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Ecological Security Assessment of Main Grain-producing Areas in China

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Abstract: The stability of grain output in main grain-producing areas has a decisive impact on China's grain security, and the ecological security of main grain-producing areas plays a decisive role in ensuring the sustainable growth of grain output. Based on the PSR model, the ecological security evaluation system is constructed, the principal component analysis method is used to evaluate the ecological security of the main grain-producing areas from 2015 to 2020, and the cluster analysis is used to classify the evaluation results. The research shows that from 2015 to 2020, the ecological security in the main grain-producing areas is generally stable, but still at a low level; Sichuan, Jiangxi, and Heilongjiang have higher ecological security levels, while Shandong, Jiangsu, and Hebei have lower ecological security levels.

Keywords: Main grain producing areas; Ecological security; PSR model; Principal component analysis; Cluster analysis.

1. Introduction

People regard food as their prime necessity; ensuring food security is a top priority in governing the country and managing state affairs. In 2020, the grain output of China's 13 main grain-producing provinces will account for 78 % of the country's total grain output. Although the grain output in these regions is stable and continues to increase, it faces problems such as land degradation, reduced biodiversity, increased soil and water pollution, and sustained growth in food production costs and food prices. This unsustainable and uncompetitive food production method urgently needs to be transformed. For the concept of ' ecological security ', there is no unified definition in academic circles. Scholars have elaborated it from broad and narrow perspectives. From a broad perspective, ecological security is divided into three levels: natural ecological security, social-ecological security, and economic ecological security, that is, the natural environment and resources needed for the survival and development of the country are not damaged, to avoid the degradation of the ecological environment. It poses a threat to the economic foundation and social stability [2]; the narrow sense of ' ecological security' focuses on the security of natural and semi-natural ecosystems. Under the intervention of human activities, ecosystems can still maintain their structure and characteristics, which emphasizes the stability and integrity of ecosystems. Therefore, it is of great significance to construct a reasonable ecological security evaluation system for the main grain-producing areas and scientifically evaluate the ecological security status of the main grain-producing areas to explore the road of ecological priority and green development.

2. Research Methods and Data Sources

2.1. Evaluation system construction

The PSR model is one of the most widely used evaluation index systems, which is mainly used to evaluate ecological security issues in the field of sustainable development[4]. It establishes an evaluation index system from three perspectives: pressure, state, and response. There is a very clear causal relationship, that is, human production and life will cause pressure on the environment, and the environmental state will change accordingly, but human society will also respond to changes in the environment, thereby restoring environmental quality or avoiding environmental degradation [5]. According to the principles of scientific, accessibility, and relative independence of index selection, this paper constructs an ecological security evaluation index system based on the PSR model (Table 1) based on referring to relevant literature. The specific meaning of the index is as follows.

2.1.1. Agricultural Ecological Pressure (P)

P refers to the ecological stress of natural disasters and human economic activities on the natural environment, which reflects the burden of human or natural disturbance on the ecosystem. Among them, chemical fertilizer, agricultural film, and pesticide pollution are the most important causes of agricultural non-point source pollution. They are extremely harmful and have a long latent period, which brings great pressure to the construction of the agricultural environment. The population and the high level of urbanization will increase the pressure on land-carrying capacity and pose a serious threat to agricultural ecological security[6].

2.1.2. Agricultural Ecological Status (S)

S refers to the status of the ecosystem and represents the health status of the ecosystem. Among them, the forest coverage index reflects the rich level of forest resources and is a representation of the ecological balance. Improving the forest coverage rate is conducive to improving the ability of ecosystem soil and water conservation, water conservation, and climate regulation. The amount of water resources per capita reflects the richness of water resources and determines crop productivity and crop yield. The multiple cropping index and the effective irrigation area rate are all efficiency indicators, which respectively measure the degree of exploitation of cultivated land use potential and the degree of water conservancy in agricultural production units and regions and are the characterization of the sustainable development of agricultural ecology. The disaster rate of crops is the characterization of the stable state of agricultural development. The frequent occurrence of agricultural disasters can easily reduce the stability of agricultural ecosystems and cause huge economic losses[7].

2.1.3. Agricultural Ecological Response (R)

R represents the countermeasures and measures that can be taken by the human-natural complex ecosystem to respond to ecological degradation and other problems, including indicators of economic strength and social organization ability. Fiscal expenditure for supporting agriculture refers to the funds used by state finance to support the development of agriculture, rural areas, and farmers, which reflects the economic strength of the country to rebuild and repair the rural ecological environment. The size of the total power of agricultural machinery is an important manifestation of the comprehensive agricultural production capacity, reflecting the level of development of agricultural mechanization in the region. Per capita GDP truly reflects the degree of social and economic development of a region, which directly determines the region's ability to invest in environmental construction. In areas with perfect infrastructure construction, the level of pollution treatment such as sewage is higher, and the utilization efficiency of resources is also higher. Green innovation is one of the effective ways to solve ecological problems, including energy conservation and emission reduction brought by technological innovation, as well as the role of technological innovation in environmental governance.

Table 1. Evaluation index system of ecological security in main grain-producing areas

Criterion	Index	Indicators Trend
Pressure(P)	P1 Population (tens of millions)	-
	P2 Urbanization Level (%)	-
	P3 Fertilizer Application intensity (kg/m^3)	-
	P4 Agricultural film application intensity (kg/m^3)	-
	P5 pesticide application intensity (kg/m^3)	-
Status(S)	S1 Forest Coverage (%)	+
	S2 Multiple Cropping Index (%)	+
	S3 Crop Disaster Rate (%)	-
	S4 Effective Irrigation Area Rate (%)	+
	S5 Per Capita Water Resources (m^3/ person)	+
Response(R)	R1 Fiscal Expenditure for Supporting Agriculture (billion yuan)	+
	R2 Total Power of Agricultural Machinery (kWh)	+
	R3 Per Capita GDP (ten thousand yuan / person)	+
	R4 Infrastructure Construction (ten million yuan)	+
	R5 Green Innovation (parts)	+

2.2. Standardization of raw data

Due to the different nature of the evaluation index, there are often differences in dimension and order of magnitude. Therefore, the original data are processed by the range standardization method to eliminate the difference. The indicators with positive effects are processed by formula (1), and the indicators with negative effects are processed by formula (2).

$$X'_{ij} = \frac{X_{ij} - \min\{X_i\}}{\max\{X_i\} - min\{X_i\}} \tag{1}$$

$$X'_{ij} = \frac{\max\{X_i\} - X_{ij}}{\max\{X_i\} - min\{X_i\}} \tag{2}$$

Among them, X'_{ij} is the standardized value of the jth sample in the *i* year, X_{ij} is the original value of the *j*th sample in the *i* year, $\max\{X_i\}$ is the maximum value of the *j*th index in all years, and $min\{X_i\}$ is the minimum value of the *j*th index in all years.

2.3. Principal Component Analysis

Principal component analysis recombines multiple indicators $X_1, X_2, \ldots, X_P$ that are originally correlated into a set of unrelated comprehensive indicators to replace the original indicators. Extracting the appropriate comprehensive index can reflect the information represented by the original variables $X_1, X_2, \ldots, X_P$ to the greatest extent, and ensure that the new index information does not overlap and remains independent[8].

F1 is the first linear combination of variables, and its expression is:

$$F_1 = a_{11}X_1 + a_{21}X_2 + \cdots a_{p1}X_p \tag{3}$$

The variance can be used to calculate the amount of information obtained from each principal component. If the variance $Var(F_1)$ is large, it indicates that F_1 contains more information. If the data receiver wants the F1 package to contain the maximum amount of information, then the F_1 that should be selected in all linear combinations should be the data with the largest variance in all linear combinations of $X_1, X_2, \ldots, X_P$. Assuming that F_1 is not fully sufficient to represent all the information in the original *p* indicators, the data analyst will select the second linear combination as the second principal component and sort the selection in turn until the selected principal component can represent all the information in the *p* indicators. To reflect the original information more effectively, the existing information displayed by F1 does not need to appear in F_2 again, that is, F_2 and F_1 remain independent and irrelevant to each other, and the variance of F_1 and F_2 decreases in turn. The covariance $Cov(F_1, F_2)=0$, so F_2 is the maximum variance of all linear combinations of $X_1, X_2, \ldots, X_P$ that are not related to F_1, that is, F_2 is the second principal component, and so on, $F_1, F_2, \ldots, F_m$ are the first, second,..., m principal components of the original variable index $X_1, X_2, \ldots, X_P$. Indicates the following :

$$F_1 = a_{11}X_1 + a_{21}X_2 + \cdots a_{1p}X_p$$
$$F_2 = a_{21}X_1 + a_{22}X_2 + \cdots a_{2p}X_p$$
$$\cdots\cdots \cdots\cdots$$
$$F_m = a_{m1}X_1 + a_{m2}X_2 + \cdots a_{mp}X_p \quad (4)$$

The corresponding eigenvalue λ_i in the correlation coefficient matrix of the original index is the contribution of the variance of the main component. The contribution rate of the variance is:

$$\alpha_i = \lambda_i / \sum_{i=1}^{p} \lambda_i \quad (5)$$

The larger the α_i is, the stronger the ability of the corresponding principal component to reflect the original information is, so the principal component can be extracted by referring to the size of α_i.

2.4. Cluster analysis

Cluster analysis is an analysis method to classify the research objects according to their characteristics, which mainly includes three types : dynamic clustering method, system clustering method and optimal clustering method. Among them, system clustering is the most commonly used method. Its principle is to find out the variables with high similarity according to some indexes, merge them into one class, and then aggregate several other variables with low similarity into another class until all variables are aggregated[9]. The most commonly used method to describe the sample is distance. The Euclidean distance method is the most commonly used in cluster analysis. Its expression is :

$$d_{ij} = \sqrt{\sum_{i=1}^{m} \left| x_{it} - x_{jt} \right|^2} \quad (6)$$

Where x_{it} and x_{jt} represent the observed values of the k th index in sample i and the observed values of the kth index in sample j, respectively. d_{ij} is the Euclidean distance between the i th sample and the jth sample. If the smaller the d_{ij}, the closer the distance between the two samples in Table i and j is, and the samples with similar properties can be divided into one category.

2.5. Data source and processing

The research period is from 2015 to 2020, and the research object is the main grain producing areas in China : Heilongjiang, Jilin, Liaoning, Inner Mongolia, Shandong, Anhui, Henan, Sichuan, Hebei, Hubei, Hunan, Jiangsu and Jiangxi. The original data such as total population, forest coverage, financial support for agriculture, urbanization rate, per capita water resources, and per capita GDP are from the China Statistical Yearbook over the years. Fiscal expenditure for supporting agriculture and per capita GDP is deflated by using consumer price index with 2015 as the base period, so as to eliminate price changes caused by inflation and other factors. The original data of crop fertilizer application amount, agricultural film application amount, pesticide application amount, cultivated land area, crop planting area, crop disaster area, effective irrigation area and total power of agricultural machinery are from China Rural Statistical Yearbook over the years. Some of the data are derived from the " China Environmental Statistics Yearbook " and " China Water Conservancy Statistics Yearbook " of the main grain-producing provinces (regions) over the years. The total number of green patent grants is derived from the national intellectual property database.

The calculation of the stock of infrastructure investment is based on the practice of Jin Ge[10]. The fixed asset investment data of ' transportation, warehousing and postal industry ', ' power, heat, gas and water production and supply industry ', ' water conservancy, environment and public facilities management industry ', ' information transmission, software and information technology service industry ' are selected. According to the base period of 2008, the fixed asset investment price index is used to reduce the depreciation rate of 9.2 % per year. The perpetual inventory method is used to calculate the added value of infrastructure investment stock in each province from 2015 to 2020 compared with the previous year.

3. Empirical Analyses

3.1. Feasibility analysis

Principal component analysis is used to study information concentration. Firstly, the KMO test and Bartlett test are used to analyze whether the data are suitable for principal component analysis. The KMO test method is an important indicator for measuring the strength of the correlation between variables. It is mainly obtained by comparing the correlation coefficient and partial coefficient of the two variables. The KMO value is between 0 and 1. The higher the KMO value, the stronger the commonality of the variables. In general, if this value is greater than 0.8, it is very suitable for analysis. If this value is between 0.7 and 0.8, it indicates that it is more suitable for analysis; if this value is between 0.6 and 0.7, it indicates that the analysis can be carried out; if this value is less than 0.6, it is not suitable for analysis. The calculation results are shown in Table 2. The KMO value of the research data is 0.620, higher than 0.6, which meets the basic requirements of principal component analysis, and passes the Bartlett sphericity test ($p < 0.05$), indicating that principal component analysis can be used.

Table 2. KMO and Bartlett test

KMO sampling suitability quantity		0.62
Bartlett's sphericity test	Approximate chi-square	1380.783
	df	105
	P value	0

3.2. Determination of main factors

R studio was used to perform principal component analysis on the standardized data, and the characteristic roots and factor contribution rates (Table 3) were obtained. According to the principle that the cumulative contribution rate exceeds 50 % and the characteristic value is greater than 1, five main factors can be extracted from 15 indicators and recorded as

F_1、F_2、F_3、F_4、F_5. The cumulative contribution rate of these five main factors reached 85.314 %, indicating that the amount of information removed was very small. If more principal components are selected, although the cumulative contribution rate can be further improved, the increase is very limited, and the increase of principal components will bring about the increase of dimensions, which makes the analysis of data more difficult. Therefore, five principal components are selected for further research. According to the gravel map (Figure 1), it can also be seen that the number of principal components determined is in line with the data facts.

Table 3. Characteristic root and factor contribution rate

	Initial eigenvalue			Extract the load sum of squares		
	grand total	Variance Percentage	accumulation %	grand total	Variance Percentage	accumulation %
1	5.459	36.396	36.396	5.459	36.396	36.396
2	2.71	18.068	54.463	2.71	18.068	54.463
3	1.745	11.632	66.095	1.745	11.632	66.095
4	1.674	11.162	77.257	1.674	11.162	77.257
5	1.209	8.058	85.314	1.209	8.058	85.314
6	0.873	5.819	91.134	-	-	-
7	0.409	2.728	93.862	-	-	-
8	0.345	2.301	96.163	-	-	-
9	0.177	1.183	97.346	-	-	-
10	0.174	1.157	98.503	-	-	-
11	0.105	0.699	99.202	-	-	-
12	0.049	0.324	99.526	-	-	-
13	0.042	0.277	99.804	-	-	-
14	0.026	0.173	99.977	-	-	-
15	0.003	0.023	100	-	-	-

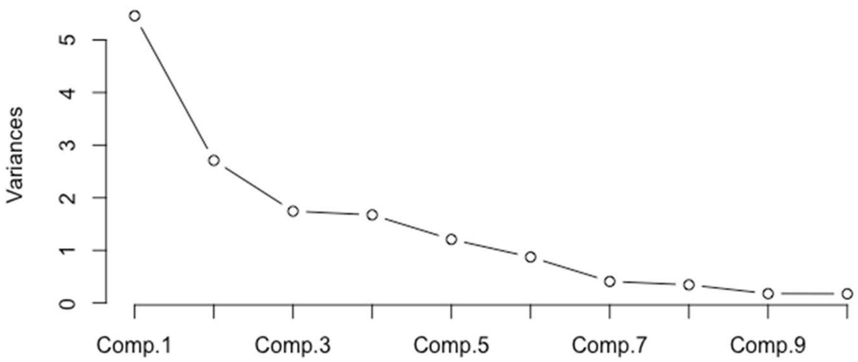

Figure 1. Gravel diagram

3.3. Principal component analysis

The software is used to calculate the principal component score coefficient. The specific results are shown in table 4, so the first five principal components are as follows:

(1) The first principal component F_1

$$F_1=0.159\times P_1+0.009\times P_2+0.109\times P_3+0.062\times P_4-0.007\times P_5 +0.133\times S_1+0.103\times S_2-0.098\times S_3+0.103\times S_4+0.102\times S_5 -0.133\times R_1-0.117\times R_2-0.101\times R_3-0.150\times R_4-0.138\times R_5 \quad (6)$$

(2) The second principal component F_2

$$F_2=-0.125\times P_1+0.321\times P_2+0.115\times P_3+0.164\times P_4-0.015\times P_5 \quad (7)$$

$$+0.133\times S_1-0.150\times S_2+0.128\times S_3-0.160\times S_4+0.169\times S_5 +0.112\times R_1+0.114\times R_2-0.237\times R_3+0.058\times R_4-0.120\times R_5$$

(3) The third principal component F_3

$$F_3=0.053\times P_1-0.007\times P_2+0.104\times P_3+0.279\times P_4+0.484\times P_5 -0.133\times S_1+0.243\times S_2+0.041\times S_3+0.246\times S_4+0.076\times S_5 +0.287\times R_1+0.044\times R_2+0.031\times R_3+0.128\times R_4+0.030\times R_5 \quad (8)$$

(4) The fourth principal component F_4

$$F_4=0.112\times P_1-0.218\times P_2+0.051\times P_3+0.141\times P_4+0.036\times P_5 +0.189\times S_1-0.248\times S_2-0.107\times S_3-0.245\times S_4+0.335\times S_5 \quad (9)$$

$+0.135\times R_1-$

$0.331\times R_2+0.218\times R_3+0.141\times R_4+0.191\times R_5$

(5) The fifth principal component F_5

$$F_5=-0.154\times P_1+0.036\times P_2+0.123\times P_3+0.004\times P_4-0.358\times P_5+0.246\times S_1+0.319\times S_2+0.511\times S_3+0.294\times S_4+0.133\times S_5-0.002\times R_1-0.146\times R_2+0.135\times R_3+0.108\times R_4+0.283\times R_5 \quad (10)$$

Table 4. Component score coefficient matrix

name	component				
	F_1	F_2	F_3	F_4	F_5
P1 Total population	0.159	-0.125	0.053	0.112	-0.154
P2 Urbanization level	0.009	0.321	-0.007	-0.218	0.036
P3 fertilizer application intensity	0.109	0.115	0.104	0.051	0.123
P4 agricultural film application intensity	0.062	0.164	0.279	0.141	0.004
P5 pesticide application intensity	-0.007	-0.015	0.484	0.036	-0.358
S1 forest coverage rate	0.133	0.133	-0.133	0.189	0.246
S2 multiple cropping index	0.103	-0.15	0.243	-0.248	0.319
S3 crop disaster rate	-0.098	0.128	0.041	-0.107	0.511
S4 effective irrigation area rate	0.103	-0.16	0.246	-0.245	0.294
S5 per capita water resources	0.102	0.169	0.076	0.335	0.133
R1 Fiscal expenditure on agriculture	-0.133	0.112	0.287	0.135	-0.002
R2 total power of agricultural machinery	-0.117	0.114	0.044	-0.331	-0.146
R3 GDP per capita	-0.101	-0.237	0.031	0.218	0.135
R4 infrastructure construction	-0.15	0.058	0.128	0.141	0.108
R5 Green Innovation	-0.138	-0.12	0.03	0.191	0.283

According to the characteristic root and factor contribution rate of Table 3, the variance contribution rate of the five factors is weighted (Formula 11), and the final comprehensive score formula (Formula 12) can be obtained.

$$F=(36.396\times F_1+18.068\times F_2+11.632\times F_3+11.162\times F_4+8.058\times F_5)/85.314 \quad (11)$$

$$F=0.427\times F_1+0.212\times F_2+0.136\times F_3+0.131\times F_4+0.094\times F_5 \quad (12)$$

Finally, the ecological security status index and ranking of the main grain producing areas were obtained, and the comprehensive score F was calculated. The larger the comprehensive score F value, the higher the ecological security level in the region. If the principal component score of an area is less than 0, it indicates that the ecological security level of the area is lower than the average level of ecological security in the main grain producing areas of the country. On the contrary, it is higher than the national average level. Due to space limitations, only the 2020 results are shown (Table 5), and the complete results are obtained from the attached table.

Table 5. Ecological security status and ranking of major grain producing areas in 2020

	F	billing	F_1	billing	F_2	billing	F_3	billing	F_4	billing	F_5	billing
Heilongjiang	0.713	1	1.064	2	0.144	6	1.606	3	0.512	7	-0.611	10
Jiangxi	0.693	2	0.909	3	0.603	4	-0.343	12	1.565	3	0.208	6
Sichuan	0.518	3	-0.640	9	1.383	1	1.770	1	1.572	2	0.549	3
Jilin	0.502	4	1.154	1	-0.067	9	0.136	7	0.472	8	-0.598	9
Hunan	0.351	5	-0.103	7	0.889	3	-0.003	10	0.954	5	0.871	2
Hubei	0.236	6	-0.029	6	0.115	7	0.017	9	1.526	4	0.231	5
Inner Mongolia	0.191	7	0.562	5	-1.002	11	1.618	2	0.576	6	-1.398	13
Anhui	-0.179	8	-0.470	8	0.097	8	0.030	8	0.259	10	-0.388	8
Henan	-0.254	9	-1.202	11	1.007	2	1.068	4	-0.716	13	-0.067	7
Liaoning	-0.265	10	0.698	4	-1.556	12	-1.370	13	0.324	9	-0.947	12
Hebei	-0.446	11	-0.981	10	0.256	5	0.387	6	-0.570	11	-0.632	11
Jiangsu	-0.890	12	-2.224	13	-2.014	13	0.677	5	1.779	1	1.692	1
Shandong	-0.900	13	-1.825	12	-0.272	10	-0.113	11	-0.663	12	0.405	4

3.4. Cluster analysis

Although the results of principal component analysis can show the ecological security status and ranking of the main grain producing areas, it fails to classify the security level and cannot intuitively judge the security level. Therefore, on the basis of principal component analysis, according to the comprehensive scores of ecological securities in the main grain producing areas from 2015 to 2020, this paper selects the shortest distance method in the system clustering method to divide the ecological security level into four categories : excellent, good, general and poor, and the results are shown in table 6.

Table 6. Ecological security level of main grain producing areas

	2015	2016	2017	2018	2019	2020
Heilongjiang	excellent	excellent	excellent	excellent	excellent	excellent
Jiangxi	excellent	excellent	excellent	excellent	excellent	excellent
Sichuan	good	good	good	good	good	good
Jilin	good	excellent	good	excellent	excellent	good
Hunan	good	good	good	good	good	good
Hubei	good	good	good	good	good	good
Inner Mongolia	good	good	good	good	good	good
Anhui	general	general	general	general	general	general
Henan	general	general	general	general	general	general
Liaoning	general	general	general	general	general	general
Hebei	general	general	general	general	general	general
Jiangsu	general	general	worse	worse	worse	worse
Shandong	worse	worse	worse	worse	worse	worse

4. Conclusions and Discussions

Based on the PSR model, this paper constructs an ecological security index system for China 's main grain producing areas based on three secondary indicators of pressure, state and response, and 15 specific tertiary indicators.

From the comprehensive score obtained from the principal component analysis, the ecological security status of Heilongjiang, Jiangxi and Sichuan in 2020 is better, while the ecological security status of Hebei, Jiangsu and Shandong is poor. Further analysis shows that the areas with higher ecological security level have higher pressure level scores, that is, there are fewer environmental pressure factors in these areas, the application intensity of pesticides, agricultural films and fertilizers is low, and the population growth and urbanization level are at a reasonable level. The scores of pressures, state and response in areas with good ecological security level are evenly distributed. Most of the areas with general ecological security level have low response level scores, that is, the intensity of ecological environment protection in these areas needs to be improved ; most of the areas with poor ecological security level have low scores in the state layer. The possible explanation is that these areas have an early industrialization process, a high proportion of secondary industries, and extensive development has led to the destruction of the ecological environment. Therefore, the formulation of policies to improve the ecological security situation should reasonably consider the regional stage and cannot be simply one-size-fits-all.

From the results of cluster analysis, the overall ecological security of China's main grain producing areas tended to be stable from 2015 to 2020, but the overall level was not high ; Heilongjiang's ecological security level has been significantly improved, while Jiangsu's ecological security level has been significantly reduced. Jilin 's ecological security level fluctuates between good and excellent levels, and the rest of the provinces have no significant changes. Further analysis found that compared with other areas with higher ecological security levels, Heilongjiang's ecological security has improved significantly because of its higher level of response layer. Therefore, at present, areas with low ecological security level should increase financial support for agriculture, improve infrastructure construction, and improve the level of green innovation.

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