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Ecological Risk Assessment and Environmental Policy Analysis Based on Bayesian Networks

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Abstract: At present, ecological and environmental problems are becoming increasingly serious. Traditional risk assessment methods are difficult to fully integrate the complex relationships among multiple variables and lack the ability to dynamically analyze uncertainty and conditional dependence, which affects the scientific nature of environmental policies. To address this problem, this paper proposes an ecological risk assessment and environmental policy analysis framework based on Bayesian networks, aiming to effectively quantify ecological risks and provide support for policy decisions. In terms of methodology, first, a Bayesian network structure is constructed with ecosystem elements as nodes and causal relationships as edges; second, the conditional probability table is determined by combining expert knowledge with historical data; then, node sensitivity analysis and scenario simulation are carried out to identify key risk factors and sources of uncertainty; finally, the regulatory effect of policy intervention on risks is evaluated. The study took a typical river basin as an example, and the results showed that driven by pollutant concentrations and land use changes, the river basin ecosystem risk index reached 0.72, among which water quality deterioration and biodiversity decline were the main sources of risk; policy simulation showed that by increasing sewage treatment rate and vegetation coverage rate, the risk index could be reduced to 0.48, a reduction of 33.3%. Studies have shown that Bayesian networks can effectively reveal causal relationships and the impact of policy interventions in complex ecosystems, providing a scientific basis for the precise formulation of environmental policies.

Keywords: Bayesian network, ecological risk assessment, environmental policy analysis, uncertainty quantification.

1. Introduction

As global ecological and environmental problems become increasingly severe, the risks facing ecosystems are becoming more complex. Water pollution, land degradation, biodiversity loss and other issues have become huge challenges that need to be urgently addressed worldwide. These problems not only cause serious damage to natural ecosystems, but also threaten the long-term sustainable development of human society. However, traditional ecological risk assessment methods often rely on static single indicators or single factor analysis, which is difficult to fully reflect the complex causal relationships and interactions between various elements in the ecosystem. Risk factors in ecosystems are usually multidimensional and interdependent, such as pollutant concentrations, climate change, land use changes, etc. The complex interactions between them require a tool that can dynamically capture the relationship between these factors. Bayesian Network (BN), as a graphical model based on probabilistic reasoning, performs well in dealing with uncertainty, causality and multiple dependencies in complex systems. With the help of Bayesian Network, ecological risks can be quantified more accurately and provide scientific support for environmental policy decisions. Therefore, ecological risk assessment methods based on Bayesian Networks have gradually become an important tool in ecological and environmental research.

This paper proposes a framework for ecological risk assessment and environmental policy analysis based on Bayesian networks. The paper first constructs a Bayesian network model with ecosystem elements as nodes and causal relationships as edges, and combines expert knowledge and historical data to estimate the conditional probability of the system, and then conducts a quantitative analysis of ecological risks. Secondly, through sensitivity analysis and scenario simulation, the regulatory effects of different environmental policies (such as increasing sewage treatment rates and restoring vegetation, etc.) on ecological risks are evaluated. Through this framework, this paper not only provides a new tool for risk assessment in complex ecosystems, but also provides a scientific basis for policy making. Especially in the context of multi-factor interactions in ecosystems, Bayesian network methods can reveal key risk factors and provide optimization directions for policy adjustments. Research shows that appropriate policy intervention can significantly reduce the overall risk of the ecosystem and provide effective decision-making support for environmental management.

The paper is organized as follows: The second part reviews the relevant ecological risk assessment methods and the application of Bayesian networks in environmental science, analyzes the shortcomings of existing research and the advantages of Bayesian network methods. The third part elaborates on the research methods of this paper, including the key steps such as the construction process of Bayesian network, the selection of nodes, the determination of causal relationships, the construction of conditional probability tables, and discusses the verification and evaluation methods of the model. The fourth part presents a case analysis based on a typical river basin, uses the Bayesian network model to quantitatively assess the ecological risk of the river basin, analyzes the risk contribution of factors such as pollutant concentration and land use change, and conducts policy simulation. It evaluates the changes in the ecological risk index under different policy scenarios such as increasing sewage treatment rates and restoring vegetation, and proposes an optimization plan for policy intervention. The fifth part summarizes the main conclusions of the study, discusses the limitations of the method, and provides prospects for future research directions and practical applications.

2. Related Work

In recent years, research on environmental pollutants has gradually deepened, especially on the impact of pollutants in water, soil and air on ecosystems and human health. Multiple studies have focused on the ecological risk assessment of different types of pollutants, revealing the spatial distribution of pollutants, sources of pollution, and potential threats to ecology and health through a variety of methods. Yin compiled the concentration distribution of antibiotics in China's seven major river systems from 2010 to 2020 through literature survey, and conducted an ecological risk assessment of 13 typical antibiotics, revealing the differences in antibiotic pollution levels and ecological risks in different rivers [1]. Ankley et al. reviewed the ecotoxicology and risk assessment of perfluoroalkyl substances (PFAS), discussed data gaps and uncertainties, and proposed methods to improve the assessment, such as strengthening monitoring and supporting bioaccumulation prediction model research [2]. Jian-Hua et al. measured the concentration of trace metals in the Poyang Lake area and used the single factor index method and the Nemerow pollution index method to conduct risk assessment, revealing the potential risks of Pb and Hg as major pollutants to the ecosystem and human health [3]. Wang S et al. identified organophosphate esters (OPE) in 25 urban wastewater treatment plants in China through suspect and non-target screening techniques, assessed their ecological risks to aquatic organisms, and found that many OPEs were not effectively removed after treatment. They proposed risk-based research priorities and provided guidance for future wastewater treatment programs and regulatory changes [4]. Xiao et al. evaluated the sources and pollution risks of heavy metals in road dust in Anshan, Liaoning Province using methods such as potential ecological risk index, pollution index, and geoaccumulation index. They revealed that traffic emissions and industrial activities were the main sources of pollution and assessed the health risks to children and adults [5]. Egbueri et al. evaluated the heavy metal pollution and health risks in groundwater in Onitsha, Nigeria, and found that most samples were unfit for drinking, and children and adults faced moderate to high chronic risks and a higher risk of cancer, mainly due to anthropogenic pollution sources[6]. Kaikkonen et al. reviewed the application of Bayesian networks (BN) in environmental risk assessment (ERA), evaluated its development potential in model implementation and participatory modeling, and proposed guidelines and development directions for the use of BN in ERA [7]. Hoque studied and measured the heavy metal concentrations in urban river sediments near a tanning industrial park and assessed their risks to ecology and human health. He found that the sediments were severely contaminated with cadmium and chromium, posing potential non-carcinogenic health risks to adults and children [8]. Previous studies have focused on the risk assessment of single pollutants and have not fully considered the interactions of complex pollutants. This paper, through the innovative application of the Bayesian network model, systematically analyzed the risks of multiple pollution sources and their interactions, thereby improving the accuracy and reliability of ecological risk assessment.

3. Methods

3.1. Model Construction

In the process of constructing an ecological risk assessment model based on a Bayesian network, we first need to select nodes that represent key elements of the ecosystem [9], including water quality, biodiversity, pollutant concentrations, and land use types. These nodes reflect important environmental factors in the ecosystem, and changes in each factor may have a profound impact on the overall health and stability of the ecosystem. Water quality directly affects aquatic organisms and ecosystem functions, biodiversity [10] represents the stability and functional diversity of the ecosystem, pollutant concentrations [11] are the main source of ecosystem risk, and changes in land use types affect the health of the ecosystem by changing hydrological, climatic, and habitat conditions. After determining the nodes, the causal relationship between the nodes is constructed through literature analysis and expert knowledge. For example, an increase in pollutant concentration usually leads to deterioration of water quality, which in turn affects biodiversity and habitat quality, while changes in land use will change water quality and habitat conditions, thereby indirectly affecting biodiversity. In this way, the Bayesian network [12] can effectively capture the complex causal relationship between the various elements in the ecosystem and provide scientific support for subsequent ecological risk assessment and policy analysis. Figure 1 is a causal relationship diagram.

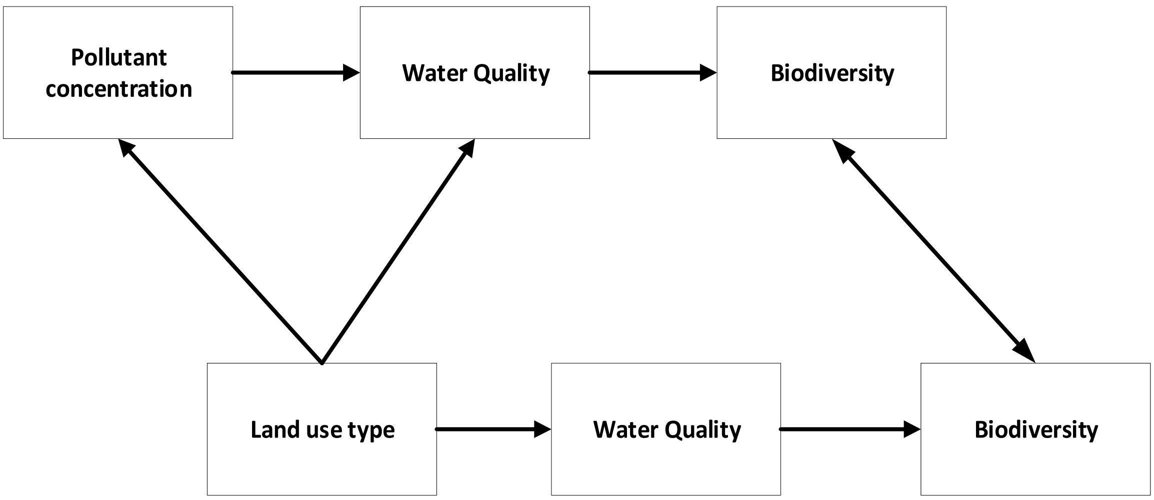

Figure 1. Cause and effect diagram

3.2. Determination of the Conditional Probability Table

The construction of the conditional probability table (CPT) is one of the core steps in the Bayesian network model [13], and its accuracy directly affects the prediction results of the model. The conditional probability table is used to represent the probability distribution of each node given its parent node. In this study, the determination of the conditional probability table depends on the combination of historical monitoring data and expert knowledge. Specifically, the distribution of each ecological element is first obtained through historical monitoring data, and the marginal probability distribution of each node is calculated according to different ecological states. Then, combined with the knowledge of domain experts, the conditional probabilities between nodes are adjusted and supplemented to ensure that the model can accurately reflect the dependencies between various factors in the ecosystem.

In the case of insufficient data or incomplete information, the maximum likelihood estimation (MLE) [14] and Bayesian update method are used to further determine the conditional probability. The maximum likelihood estimation method infers the most likely parameter value from the existing data, while the Bayesian update combines prior knowledge and new observation data to make probability adjustments and gradually update the conditional probability table of each node. This method can effectively deal with data uncertainty and improve the accuracy and robustness of the model. There is a causal relationship between pollutant concentration (P) and water quality (W), and the conditional probability table is shown in Table 1:

Table 1. Conditional probability table

Pollution Concentration (P)	Good Water Quality (W)	Medium Water Quality (W)	Poor Water Quality (W)
Low	0.8	0.15	0.05
Medium	0.4	0.5	0.1
High	0.1	0.3	0.6

In Table 1, assuming that "pollutant concentration" is the parent node and "water quality" is the child node. Each value in the table represents the conditional probability of water quality being in different states under the condition of a given pollutant concentration. Through similar methods, conditional probability tables can be constructed for other nodes, and probabilistic reasoning and updating can be performed in the Bayesian network to achieve dynamic assessment of ecological risks.

3.3. Model Analysis

In Bayesian network model analysis, sensitivity analysis and scenario simulation are two key steps. Sensitivity analysis evaluates the impact of various factors on the ecological risk index[15], identifies the key risk factors that have the greatest impact on the risk assessment results, such as changes in pollutant concentrations, land use types, or water quality, and helps determine the dominant factors in the system, thereby providing a scientific basis for policy intervention. Scenario simulation predicts changes in risks under different management measures and simulates various policy scenarios (such as increasing sewage treatment rates, increasing vegetation restoration, strengthening pollution emission control, etc.), to show decision makers the potential impact of different policies on ecosystem health, support policy optimization and adjustment, and ultimately provide theoretical support and decision-making basis for environmental management and risk control.

3.4. Case Analysis

This paper takes a typical watershed as an example and applies Bayesian network to conduct ecological risk assessment. The basin faces problems such as water pollution and biodiversity decline. Data sources include water quality monitoring (such as nitrogen and phosphorus content, heavy metal concentration), pollutant emissions (industrial wastewater, agricultural drainage), land use changes (agricultural expansion, urbanization) and biodiversity (species richness, etc.). By combining historical monitoring data and expert knowledge, key nodes such as water quality, pollutant concentrations, biodiversity and land use were identified, and the corresponding conditional probability tables were constructed. In the model analysis, different policy intervention scenarios were designed (such as improving sewage treatment capacity, reducing fertilizer use, and strengthening wetland protection), and the ecological risk index under these scenarios was predicted. The results show that under the scenario of strengthening pollution control and ecological restoration, the overall ecological risk of the watershed is significantly reduced, verifying the effectiveness of the Bayesian network model in ecological risk assessment and providing a scientific basis for ecological management of the watershed.

4. Results and Discussion

4.1. Model Performance and Risk Assessment Results

The application of the Bayesian network model in the watershed ecosystem verifies its effectiveness, and sensitivity analysis shows that pollutant concentration and land use change are the main influencing factors. Water quality deterioration (e.g., average nitrogen concentration of 2.5 mg/L, average phosphorus concentration of 0.3 mg/L) and biodiversity decline are the main risks, especially in downstream wetlands and lake areas. The study shows that future ecological risk management should focus on pollutants and land use changes. Figure 2 shows the relationship between water pollutant concentration and ecological risk.

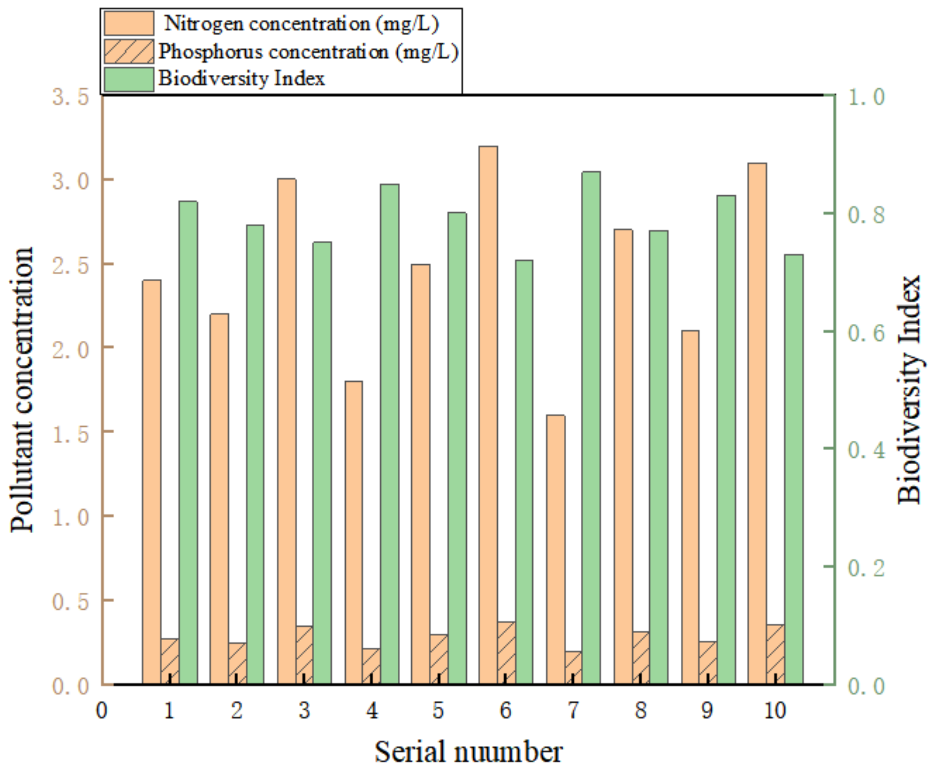

Figure 2. Relationship between water pollutant concentration and ecological risk

4.2. Policy Scenario Simulation Analysis

Under different policy intervention scenarios, the ecological risk index of the river basin showed a significant downward trend. By comparing changes in risk indexes under different scenarios, it was found that increasing sewage treatment rates and increasing vegetation coverage are effective policy measures. For example, under the baseline scenario, the basin ecological risk index is 0.72, but by increasing the sewage treatment rate by 20% and the vegetation coverage by 15% (Scenario 4 in the figure), the ecological risk index drops to 0.48, a decrease of 33.3% compared with the baseline scenario. This result shows that enhanced pollution control measures and ecological restoration measures can significantly improve water quality and promote biodiversity recovery, thereby effectively reducing ecological risks. Figure 3 shows the changes in the ecological risk index of the river basin under different policy scenarios.

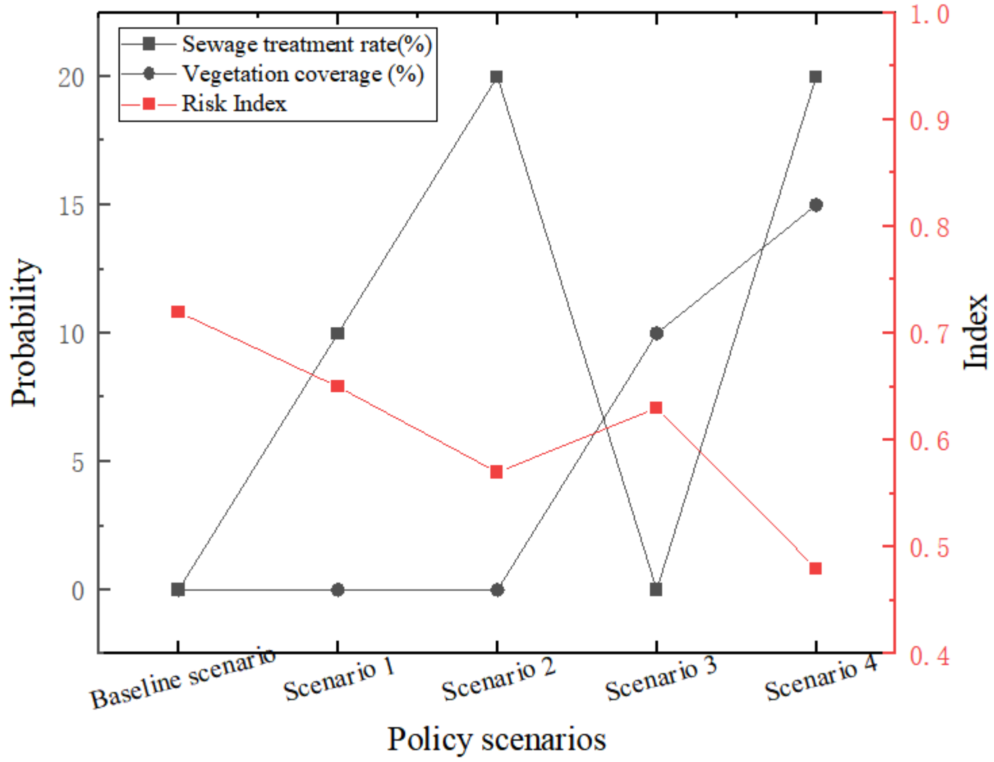

Figure 3. Changes in the watershed ecological risk index under policy intervention scenarios

As can be seen from Figure 3, when the sewage treatment rate is increased by 10% (the picture shows scenario 1), the ecological risk index drops to 0.65, which is lower than the baseline scenario. When the sewage treatment rate is increased by 20% (scenario 2 in the figure), the risk index further drops to 0.57, showing the significant effect of pollution control measures. In addition, when the vegetation coverage rate increases by 10% (scenario three in the figure), the ecological risk index drops to 0.63, indicating that ecological restoration measures also have a certain effect on risk reduction. The most significant change occurs in scenario four. When the sewage treatment rate is increased by 20% and the vegetation coverage rate is increased by 15%, the risk index drops to 0.48, which is 33.3% lower than the base scenario. This result shows that by comprehensively adopting pollution control and ecological restoration measures, ecological risks in the watershed can be significantly reduced while improving the quality of the ecological environment. Therefore, the optimization of policy measures can effectively realize risk control of watershed ecosystems, and these comprehensive intervention strategies should be given priority in the future.

4.3. Advantages and Disadvantages of the Method and Policy Implications

This study uses the Bayesian network model, causal inference and uncertainty quantification to reveal the dynamic relationship between ecosystem elements and provide a scientific basis for environmental risk assessment. This method integrates multi-source data, identifies key risk factors and quantifies uncertainty, but it relies on the quality of input data, especially the accuracy of conditional probability tables, which may lead to biased evaluation results when the data is inaccurate. Policy recommendations emphasize giving priority to highly sensitive factors such as land use change and pollutant concentrations, especially strengthening land use control, limiting agricultural expansion and urbanization, reducing heavy metal and nutrient emissions, and combining regional spatial analysis tools to improve policy effectiveness. Figure 4 shows the changes in the basin ecological risk index under different policy scenarios, which helps to understand the effects of the implementation of various measures. Figure 4 shows the impact of land use and pollutant control on ecological risk.

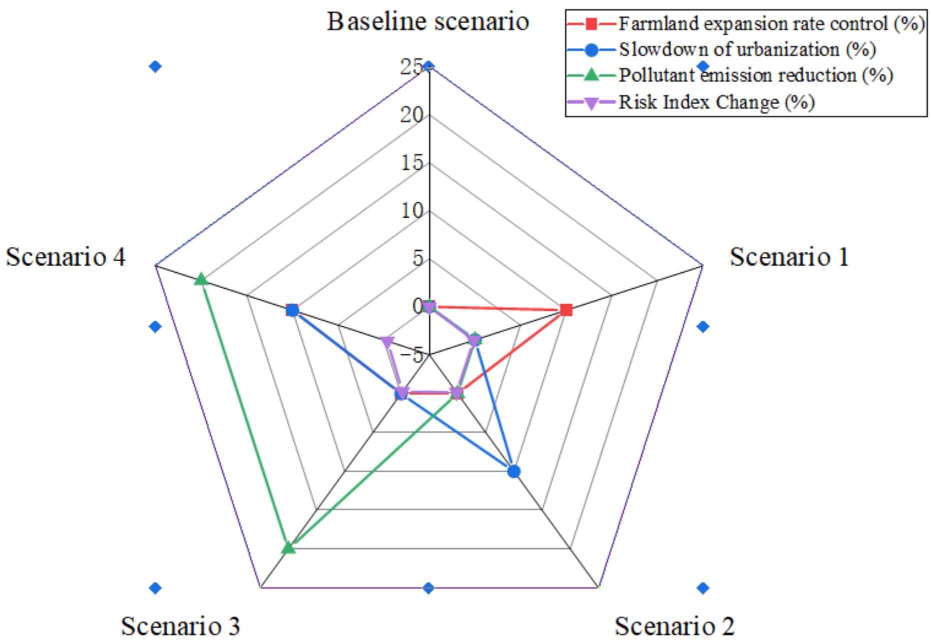

Figure 4. Impact of land use and pollutant control on ecological risks

It can be seen from Figure 4 that land use change control and pollutant emission reduction have a significant impact on ecological risks. When the farmland expansion rate is controlled by 10%, the ecological risk index drops by 12.5%; similarly, when the urbanization process is slowed down by 10%, the risk index drops by 15%. More significantly, when pollutant emissions are reduced by 20%, the ecological risk index drops by 25%. When the three policy measures are implemented in combination, the risk index drops by 40%, showing the powerful effect of the comprehensive intervention strategy in reducing ecological risks. In general, the Bayesian network model provides an effective analytical tool for watershed ecological risk assessment, but it is highly dependent on data. In the future, when implementing policies, we should focus on highly sensitive factors, such as land use change and pollutant control, and combine regional spatial analysis tools to improve the regional applicability of the model, so as to formulate more precise and feasible policies.

5. Conclusion

Based on the Bayesian network model, this study successfully quantified the ecological risk of a typical watershed and provided a scientific basis for environmental policy. The results show that pollutant concentrations and land use changes are major ecological risk factors, and that deterioration of water quality and decline in biodiversity significantly increase the vulnerability of ecosystems. Policy simulation shows that by improving the sewage treatment rate and vegetation coverage, the basin ecological risk index can be reduced by 33.3%. The research contribution is to propose an ecological risk assessment method based on comprehensive data and dynamic analysis, which makes up for the shortcomings of traditional methods in dealing with complex relationships and uncertainties, and provides decision support for policy making. The practical significance of the research lies in providing policymakers with an effective risk assessment tool that helps identify key risk factors and optimize ecological protection measures. However, the model depends on data quality, especially the construction of conditional probability tables, and the study is based on a single basin, which may limit the universality of the model. Future research can expand the scope of model application, combine data from more regions, and consider external factors such as climate change and human activities to further improve the accuracy and comprehensiveness of the assessment.

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