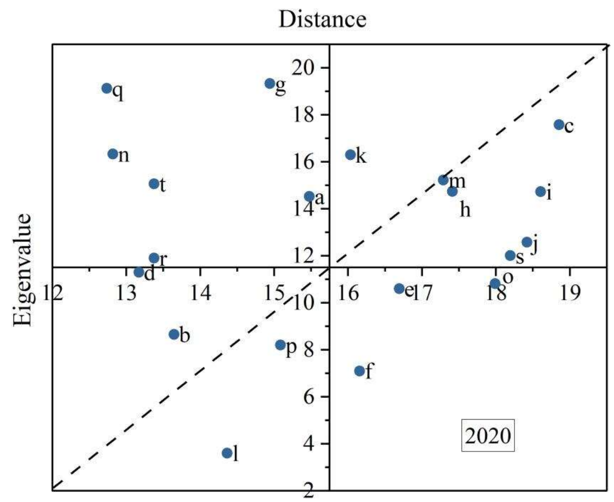

Figure 2: Moran scatter of sustainable Agricultural Development in Area A in 2020

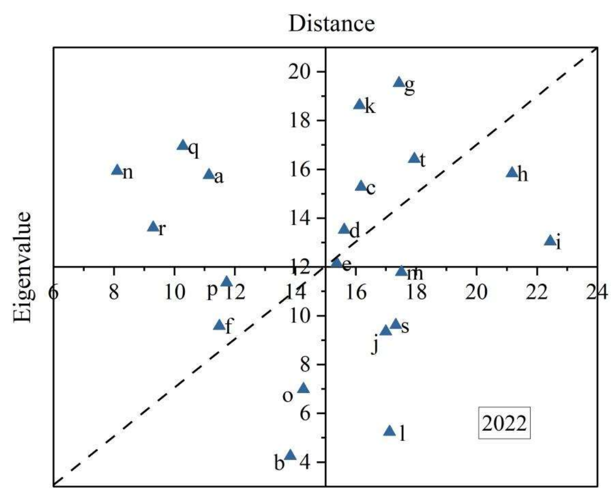

Figure 3: Moran scatter of sustainable Agricultural Development in Area A in 2022

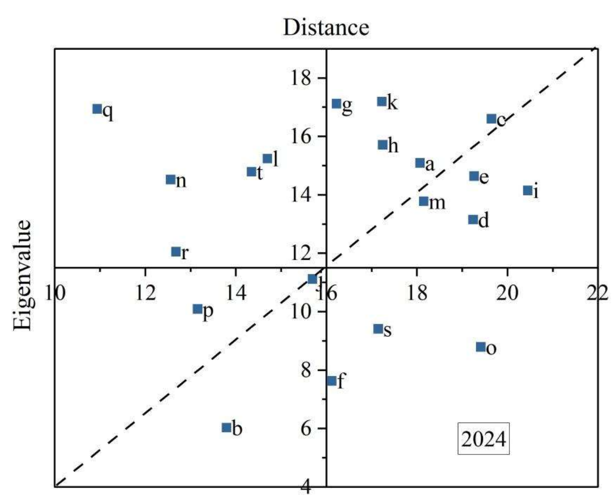

Figure 4: Moran scatter of sustainable Agricultural Development in Area A in 2024

As shown in the figure above, the spatial evolution characteristics of agricultural sustainable development in Area A from 2020 to 2024 are primarily characterized by high-high clustering (HH), indicating that regions with high development levels are concentrated in contiguous areas. In 2020, HH zones were mainly distributed in the core areas of alluvial plains (such as Zones k, m, and h), where agricultural resources are abundant and economic indicators are leading. LL zones (low-value-low-value): Scattered across ecologically fragile zones (such as the b and l zones), these areas suffer from severe soil erosion and scarce arable land resources. A small number of high-low (HL) and low-high (LH) zones indicate localized development imbalances (e.g., significant differences between the d zone and the adjacent o zone). Overall, there is a strong positive correlation (with minimal regional differences), reflecting the relative balance of initial development.

By 2022, polarization becomes pronounced, with HH zones further concentrating. HH zones are strengthened, with core plain zones (k, g, t) consolidating their advantages through technological intensification, forming “growth poles.” LL zones expand: ecologically fragile zones (b, l, o) fall into a “low-development trap,” with soil erosion and resource shortages compounding. Transition zones decrease, with HL/LH zones transforming into distinct HH or LL zones. By 2024, the number of high-high (HH) zones has significantly increased, while regions with low characteristic values have notably decreased. HL/LH zones expand: phenomena such as “high values surrounded by low values” (HL) or “low values surrounded by high values” (LH) emerge (e.g., the t zone has high forest coverage but is surrounded by low-economic-level zones). LL zones correspondingly decrease, and differences in agricultural sustainable development levels between regions narrow.

Overall, it can be seen that the number of high-value clusters for agricultural sustainable development has increased year by year, primarily driven by improvements in regional economic levels and scale effects, which have promoted an overall increase in the level of agricultural sustainable development within regions. At the same time, the scope of low-value clusters has gradually shrunk, indicating that differences in the level of agricultural sustainable development between counties are gradually narrowing, reflecting the gradual optimization and effectiveness of regional agricultural policies and economic development strategies.

V. Conclusion

This study employs an integrated model combining “comprehensive evaluation” and “multi-level factor analysis” to conduct a multi-dimensional evaluation of agricultural sustainable development in Region A.

Following KMO test (0.892) and Bartlett's test (P=0.000), factor analysis was used to reduce dimensions and extract three principal components (cumulative contribution rate of 85.766%), ultimately establishing 18 core indicators covering three dimensions: resource environment (9 indicators), production and economy (9 items), and population and society (4 items). We excluded weakly correlated indicators with loadings <0.4 (B16, B17, etc., 4 items), significantly improving evaluation efficiency.

From 2020 to 2024, per capita arable land (C1) decreased from 0.14 hm²/person to 0.12 hm²/person (a decrease of 14.3%), per capita water resources (C2) decreased by 5.7% (from 1,825.36 to 1,720.59 m³/person). The proportion of soil erosion (C6) decreased by 20.0% (from 15.73% to 12.58%), and forest coverage (C4) increased by 9.9% (from 23.18% to 25.47%).

The economic dimension accounted for 62.8% of the weighting (AHP results), with agricultural total output value (C9) having the highest weighting (0.118). In 2022, economic indicators generally declined (e.g., agricultural total output value growth rate -2.34%), but rebounded strongly in 2023 (+7.72%), Agricultural labor productivity (C7) increased by 18.7% over five years (from 38,500 yuan to 45,700 yuan per person).

The Moran scatter plot shows that the proportion of high-value clusters (HH) increased from 25% to 40% between 2020 and 2024, while low-value areas (LL) decreased, reflecting the synergistic effect of policies in promoting balanced regional development.

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