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Retraction

Retracted: Risk Assessment of Agricultural Economic Management Based on the Multivariate Statistical Computing Method

Security and Communication Networks

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Security and Communication Networks has retracted the article titled "Risk Assessment of Agricultural Economic Management Based on the Multivariate Statistical Computing Method" [1] due to concerns that the peer review process has been compromised.

Following an investigation conducted by the Hindawi Research Integrity team [2], significant concerns were identified with the peer reviewers assigned to this article; the investigation has concluded that the peer review process was compromised. We therefore can no longer trust the peer review process, and the article is being retracted with the agreement of the Chief Editor.

The author does not agree to the retraction.

References

[1] Y. Zhou, "Risk Assessment of Agricultural Economic Management Based on the Multivariate Statistical Computing Method," *Security and Communication Networks*, vol. 2022, Article ID 8547306, 11 pages, 2022.
[2] L. Ferguson, "Advancing Research Integrity Collaboratively and with Vigour," 2022, https://www.hindawi.com/post/advancing-research-integrity-collaboratively-and-vigour/.

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Research Article

Risk Assessment of Agricultural Economic Management Based on the Multivariate Statistical Computing Method

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The modernization process of Chinese agriculture has posed new challenges to agriculture economic management. However, existing studies focus on financial and ecological and environmental risks of agriculture economic management while lacking the necessary attention to other types of agricultural economic management. Therefore, we first propose that the risk of agricultural economic management is of five types—economic, social, political, cultural, and ecological and environmental risks—and further clarify the interactions among the five risk types. Given that the five types of risks are nested with each other, we adopted a multivariate statistical algorithm based on complex network theory to scientifically evaluate the risk management of agriculture economy. The results show the applicability of the algorithm to risk clustering analysis and risk coefficient estimation. The article concludes with the corresponding theoretical and practical implications.

1. Introduction

The high attention of the Chinese government has greatly promoted the modernization and transformation of Chinese agriculture, presenting a sea of changes with respect to increasing the agricultural output value, improving agricultural production conditions, improving the new agricultural business system, and forming new dynamics of agricultural development, which have made China leap to the forefront of the world in agricultural opening achievements and made rural residents' life move toward an overall well-off position [1]. One of the important reasons for the success of agricultural modernization is the market-oriented transformation of agricultural economic management. Although the transformation is a proactive choice to adapt to the new situation of international comprehensive national power competition in the post-financial crisis era [2], the market-oriented transformation of agriculture also brings huge new risks and challenges. However, the academic community focuses on the financial risks and ecological and environmental risks of agriculture while paying less attention to other risks of agricultural economic management [3, 4], and it also lacks a systematic classification of the types of risks of agricultural economic management [5], which leads to the insufficient explanatory power of theories on the anti-risk capacity of China's agricultural economy; in addition, it is necessary to adopt a scientific approach to the types and structures of agricultural economic management risks and their related relationships. Systematic analysis is necessary to provide reference for the risk response strategy of China's agricultural economic management.

In fact, after China's accession to the World Trade Organization, the pace of agricultural opening to the outside world has accelerated significantly, and it has become a major country in the world in terms of agricultural opening to the outside world. In the more open global market and agricultural competition, competitiveness has become a hot spot in China's agricultural economic management [6]. In an open market environment, the ability of agricultural production operators to produce agricultural products that outperform similar or alternative products in a given market in terms of buyer value, thus battling to win and maintain market share in competition and winning profits for agricultural production operators, is agricultural market competitiveness [7, 8]. The international competitiveness of agricultural products consists of three dimensions, namely, price competitiveness, quality competitiveness, and reputation competitiveness, which are organically constituted [9]. From the perspective of the international market, the all-round competition based on quality and technological content replaces the pure price competition [10]. To improve the competitiveness of China's agricultural products, the focus is on improving the quality of agricultural products and fully transforming the comparative advantages of agricultural products into competitive advantages [11]. Among them, industrialization is an important way to improve the competitiveness of agriculture. How to determine the focus of support in the negotiation process of China's accession to the WTO and how to coordinate the role of financial expenditures and other resources, including positions and allies in international multilateral negotiations, to improve the efficiency of government support and the comprehensive competitiveness of agricultural products are of great significance [12, 13]. On the other hand, in the context of world agricultural and rural development dynamics, agriculture faces the pressure and challenges of mitigating and adapting to climate change and feeding a large number of people, and the promotion of sustainable agriculture is an important means of adapting to climate change, reducing greenhouse gas emissions from agriculture and mitigating deforestation, among other issues. Climate [14], climate change [15], agricultural adaptation [16], and crop modeling [17] have become hot topics in international agricultural economics research. The research frontier of agricultural economic management in China is also in line with the international agricultural economics research lineage and evolutionary trends [18]. Climate change, mainly characterized by rising temperatures, is a serious challenge common to all countries in the world today [19], and most farmers are able to recognize the phenomenon of climate change and the impact of climate change on agricultural production [20]. Among them, farmers' age [21], education level [22], income level [23], and their level of awareness of climate change [24] have a significant impact on whether they adopt adaptive behaviors. In addition, log production function models have been widely used to analyze the impact of climate change on the yield of major food crops [25], emphasizing the introduction of more active and effective climate policies to effectively mitigate the adverse effects of climate change on food production in China [26]. Obviously, the current research focuses on the financial and environmental risks of agricultural economic management, and the relevant research system is fragmented and lacks a comprehensive assessment of the risks of agriculture economic management. More importantly, risk evaluation still adopts traditional hierarchical analysis or factor analysis while ignoring the complex structure of agricultural economic management risks, which urgently needs to be deconstructed by applying the theory of complex networks. Therefore, this article first analyzes the types of risks in agriculture economic management and the logical relationship between each type in depth, and it adopts the factor analysis method based on the complex network analysis theory to make a comprehensive assessment of the risks in agriculture economic management in order to provide theoretical references for risk management countermeasures in agricultural economic management.

This article is mainly composed of five sections. The first section introduces the importance of scientifically evaluating the risks of agricultural economic management. The second section identifies and introduces five risk factors in agricultural economic management, including economic, social, political, cultural, and ecological and environmental risks. The third section explains a multivariate statistical algorithm based on a complex network. The fourth section provides the data analysis results. The fifth section discusses the theoretical and practical contribution of this article.

2. Identification of Risk Factors in Agricultural Economic Management

In contrast to previous studies that focused solely on the economic risks and the environmental risks of agriculture, we argue that agriculture economic management has various types of risks, which can be roughly divided into five types according to different causes: economic risks, social risks, political risks, cultural risks, and ecological and environmental risks.

Economic risks. The main tasks of agriculture economic management are to reduce production capacity in agriculture through structural adjustment, to reduce the cost of corn planting in the "sickle curve" area, and to make up for the shortcomings. According to the Ministry of Agriculture's guidelines on "de-capacity," optimizing the structure and appropriately reducing corn production capacity are the top priority of the current reforms on agriculture. The cost of removing production capacity requires subsidies for fallowing, subsidies for credit guarantee costs, and subsidies for science and technology innovation. The paths to reduce agricultural production costs include moderate scale operation, development of agricultural science and technology, and improvement of agricultural infrastructure; the costs required to make up for the shortcomings of agricultural development include those of endogenous factors. Therefore, from the perspective of the three tasks of "removing production capacity," reducing costs, and making up for shortcomings, agriculture economic management requires a considerable amount of cost expenditure [27].

Against the background of a further slowdown in international economic growth and a domestic economic situation that is "stabilizing and improving" but with difficulties and challenges, the government, as the main bearer of the costs of agriculture management, will incur huge pressure on its fiscal balance to eliminate the huge reform costs. At the same time, increasing the share of fiscal expenditure on agriculture economic management will inevitably reduce fiscal investment expenditure in other areas, which will lead to a certain degree of shrinkage of production capacity in other areas, thus reducing the total output level of the society as a whole. In the case that farmers' production skills have not yet been transformed and the scope of production and operation has not been completely adjusted, crop rotation and fallow required by the agriculture economic management and the short-term break in industrial transformation caused by "grain to feed" may also affect the development of rural economy [28].

Social risks. Agriculture economic management also involves certain social risks. First, the adjustment of agricultural production and management structure and regional production structure is also the process of interest structure adjustment, and the change in the interest pattern will inevitably lead to social contradiction and even conflicts. Second, agriculture economic management requires large-scale agricultural operation, which is premised on the transfer of agricultural land management rights, and the transfer of agricultural land management rights also entails a series of risks, such as land loss, unemployment, loss of livelihood security, division of rural areas between two classes, and damage to farmers' rights and interests. In addition, the cost-sharing mechanism of agricultural economic management has not yet been formed, the responsibility and rights of sharing subjects are not divided, and the costs are unevenly shared among classes, regions, and urban–rural areas, which may lead to increased conflicts among classes, regions, and urban–rural areas, thus causing social risks [29].

Political risk. Agriculture economic management involves international and domestic political risks. The international political risk of agricultural economic management refers to the manipulation of international food market prices by some big countries, which makes China's food production and import and export subject to the control of others, such as the entry of a large amount of foreign investment capital into the food market to buy and sell short and hoard, thus causing the risk of instability of the national regime. First, agriculture economic management requires large-scale transfer of agricultural land to accommodate large-scale operation, but "if important areas such as rural contracted land are controlled by private capital, the economic foundation of socialism in China will no longer exist," and the nature of the socialist state will be challenged. Second, if agriculture economic management leads to a slowdown in rural economic development, an increase in unemployment, and social class confrontation, the rural society will become unstable. Furthermore, as agriculture economic management progresses, farmers' property income, compensatory income, and transfer income will increase, but this will also provide opportunities for corruption among village cadres, which will lead to confrontation between villagers and village cadres, strain relations between the cadres and the villagers, and affect the party's ruling base in rural areas. Finally, there is a risk that the transfer of agricultural land management rights will weaken the functioning of villagers' self-governing organizations and weaken the party's ruling base in rural areas. The transfer of agricultural land intensifies the tendency of individual villagers to decentralize, and the growing power of local clans and families will affect the authority of grass-roots organizations, which will reduce the villagers' self-governing organizations to mere institutions responsible for handling daily village affairs, thus weakening the ruling party's foundation in rural areas [30].

Cultural risks. Any nation contains both urban and rural cultures, and the different cultures of urban and rural areas are both complementary and conflicting. In the pre-modern agricultural society, the Chinese countryside had strong stability and was in an almost balanced and stable state, which was formed thanks to the long-standing rural culture. However, during the agriculture economic management process, along with the gradual penetration of urban industrial and commercial capital and urban culture into the countryside, the traditional local, human, and acquaintance society in the Chinese countryside has been reduced due to living customs and cultural background. The traditional local, human, and acquaintance society in rural China will be challenged by the differences in living customs and cultural backgrounds, and rural production lifestyles, value pursuits, family values, and ethics will be changed accordingly. In this context, individualism and money worship, lack of social integrity and faith, and moral crisis may occur in the rural society, and the farming culture will gradually disappear [31].

Ecological and environmental risks. Developing ecological agriculture and protecting the ecological environment are two of the main objectives of China's agricultural economic management. As an agricultural production method that follows the laws of ecological economy and is closely related to the reality of Chinese agriculture, ecological agriculture will become an effective way to achieve reforms in Chinese agriculture. However, agriculture economic management poses ecological and environmental risks. First, the nonagricultural use of agricultural land will threaten the rural ecological environment. In the process of land transfer, a considerable amount of public land is transformed into nonagricultural construction land, and nonagricultural use of agricultural land will inevitably bring a series of environmental pollution and ecological damage, such as air pollution, water pollution, and noise pollution. Second, once the agricultural land is not properly organized and technically managed, the stability of the agricultural ecosystem will be damaged, and the productivity and soil properties of the agricultural land will be affected, because of which land degradation will be inevitable. Finally, large-scale agricultural management will bring great threats to the ecological environment. The scale operation of agriculture destroys biodiversity, and the excessive reliance on and use of synthetic chemicals have laid hidden dangers on human food and water safety; the scale operation weakens or even breaks the material–energy cycle between agriculture and nature, completely rejecting the natural succession of biological communities and self-regulation within the tolerance limit and breaking the local microcirculation of agriculture [32].

Although agricultural economic management is a change in the agricultural field, due to its comprehensiveness and complexity and the interconnectedness of social systems, the five types of risks are not isolated from each other in a specific environment, but affect each other, are contagious, reinforce each other, and overlap with each other. When impacted by external or internal contingent events, each risk point will resonate and link up under the influence of the domino effect and eventually evolve into systemic risk (see Figure 1), and its impact will go far beyond the agricultural sector itself. For example, in order to optimize the

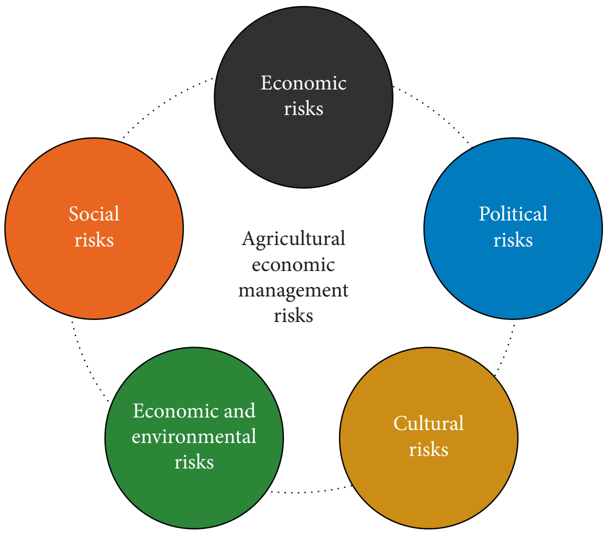

Figure 1: Agricultural economic management risks.

regional industrial structure and protect the ecological environment, the government must increase the subsidies for farmers in ecological functional areas when designating ecological functional areas and implementing the fallow crop rotation system, while under the hard constraint of government fiscal expenditure, the increase in agricultural expenditure will inevitably reduce fiscal expenditure in other areas, and the reduction in fiscal expenditure in other areas will affect their employment absorption capacity, resulting in an increase in social unemployment and instability. In addition, if the ecological function zones are designated to strictly prohibit certain types of agricultural production and operation activities and the fallow rotation system is implemented, the number of structurally unemployed farmers will increase, and the income of rural residents will decrease; in addition, if the fallow subsidies are not fully provided or misappropriated, farmers' dissatisfaction will accumulate, and grievances against the government will be formed. In this case, the increase in unemployment not only directly affects the speed of economic development but also affects the stability of rural areas and the society as a whole. In addition, if the scale of agricultural land transfer is too large and too fast, the large-scale operation will replace the small farmers' economy too quickly; especially, if most of the rural land is controlled by private capital, the villagers' autonomy will be reduced, and the party's ruling foundation in rural areas will be shaken, thus creating political risks. In addition, if the government does not fully deal with the employment issue of farmland transfer, the large-scale transfer of farmland by the government will inevitably lead to the increase in rural unemployment and the loss of farmers' interests.

3. Methodology

Traditional risk assessment methods generally construct the evaluation index system first and then model it using hierarchical analysis and other methods, but given that the risks of agricultural economic management in fact constitute a complex network structure, the individual risk evaluation factors interact with each other and are difficult to be stripped away. Therefore, based on complex network theory, we adopted the factor analysis algorithm for risk modeling of agricultural economic management. Importantly, the association structure in a complex network is a collection of several network nodes, and the edges between the nodes within the collection are dense while the edges between the collections are relatively sparse. Complex network association structure mining can clearly and accurately characterize the topology of network structure, help reveal the functional characteristics of each dimension of complex systems, understand the group characteristics of complex networks, and scientifically evaluate abstract models [33, 34]. Specifically, the method starts from the correlation matrix of many observed variables and groups the observed variables according to the magnitude of the correlation so that the correlation between observed variables within the same group is high and the correlation between variables in different groups is low (Figure 2). Each group of variables can be represented by an unobservable implicit variable, called the common factor, which acts on all variables. On this basis, the original variables are decomposed into a sum of two parts, one representing a linear combination of a few unobservable implied variables and the other a special factor, which is unrelated to the common factor and only correlates with the original variables themselves.

There are n samples, each with p observations. These p observations can be expressed as p components of a random vector $X = (X_1, X_2, \ldots, X_p)^T$ after normalization. Let the mean vector $E(X) = 0$ of this random vector X and the covariance matrix $\mathrm{cov}(X) = \Sigma$ be equal to the correlation array of X. $F = (F_1, F_2, \ldots, F_m)^T$ $(m < p)$, which denotes the m common factors with mean vector $E(F) = 0$. The covariance matrix $\mathrm{cov}(F) = \mathrm{In}$, where In denotes the unit diagonal array. $\varepsilon = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_p)^T$ is called the special factor, which is only related to the components X_i $(i = 1, 2, \ldots, p)$ of the random vector X, is independent of each other and F, and has $E(\varepsilon) = 0$; let the components of ε be independent of each other; the covariance matrix $\Sigma\varepsilon$ is given as follows:

$$\mathrm{cov}(\varepsilon) = \sum_{\varepsilon} = \begin{bmatrix} \sigma_{11}^2 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma_{pp}^2 \end{bmatrix}. \tag{1}$$

Based on the above-mentioned description, the following model is defined as a factor model:

$$\begin{cases} X_1 = k_{11}F_1 + k_{12}F_1 + \cdots + k_{1m}F_m + \varepsilon_1, \\ X_1 = k_{21}F_1 + k_{22}F_1 + \cdots + k_{2m}F_m + \varepsilon_2, \\ \quad\quad\quad \cdots\cdots \\ X_p = k_{p1}F_1 + k_{p2}F_1 + \cdots + k_{pm}F_m + \varepsilon_p, \end{cases} \tag{2}$$

where $k = (k_{ij})_{pxm}$ is the coefficient matrix, usually called the factor loading matrix. The larger the absolute value of each factor loading k_{ij}, the greater the correlation between X_i and F_j. Usually, there is $|k_{ij}| \leq 1$. According to equation (2), the covariance between the variables X_i and F_j is as follows:

$$\operatorname{cov}\left(X_i, F_j\right) = \operatorname{cov}\left(\sum_{j=1}^{m} k_{ij} F_j + \varepsilon_i, F_j\right). \tag{3}$$

Since $F_1, F_2, \ldots, F_m$ are independent of each other and $F_1, F_2, \ldots, F_m$ and $\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_p$ are also independent of each other, it follows that

$$\operatorname{cov}\left(X_i, F_j\right) = k_{ij}. \tag{4}$$

That is to say, the factor loading k_{ij} indicates the degree of correlation between X_i and F_j. According to equation (2), the correlation coefficient between the variables X_i and X_j is as follows:

$$r_{ij} = k_{i1}k_{j1} + k_{i2}k_{j2} + \cdots + k_{im}k_{jm}. \tag{5}$$

Equation (5) shows that the correlation coefficient between X_i and X_j is also larger when both variables X_i and X_j have larger loadings on a common factor.

For a complex network graph G with n nodes, let its adjacency matrix be A. Let $X = (X_1, X_2, \ldots, X_n)$ be a random vector, where each component $X_i (i = 1, 2, \ldots, n)$ represents the weights of the edges between node i and other nodes in the network, and n denotes the weights of the edges of node i with other nodes in the network. Based on this definition, the n components of the i-th row vector a_i of the adjacency matrix A can be regarded as the n sampled values of the random variable X_i corresponding to node i. In a complex network, the association structure is a division of the set of nodes in the network, and each subset of nodes is called an association. The edges between nodes belonging to the same association are tightly connected, while the edges between nodes belonging to different associations are relatively sparse. This definition implies the fact that if node i and node j belong to the same association in a complex network G, the components of the corresponding row vectors a_i and a_j of nodes i and j in A are relatively similar. Since the row vectors a_i and a_j can be regarded as vectors of n sampled values of random variables X_i and X_j, respectively, the distributions of random variables X_i and X_j are similar, so it is known that there is a large correlation between X_i and X_j. Based on the above-mentioned analysis, if the nodes i and j belong to the same association, the correlation between the random variables X_i and X_j in the complex network G is larger.

According to the theory of factor analysis, n random variables $X_i (i = 1, 2, \ldots, n)$ with large correlations with each other can be linearly represented by m common factors F_i $(i = 1, 2, \ldots, m)$. Each common factor reflects a set of random variables with large correlation. The specific formula is shown as follows:

$$\begin{cases} X_1 = k_{11}F_1 + k_{12}F_1 + \cdots + k_{1m}F_m + \varepsilon_1, \\ X_1 = k_{21}F_1 + k_{22}F_1 + \cdots + k_{2m}F_m + \varepsilon_2, \\ \quad \cdots\cdots \\ X_n = k_{n1}F_1 + k_{n2}F_1 + \cdots + k_{nm}F_m + \varepsilon_n, \end{cases} \tag{6}$$

where a_{ti} denotes the components of the adjacency matrix A of the network graph G. $\overline{a_i} = \sum_{t=1}^{n} a_{\mathrm{it}}/n$ denotes the mean of the elements in the i-th row vector of the matrix A.

$$r_{ij} = \frac{n-1}{n} \frac{\sum_{i=1}^{n} \left(a_{ti} - \overline{a_i}\right)\left(a_{tj} - \overline{a_j}\right)}{\sqrt{\sum_{i=1}^{n} \left(a_{ti} - \overline{a_i}\right)^2} \sqrt{\sum_{t=1}^{n} \left(a_{tj} - \overline{a_j}\right)^2}.} \tag{7}$$

Given that matrix R is most similar to matrix $R = (r_{ij})_{n\times n}$, the elements of the two matrices R and R' are obtained from equations (7) and (8), respectively.

$$R'' = R + 1 = \begin{bmatrix} r_{11} + 1 & \ldots & r_{1n} + 1 \\ r_{21} + 1 & \ldots & r_{2n} + 1 \\ & \ldots & \\ r_{n1} + 1 & \ldots & r_{nn} + 1 \end{bmatrix}. \tag{8}$$

Since equation (8) is the Pearson correlation coefficient formula and each variable on the right-hand side of the equation is greater than zero, we have $|r_{ij}| \leq 1$ $(i, j \in [1, n])$, from which we know that element $r_{ij}'' \in [0, 2]$ in R''. By normalizing each row of R'', we get the following:

$$R''' = \frac{R''}{2}. \tag{9}$$

The transformation from matrix R' to R'' is linear and does not change the relative magnitudes of the components. The optimization problem (7) is approximated by the above-mentioned mathematical transformations into an optimization problem with nonnegative matrix decomposition, i.e., matrix R' is decomposed into the product of matrices K and K^T such that $||R''' - R'||_2$ is minimized and satisfies $(k_i, k_j) = 1$, $i, j \in [1, n]$, where k_i and k_j denote the row vectors of the i-th and j-th rows of matrix K, respectively. Currently, there are many techniques to decompose the above-mentioned matrices to obtain the affiliation matrices of the network nodes to each association structure and then identify the association structures existing in the network. Although the above-mentioned algorithms can mine the association structure, the characteristics of non-negative matrix decomposition algorithms determine that these algorithms can only obtain the association affiliation information of each network node and cannot further sense the hierarchical association structure in the network. Therefore, it cannot reveal the hierarchical organization among nodes in many real complex networks. In the subsequent subsections of this chapter, we improve the existing association splitting and clustering algorithms based on the factor analysis modeling of network association structure to realize the mining of hierarchical association structure in complex networks.

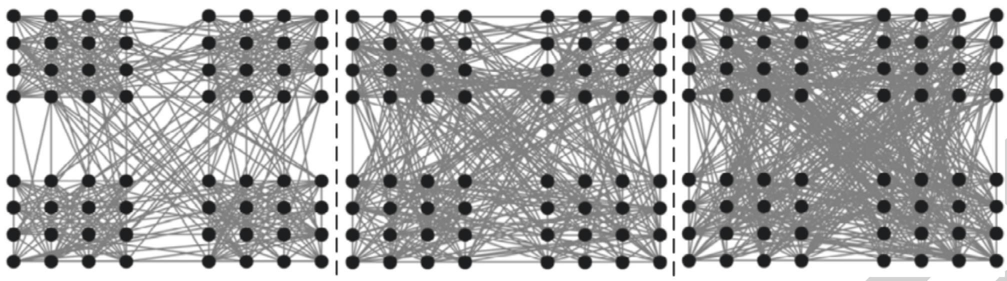

Figure 2: Schematic diagram of complex network.

A local minimum edge is defined as the set of edges in a complex network graph G that satisfy the following conditions:

$$r_{ij} = \min\{r_{xy} | (x = i, y\varepsilon\tau(i) - \{i\}) \cap (x = j, y\varepsilon\tau(j) - \{j\}). \quad (10)$$

$\tau(i)$ denotes the set of all neighboring nodes of node i. According to the definition of equation (10), the edges in this set are usually not directly adjacent to each other, and their weights are the minimum of the set of locally contiguous edges. A small network with several nodes is illustrated in Figure 3. The network has a typical two-association structure, with nodes of different colors. The weights of the connected edges between the nodes are similarities calculated by equation (8). According to equation (10), the set of local minimum edges in the current network topology can be found, and each local minimum edge is represented by a thick black line. It can be seen that two local minimum edges are not adjacent to each other and the influence of removing two edges at the same time is small.

In a complex network with a typical association structure, if removing an edge in the set of local minimal edges can increase the similarity of the edges between the nodes within the association connected to that edge, then selecting that edge as the edge to be removed can guarantee the association structure in the network with a higher probability of detection by the association splitting algorithm. In order to explore the mathematical characteristics of such edges, Figure 4 shows a part of the network structure graph truncated from the general complex network. This part of the network graph has a typical association structure, where the solid lines show the actual edges between the nodes of the network and the dashed lines show the edges between the nodes and the unintercepted part of the network and ignore the irrelevant details.

For a weighted network graph G, its adjacency matrix is A. Let $X = (x_1, x_2, \ldots, x_n)$ and $Y = (y_1, y_2, \ldots, y_n)$ denote the row vectors of nodes X and Y in the adjacency matrix A of the network. Var(X) denotes the variance of the random vector corresponding to node X, and cov(X) denotes its covariance coefficient. Using the above-mentioned symbolic definitions, the covariance coefficients between nodes X and Y change after removing the continuous edge between X and K as follows:

$$\begin{aligned}
&\operatorname{cov}(X, Y) - \operatorname{cov}(X', Y) \\
&= \frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y}) - \frac{1}{n}\sum_{i=1}^{n}(x_i' - \overline{x})(y_i - \overline{y}) \\
&= \frac{1}{n}\sum_{i=1}^{n}\left(x_i - x_i' - \overline{x} + \overline{x'}\right)(y_i - \overline{y}) \\
&= \frac{1}{n}(y_k - \overline{y})x_k.
\end{aligned} \quad (11)$$

Removing the edges between X and K increases the value of cov(X, Y) when $y_k = 0$. The $y_k = 0$ in Figure 5 indicates that there is no network edge between nodes Y and K. The variance between nodes X and Y changes after removing the edges between X and K as follows:

$$R_{XY} = \frac{\operatorname{cov}(X, Y)}{\sqrt{\operatorname{Var}(X)}\sqrt{\operatorname{Var}(Y)}}. \quad (12)$$

Overall, the specific workflow for the application of our multivariate statistical algorithm in risk assessment of agriculture economic management is shown in Figure 6. The algorithm models the relationship between network nodes and associations by factor analysis, and based on this, the similarity between nodes is calculated as the weight of the connected edges of the network with the help of the formula. The algorithm finds all the local minimum edges that satisfy the conditions in the current network topology and removes them. If all the local minimum edges in the current network do not satisfy the condition, all the found edges are deleted at once. The above-mentioned process is repeated until the algorithm finds the optimal association structure. In order to evaluate the merit of the current association structure in the network and stop the iterative process of the algorithm, the proposed algorithm in this section uses a similarity-based modularity formula. This formula compensates for the shortcomings of the classical modularity definition and enables a more accurate evaluation of the association classification results.

4. Results and Discussion

Figure 7 shows the experimental results of the factor analysis–based association splitting algorithm proposed in this section for this network graph. From the information labeled

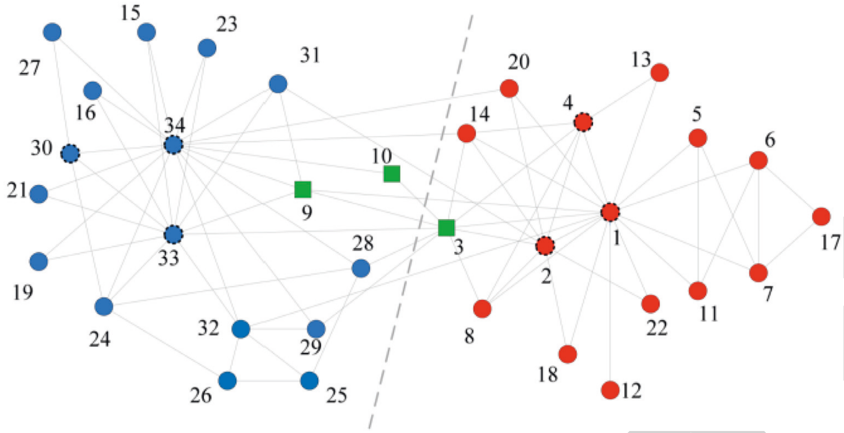

Figure 3: A tiny complex network with local weak edges.

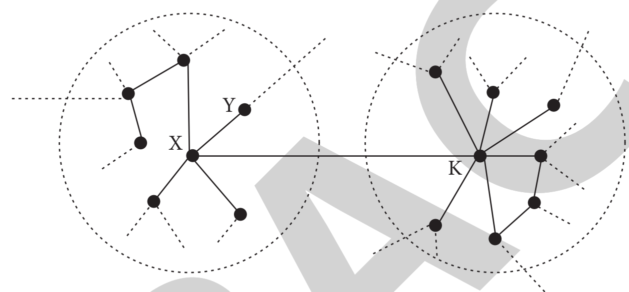

Figure 4: A typical part of complex network with two communities. (a) Community 1. (b) Community 2.

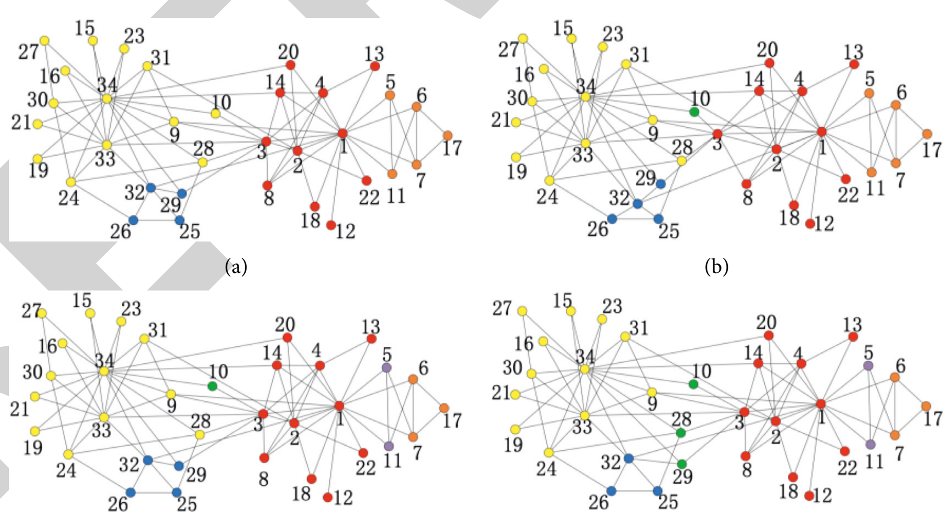

Figure 5: A tiny complex network with a number of nodes.

in the figure, we can know that the algorithm divides the network graph into 15 associations and the nodes belonging to the same association are labeled with the same color. The edges within each association are relatively tightly connected, while the edges between associations are sparsely connected. Furthermore, the right part of Figure 8 shows a tree diagram of the association splitting process in the risk network, and the left part shows the change in the similarity-based modularity index value based on the formula as each association splitting behavior occurs. The tree diagram on the right side of the figure shows that the algorithm proposed in this section can effectively discover the hierarchical

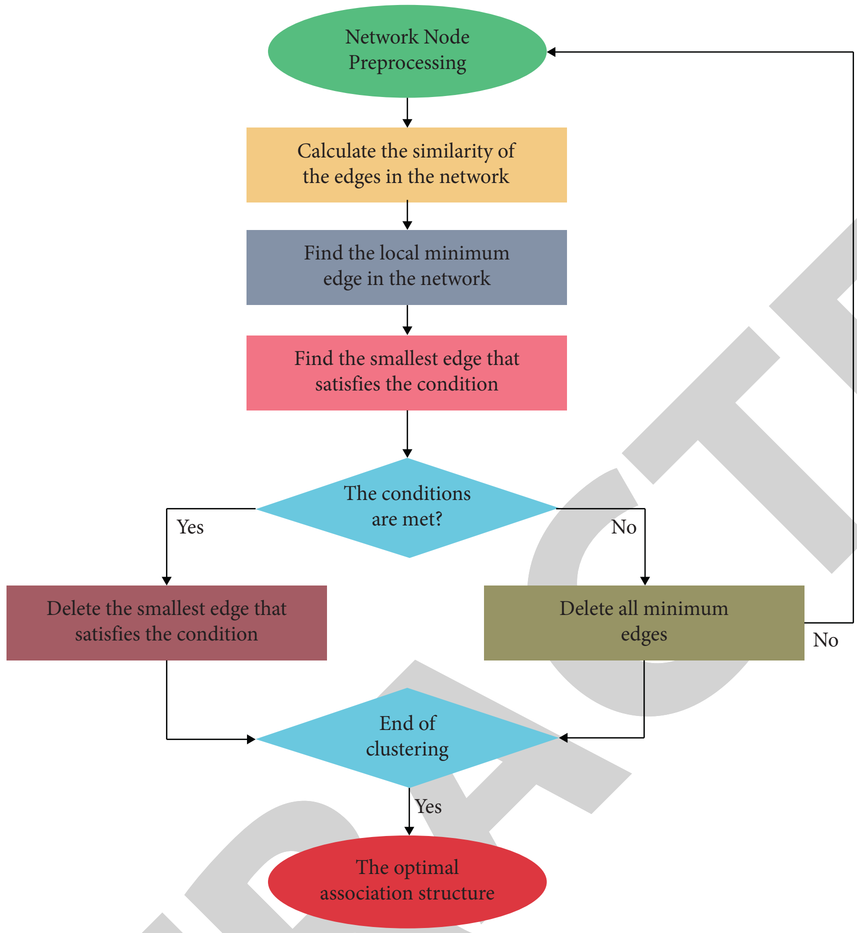

Figure 6: The workflow of the tiny complex network algorithm.

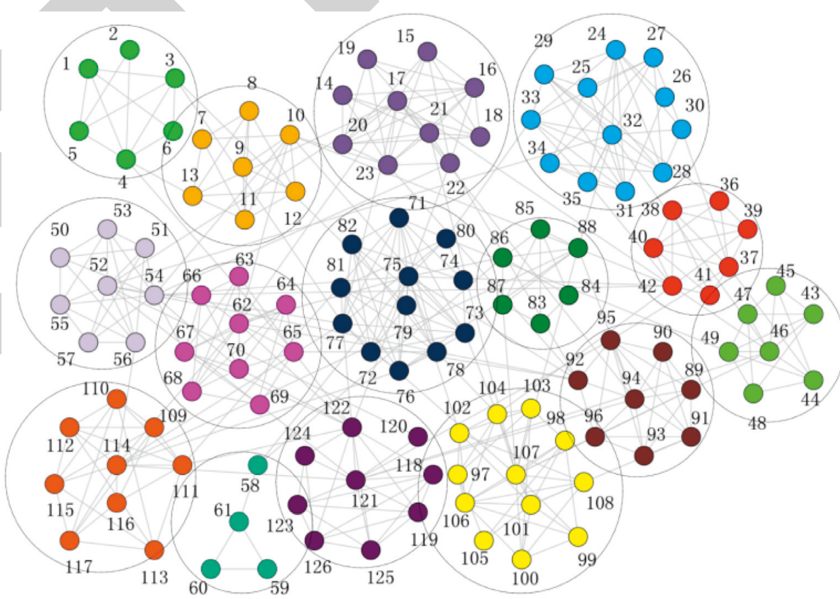

Figure 7: Community split tree diagram.

association structure. For example, association I is the first one to be discovered, which is a complete graph with three nodes and has only one edge between node 61 and the rest of the network, so the association structure is isolated. After that, it is gradually split into several associations according to the criterion of similarity between agricultural economic

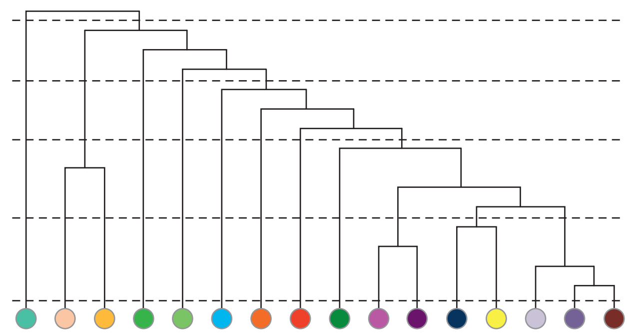

FIGURE 8: Community split tree diagram.

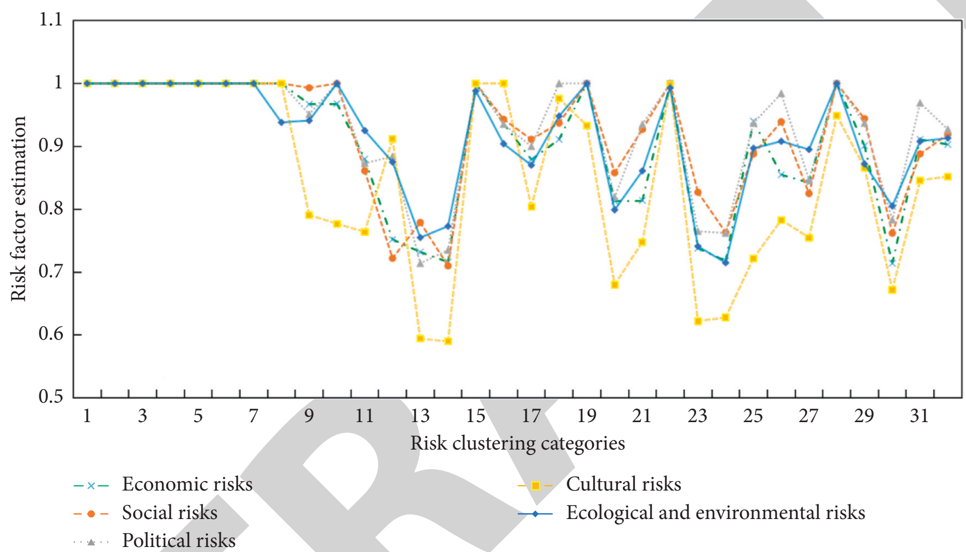

FIGURE 9: Community split tree diagram.

management risks. Each time the new association structure is split, the modularity index based on similarity increases, thus demonstrating the gradual rationalization of the association classification results.

The statistical yearbook of the National Bureau of Statistics, statistical bulletin, and China Rural Statistical Yearbook were used to model each risk dimension. Figure 9 shows the clustering analysis and coefficient estimation for each risk dimension. The results show that the risk dimensions tend to be consistent in terms of trend changes and the clustering pattern is also relatively consistent despite the slight differences, indicating that the algorithm has high applicability in assessing risk.

5. Conclusions

Current agricultural economic management focuses on the evaluation of economic and ecological risks while neglecting other possible risk dimensions, making it difficult to adapt to the changing needs of the market. More importantly, the current research still adopts traditional analysis methods and greatly ignores the interrelationships among risk dimensions. Therefore, this article first proposes five risk dimensions of agricultural economic management—economic, social, political, cultural, and ecological and environmental risks—and further clarifies the logical network relationships of different risk dimensions based on the identification of risk evaluation dimensions of agricultural economic management. The complex network analysis is used to further identify and evaluate the risks of agricultural economic management. Therefore, this article adopts a factor analysis technique based on complex network theory and empirically tests the applicability of this multivariate statistical calculation method. This article shows that the risks in agricultural and forestry economic management is of a complex network structure and the assessment of risks cannot be cut simply from the evaluation of each dimension; however, the intrinsic network structure of risks must be considered comprehensively to produce correct estimation results. This article theoretically innovates the identification of risk dimensions of agricultural economic management and applies factor analysis techniques based on complex network theory methodologically, but there are still the following shortcomings: first, this article has not yet developed an ephemeral trend analysis, and expanding the analysis on the time scale can further resolve the volatility of risks. Second, the method adopted in this article still lacks the support of a large amount of data and the cross-sectional comparison with other evaluation methods. Finally, there is still room for improvement in the way the risk dimensions are classified in this article.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interest or personal relationships that could have appeared to influence the work reported in this article.

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