Regional ecosystem health assessment using the GA-BPANN model: a case study of Yunnan Province, China

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ABSTRACT

Background: Regional ecosystem health assessments are the basis for the sustainable development of society. However, an ecosystem is a complex integration of ecosystem mosaics and subsystems that influence each other, making it difficult to evaluate them using traditional assessment methods of linear and explicit functions. We introduce a back-propagation neural network model optimized by a genetic algorithm to evaluate ecosystem health in 16 districts in Yunnan Province. Result: (1) The model required fewer inputs to evaluate complex and nonlinear systems, avoided the need for subjective weights, and performed well in this practical application to regional ecosystem health assessment. (2) The ecosystem health in Yunnan Province was increasing, and there was a significant positive spatial autocorrelation during 2000–2020, showing that districts with high Ecosystem Health cluster together and the ecological protection policy of the region has produced a diffusion effect, leading to continuous improvement of the ecological health of the surrounding areas. High-low outlier areas of ecosystem health should be paid more attention, because of the increasing instability of local health levels. Conclusion: This study provides a methodological exploration for assessing spatial mosaics of different ecosystems at a regional scale.

Introduction

A natural ecosystem provides the material base and ecological services on which human beings depend for their survival. Maintaining a healthy ecosystem can ensure the survival of humans and the sustainable improvement of society and the financial system (Peng et al. 2015). However, human demands and interference in nature have intensified with the rapid advancement of society, which has greatly affected the structure and function of the ecosystem. This has resulted in a series of ecological environmental problems, such as soil erosion (Xiao et al. 2013), forest degradation (Hanberry and Abrams 2018), and reduction of biodiversity (Ortiz and Levins 2017). In the 1980s, the concept of ecosystem health (EH) was used to measure the capacity of ecosystems to self-organize and self-regulate to confront stress on a spatiotemporal scale, reflecting the stability and sustainability of ecosystems (Rapport 1989). The region is the key scale for EH assessment (Ren, Wu, and Peng 2000). In addition, effective EH assessments can identify ecological or financial crises and play an important role in regional ecosystem management (Sun et al. 2016). Scientific supervision and assessment of EH are essential for the sustainable development of regional ecosystems.

Regional ecosystem health emphasizes the spatial mosaic pattern of different types of ecosystems and is a comprehensive measure of ecosystems. The assessment of EH is a result of the interaction of various subsystems, where changes in any element will lead to changes in the entire system. The indicator system approach is widely used in EH assessment because of its comprehensive measurement of ecosystems, including by the pressure–state–response model (Spiegel et al. 2001; Sun et al. 2019), subsystem model (Fisher et al. 1998), vigor-organization-resilience (VOR) model (Costanza 1992, 2012), and the natural–social–economic model (Cui and Yang 2002; Wiegand et al. 2010). Among these models, the VOR model proposed by Costanza et al. (Costanza 1992) has been widely used in previous studies because it focuses on the evaluation of the integrity and sustainability of the regional ecosystem structure. With the continuous development of the assessment framework, the specific indicators and methods of integrating indicators for assessment have gradually diversified (Lu et al. 2015). However, due to the complexity and nonlinear characteristics of ecosystems, merely increasing the number of indicators cannot fully reflect the state of regional EH. Therefore, it is necessary to consider: 1) how to

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conduct a dynamic nonlinear simulation of complex systems instead of static linear superposition when conducting an integrated assessment of regional EH, 2) how to make a reasonable assessment of complex systems with limited indicators in practical applications, and 3) how to remove the subjective factor of artificially determined weights in measuring the importance of each indicator.

Recently, artificial intelligence (AI) has rapidly developed in the fields of data prediction, optimization, evaluation, and classification. Among various AI techniques, the back-propagation artificial neural network (BPANN) model, which is a non-linear statistical data modeling tool based on biological neural networks, can be used for ecosystem health (EH) assessment. Some attempts have been made to assess the EH of natural or artificial ecosystems, such as forests, rivers, wetlands, and districts, and have achieved good application results (Meng et al. 2013; Mo et al. 2009; Su et al. 2019). Firstly, when compared with traditional assessment methods, the ANN assessment method can continuously optimize the gradient of the loss function between the input and output values to dynamically simulate the relationship between the influencing factors, which overcomes the deficiency of the linear superposition of traditional methods, leading to relatively limited results. Secondly, the BPANN model has a certain fault tolerance that can accommodate unclear and incomplete information. Even with limited evaluation indicators, BPANN can still provide a reasonable evaluation of the complex system of regional EH (Gupta et al. 1985; Thukaram and Kashyap 2003). Finally, the model has a strong self-learning and self-adaptive capability, which can automatically extract the rules between the input and output data through learning and determine the network weights adaptively. This greatly reduces the negative impact of subjective weights on the assessment results (Pinyi and Si 2019).

In this study, the BPANN model was introduced to evaluate the regional EH. The indicators were synthesized using the BPANN model based on the establishment of a suitable indicator system. However, BPANN has the disadvantages of slow learning convergence and overfitting in algorithms, which leads to errors in model construction (Tan, Bong, and Rigit 2012). Genetic algorithms (GAs) have better stability, global searching ability, and capacity to automatically acquire and accumulate spatial knowledge and control the searching process adaptively (Wu, Zhou, and Li 2020), and have been applied to optimize the abovementioned defects in the BPANN model. Therefore, in this study, the GA-BPANN combined model was established to assess the regional EH while evaluating the potential of the method. Yunnan Province, as part of the most significant ecological barrier for the Yangtze River Basin, plays a key role in maintaining regional EH (Peng and Wang 2019). The region is endowed with rich ecological resources, but the towns and villages are poor, necessitating the development of tourism and urbanization as important means for local social and economic development (Akinboade and Braimoh 2010; Truong, Hall, and Garry 2014). Therefore, to ensure the sustainability of regional development, scientific observation and assessment of EH at appropriate spatial and temporal scales are urgently required. Specifically, this study had two main objectives: 1) to apply the GA-BPANN model to the field of EH assessment and validate the effectiveness of the model and 2) to quantify the EH in Yunnan Province scientifically. The EH results will reflect the implementation of the regional ecological environment protection strategy and urban development policy during the 20-year time span. The results of this study may help to formulate a scientific regional plan and provide scientific support for clarifying the priorities for protection.

**Materials and methods**

**Study area**

Yunnan Province, located in the southwest of China, lies between 97°31'-106°11' E and 21°08'-29°15' N, covering an area of approximately 39.4 × 10^4 km^2. The study area includes 16 city-level administrative units (Figure 1) and has a high proportion of plateaus, hills, and mountains, with elevations ranging from 77 to 6740 m. The climate is subtropical moist monsoon and the study area has high vegetation coverage, integrated ecosystems, and rich biodiversity. However, human intervention and urbanization have intensified the pressure on the environment. Thus, understanding the changes in regional EH in recent years and evaluating the development of the different districts are critical aims for researchers and policymakers.

**Data collection**

In this study, 30 m land use data and the normalized difference vegetation index (NDVI) were generated from Landsat MSS/TM/ETM+ images obtained during the summers of 2000, 2010, and 2020. These images were obtained from the Resources and Environmental Data Cloud Platform of the Chinese Academy of Sciences (http://www.gscloud.cn/) and the USGS Landsat missions (https://landsat.usgs.gov/index.php). Land use was classified into six types: cropland, forest land, grassland, water body, construction land, and unused land. We used Google Earth to validate the accuracy of image interpretation, to ensure that an overall accuracy of above 87% was achieved. Indicators of landscape components were derived using FRAGSTATS 4.2.1.
Establishing evaluation indicator system

The influence of spatial patterns on ecological processes is crucial in the EH assessments of administrative divisions. In this study, six land use types with spatial adjacency were used to represent the spatial patterns of land use (Peng et al. 2015), and with reference to the classic VOR model (Rapport 1989), an EH indicator system was constructed using the concepts of vigor, organization, and resilience (Table 1).

**Ecosystem vigor (V)**

Ecosystem vigor expresses the metabolism and primary productivity of ecosystems. Previous studies have shown that NDVI is an effective representation of ecosystem vigor (Box et al., 1989; Phillips, Hansen, and Flather 2008). Thus, ecosystem vigor was evaluated using NDVI, which is expressed as follows:

\[ NDVI = \frac{(NIR - RED)}{(NIR + RED)} \] (1)

where RED and NIR represent the spectral reflectance measurements acquired in the red and near-infrared regions, respectively.

**Ecosystem organization (O)**

Ecosystem organization reflects the structural stability of ecosystems, including heterogeneity, landscape connectivity, and connectivity of vital ecosystems. The Shannon diversity index and area-weighted

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**Table 1. Ecosystem health assessment indicators system.**

| Items          | Indicators                   | Descriptions                                                                 | Data Sources                        |
|----------------|------------------------------|------------------------------------------------------------------------------|-------------------------------------|
| Vigor          | NDVI                         | Assess the primary productivity of ecosystem                                | Landsat data                        |
|                | Shannon’s Diversity Index    | These landscape indicators are introduced to show the interconnectedness of  | Calculated according to Fragstats4.2 |
|                | (SHDI)                       | the ecosystem’s organizational structure to indicate diversity, fragmentation,| with land use/cover                  |
|                | Area-weighted mean patch     |                                                                              |                                     |
|                | fractal dimension (AWMPFD)   |                                                                              |                                     |
|                | Landscape fragmentation index|                                                                              |                                     |
|                | (FN1)                        |                                                                              |                                     |
|                | Contagion (CONTAG)           |                                                                              |                                     |
|                | Forest patch fragmentation index (FN2) |                                                                              |                                     |
|                | Forest patch cohesion index  |                                                                              |                                     |
|                | (COHESION)                   |                                                                              |                                     |
| Resilience     | Ecosystem resilience (ER)    | The ability of an ecosystem to recover its original structure and function    | Calculated by 8 neighborhood method. |
|                |                              | after external disturbance.                                                  |                                     |
mean patch fractal dimension were measured to indicate landscape heterogeneity. The landscape fragmentation index and contagion index can be applied to represent the overall landscape connectivity. The connectivity of vital ecosystems can be measured by the fragmentation and cohesion index of important patches, such as forest land (He et al. 2019).

**Ecosystem resilience (R)**

Ecosystem resilience characterizes the capacity of an ecosystem to resist small-scale interference, and is distinctly affected by land use. It is calculated as the summation of area-weighted ecosystem resilience coefficients (Colding 2007) (Table 2), and the general formula can be represented as follows:

\[ ER = \sum_{i=1}^{n} (A_i \times RC_i) \]  

where ER is the resilience of the regional ecosystem, Ai is the area ratio of land use type i, RCi is the resilience coefficient of land use type i, and n is the number of land use types.

**Evaluation criteria and classification**

Because EH is a relative concept and depends on the distribution of results (Peng et al. 2015), the existing literature and threshold range of indicators were included as the criteria for setting the initial value for the EH level. Then, using the Jenks natural breaks classification method, the differences between classes were maximized. The indicators were divided into five classes (Table 3): weak (1), relatively weak (2), ordinary (3), relatively well (4), and well (5). The higher the value, the healthier the ecosystem. Thus, the classifications reflect the relative levels of EH in Yunnan Province.

**GA-BPANN model building**

**Back propagation artificial neural network (BPANN)**

The BPANN relies on back propagation of errors for training the network, and in the process of back propagation the connection weights (w1 and w2) can be adjusted constantly to obtain a mathematical model of the relationship between the assessment results and the indicators of EH, enabling the simulation of complex relationships. After iterative calculations, the final proxy model can be obtained when the error is reduced to the set range. The model structure is illustrated in Figure 2.

**Using genetic algorithm (GA) optimize the BPANN model**

The BPANN model is based on the weight modification principle, which is based on the Error Gradient Descent, until the model reaches the target accuracy range. It is very sensitive to initial weights and thresholds and because initial weights are usually generated randomly, the network easily falls into a local extremum or overfitting. Recently a new type of AI optimization algorithm, the genetic algorithm (GA), starts from the population and simulates the natural selection process of evolution in biology. It compares multiple individuals simultaneously to determine the global optimal value and improves computing efficiency by performing initialization, selection, crossover, and variation operations. From a randomly generated population of chromosomes, a subset of the most suitable chromosomes is selected, based on the survival of the fittest, by crossover and mutation toward a new population of chromosomes. The algorithm can be used to select the most appropriate model metrics for ecosystem health assessment, which enhances the stability, accuracy, and efficiency of the model (Ding, Su, and Yu 2011) (Figure 3; (Wu, Zhou, and Li 2020)).

**Steps of GA-BPANN model building**

**Sample generation and preprocessing.** Based on the evaluation criteria and classification in Table 3, the following formula was adopted to randomly generate 200 samples in each grade; among these, 160 groups were randomly selected as training sample data, 20 groups as test sample data, and the remaining 20 groups as validation sample data. Thus, a total of 1000 data samples were generated, including 800 training samples, 100 test samples, and 100 validation samples.

### Table 2. Resilience coefficient of land use (Kang et al., 2018; Peng et al., 2017).

| Land use types       | Forest land | Water body | Unused land | Cropland | Construction land | Grass land |
|----------------------|-------------|------------|-------------|----------|------------------|------------|
| RCi                  | 0.8         | 0.8        | 1           | 0.3      | 0.2              | 0.7        |

### Table 3. Classification of indicators.

| Level of EH | NDVI          | SHDI          | AWMPFD       | FN1          | CONTAG        | FN2          | COHESION      | R            |
|-------------|---------------|---------------|--------------|--------------|---------------|--------------|---------------|--------------|
| Well (5)    | (0.82,1)     | (0.89,1)      | (0.98,1)     | (0.2,0.28)   | (0.91,1)      | (0.2,0.28)   | (0.9997,1)    | (0.9,1)      |
| Relatively well (4) | (0.79,0.82) | (0.81,0.89)   | (0.97,0.98)  | (0.43,0.66)  | (0.82,0.91)   | (0.28,0.39)  | (0.9993,0.9997) | (0.84,0.9) |
| Ordinary (3) | (0.75,0.79) | (0.75,0.81)   | (0.95,0.97)  | (0.66,0.79)  | (0.76,0.82)   | (0.39,0.56)  | (0.9984,0.9993) | (0.8,0.84) |
| Relatively weak (2) | (0.7,0.75)  | (0.66,0.75)   | (0.94,0.95)  | (0.79,0.85)  | (0.68,0.76)   | (0.56,0.77)  | (0.9945,0.9984) | (0.75,0.8) |
| Weak (1)    | (0.7,0.7)    | (0.66,0.75)   | (0.94,0.85)  | (0.85,1)     | (0.68,0.88)   | (0.77,1)     | (0.99,0.9945)  | (0.75,0.75) |
where $y^k_{ij}$ is sample data generated for the $k$-th level of EH, $k = 1, 2, \ldots, 5; n_k$ is the number of samples generated from the $k$-th level of EH; $a^k_j$ and $b^k_j$ are the upper and lower limits of the $k$-th level of EH respectively.

**Determination of the parameters panel.** According to the Kolmogorov theorem, a three-layer neural network can capture approximately any nonlinear function. In the BPANN, eight indicators of EH were used as the input layer, and the assessment results were the only output layer. After repeated training, the optimal number of hidden layer nodes was set to 14. Finally, the neural network structure was 8–14–1. The function trainlm was chosen as the training function, and the model accuracy was set to 0.00001. The GA parameters were determined, where the population size was 30, the crossover probability was 0.3, and the mutation probability was 0.1. The setting parameters of the training data and test data were the same as those of the BPANN.

**Establishing the formula of fitness function $F$.** The BPANN was used to calculate the weights and thresholds of the population samples, and the expected output is denoted as $X_i$. The predicted outcome is $O_i$, and the individual fitness formula is as follows:

$$F = \frac{1}{\sum_{i=1}^{n}|X_i - O_i|}$$

where $X_i$ is the predicted output value and $O_i$ is the expected output value.

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Figure 2. Three-layer topological structure of the BPANN model.

Figure 3. Process of GA-BPANN (Wu, Zhou, and Li 2020).
Genetic algorithm optimization. GA specifically includes the three main genetic operators of selection, crossover, and variation. In this study, a subset of the most suitable chromosomes was selected for inheritance to the next generation by the roulette wheel method based on the survival of the fittest. The roulette formula is as follows:

\[ P_i = \frac{F_i}{\sum_{i=1}^{n} F_i} \quad (6) \]

where \( F_i \) is the fitness of individual i and n is the number of individuals in the population.

Advancement toward a new chromosome population by crossover and mutation followed; A specific crossover operation was performed using the real number crossover method. Its formula is as follows:

\[
\begin{align*}
    a_{xi} &= a_{ui}(1 - b) + a_{yi}b \\
    a_{yi} &= a_{yi}(1 - b) + a_{xi}b
\end{align*} \quad (7)
\]

where \( a_{xi} \) and \( a_{yi} \) are the genes of individuals x and y at the i locus, and b is a random number between [0, 1].

After selecting a certain individual, the mutation operation was accomplished by converting certain genes to other alleles with a certain probability, using the following equation:

Variation operation:

\[
a_{ij} = \begin{cases}
    a_{ij} + (\hat{a}_{ij} - a_{\text{max}}) r_2 \left( 1 - \frac{e}{E_{\text{max}}} \right)^2, r > 0.5 \\
    a_{ij} + (a_{\text{min}} - a_{ij}) r_2 \left( 1 - \frac{e}{E_{\text{max}}} \right)^2, r \leq 0.5
\end{cases} \quad (8)
\]

where \( a_{\text{max}} \) and \( a_{\text{min}} \) are the maximum and minimum bounds of the gene, respectively; \( r_2 \) is a random number, \( e \) is the number of current iterations, \( E_{\text{max}} \) is the maximum number of iterations, and \( r \) is a random number between [0,1].

Test error and verify accuracy. The weight and threshold values optimized by GA were substituted into the BPANN. The neural network was trained with training samples until the error requirements were met. Test samples were used to determine when to stop training (to avoid overfitting) and to determine which of the networks was the most accurate. Finally, a validation dataset was randomly selected from the post samples to validate the chosen model against independent data.

Assessment criteria for model performance

The error measurements used to assess the simulation performance of GA-BPANN models were the root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE), as described in equations (9), (10), and (11).

\[
    \text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (b_i - a_i)^2} \quad (9)
\]

\[
    \text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |b_i - a_i| \quad (10)
\]

\[
    \text{MAPE} = \frac{100%}{n} \sum_{i=1}^{n} \left| \frac{b_i - a_i}{a_i} \right| \quad (11)
\]

where \( b_i \) is the actual value, \( a_i \) is the value predicted by the GA-BPANN model, and n is the size of the validation sample.

Results and discussion

Performance of GA-BPANN model

The GA-BPANN model was applied to the field of regional EH assessment and the validity of the model was verified. The test samples were substituted into the trained model to test the performance of the GA-BPANN model. The results showed that RMSE was 0.00093, MAE was 0.00025, MAPE was 0.0001 and R was 0.99966. The closer that RMSE, MAE, and MAPE converge toward zero, the smaller the model error and the better the performance. The robustness of the neural network model was measured using the correlation coefficient R. The closer R is to 1, the better is the model fit. Therefore, as shown in Figure 4, the model fitted well. This is consistent with the results of previous attempts to model forest, river, wetland, and urban systems for EH assessments (Meng et al. 2013; Mo et al. 2009; Su et al. 2019). The standard BPANN model and the improved GA-BPANN model were compared for test sample data error using the same network structure, and the results are shown in Figure 5. The improved GA-BPANN model reduced the average relative error and effectively improved the accuracy and stability of the prediction.

Features and limitations of the GA-BPANN model

Regional ecosystem health is considered the ultimate goal of environmental management (Costanza 2012), and the use of comprehensive evaluation indicators is an important challenge for measuring regional ecosystem health. Traditional regional EH assessment methods are controlled by formulas and algorithms and suffer from the problems of linear superposition of assessment methods, limited indicators that cannot completely describe objective entities, and artificial determination of indicator weights. In this study, to remedy the above problems, the neural network method was controlled by the learning of the training model and the sample data, and the nonlinear mapping relationship it established was theoretically closer to the objective entity. In practice, the model determined the suitable weights by continuously simulating...
the resultant errors; the convergence process was rapid, and the trained network also had very high accuracy.

The model has three typical features. Firstly, the model has a strong nonlinear mapping capability.
solved by iterating the errors to approximate the real results with arbitrary accuracy. Considering the characteristics of the ecosystem as a nonlinear complex, the use of the GA-BPANN model to evaluate the regional EH condition may overcome the deficiency of the linear superposition of traditional methods. Secondly, the model can handle unclear or incomplete information. However, in traditional regional EH assessment methods, scholars have attempted to provide a comprehensive measure of complex systems by increasing the number of indicators. As the number of indicators is always limited, the measurement of regional ecosystems remains incomplete. In addition, there are cases in which indicators are missing or difficult to obtain. Local missing or corrupted neurons in the ANN training model did not significantly impact the final results; that is, the model could still complete the simulation properly when the local data were incomplete. This greatly improves the practical applicability of the indicator system method. Finally, the model adaptively determines the network weights. In a comprehensive assessment of EH with a large number of indicators, determining the weight of each indicator is a crucial step, which has a significant impact on the final assessment results. Traditionally, subjective methods such as Delphi, AHP, and the principal component method have been used to set weights (Liu, He, and Li 2014; Sun et al. 2019; Xie, Gu, and Lin 2014). These subjective methods are influenced by human factors and require professional knowledge and practical experience. The ANN can correct the weights by itself through machine learning during the assessment until the error in the output is reduced to an acceptable level. Good application results also verified the effectiveness of the GA-BPANN model. While debugging and modifying the GA-BPANN network model (by selecting any number of evaluation indicators for learning and establishing different evaluation models), we found that the successfully learned model obtained reliable evaluation results for any test sample and had wide applicability. Therefore, the model has potential value for use in regional EH evaluation problems.

There were also some limitations to the process of constructing the model. First, owing to the limited test sample data, the accuracy of the model for monitoring EH was somewhat limited. In the future, with expansion of real sample data, the training model can be updated to form a dynamic monitoring system for EH in Yunnan Province. The evaluation model has a degree of generalizability for regional EH assessments. As long as the evaluation indexes of the study area can be obtained, they can be substituted into the evaluation. However, the indicator system in this study was constructed from the actual situation of the case, so it would be necessary to make appropriate corrections to the model considering the profile of the new study area. Second, in order to differentiate the health status of ecosystems, we set thresholds for evaluation indicators based on a large amount of literature, and criteria of health according to relevant indicators in developed districts (Peng et al. 2007); however, these thresholds are themselves empirically determined and lack verification of their “dose-effect relationships” with ecosystem health targets. In addition, an absolutely healthy ecosystem does not exist. Therefore, the set thresholds in this study can hardly be called long-term valid indicator thresholds, but only a relative health status given the current state of development. In conclusion, ecosystem health itself is a dynamic concept, and the application of artificial intelligence methods in this study was demonstrated to be a powerful and important tool in dynamic assessment. In future research, aspects such as a more in-depth study of models, or predictive applications of trends in EH can be explored.

**Spatial and temporal changes of EH in Yunnan Province during 2000–2020**

The regional EH was divided into five levels, with the level of EH in Yunnan Province in the last 20 years falling between relatively weak (2) and well (5). Table 4 shows that the total number of “ordinary” districts was six in 2000 and decreased to one in 2020; and the number of “relatively well” districts was seven in 2000 and increased to 11 in 2020; these results indicate that the level of EH in Yunnan province increased overall, which is consistent with the report by Shi (Shi et al. 2021).

The results show that a series of ecological protection and restoration projects, such as the protection and management of nine highland lakes in Yunnan Province, the national greening action, and the rainforest restoration action were effective. In 2000, 2010, and 2020, “relatively well” areas accounted for the largest proportion of the province (43.75%, 62.5%,

| Table 4. Assessment results based on the GA-BPANN model. |
|-----------------|-------|-------|-------|
| **Name**        | 2000  | 2010  | 2020  |
| Baoshan         | 4     | 4     | 4     |
| Chuxiong        | 3     | 4     | 4     |
| Dali            | 4     | 4     | 4     |
| Dehong Autonomous Prefecture | 4 | 4 | 4 |
| Diqing Tibetan Autonomous Prefecture | 4 | 4 | 4 |
| Hani-Yi Autonomous Prefecture of Honghe | 3 | 3 | 4 |
| Kunning         | 2     | 3     | 3     |
| Lijiang         | 4     | 4     | 4     |
| Lincang         | 3     | 3     | 4     |
| Nujiang of the Lisu Autonomous Prefecture | 4 | 4 | 5 |
| Puer            | 3     | 4     | 5     |
| Qingjing        | 2     | 2     | 2     |
| Wenshan Zhaqong and Miao Autonomous Prefecture | 3 | 4 | 4 |
| Sipinggapanha    | 5     | 5     | 5     |
| Yuxi            | 4     | 4     | 4     |
| Zhaotong        | 3     | 3     | 4     |
and 68.75%, respectively), showing that the ecosystems in the region were mostly in good health and continued to improve each year; however, the rate of improvement has slowed down. Yunnan Province originally had a good ecological base and the government attaches great importance to the construction of an ecological security barrier in the southwest by introducing important supporting policies such as the Regulations on the Management of Nature Reserves in Yunnan Province and the Regulations on the Management of National Parks in Yunnan Province. These have ensured the continuous improvement of regional EH.

However, due to the long lag in the economic level of Yunnan and the increasing speed of tourism development and urbanization in recent years (aiming to improve the quality of life of local people), the contradiction between supply and demand of resources has become increasingly prominent, and has affected the growth rate of EH. In addition, the global financial crisis erupted in late 2008, and in 2010, Yunnan Province was hit by a once-in-80-years mega-drought disaster. The drought lasted for a long time and was widespread, causing a serious impact on natural resources. Under the dual pressure of the severe external economic situation and the destruction of its own resources and environment, the local government undertook a large number of primary projects and industries to quickly relieve the economic pressure, which is one of the reasons why the rate of EH improvement has decreased in the past 10 years. Consistent with our study, Liu Jiao found that the rate of enhancement of ecological safety of land in Yunnan Province from 2000 to 2015 showed a trend of increasing and then decreasing (Jiao et al. 2021), and the rate of change began to decrease from 2009 onwards, due to increasing population density and application of fertilizer.

Figure 6 shows the significant differences in the spatial distributions of the 16 units. Ordinary and relatively weak levels were mostly distributed in the central and northeastern parts of Yunnan Province. The western and southern parts had better EH and were constantly improving. The overall layout is consistent with the planning goals to build an ecological barrier on the southeastern edge of the Tibetan Plateau and another on the southern border, while intensifying the development of the districts to the northeast and in the center. In this region, the highest level of

![Figure 6](image_url)
population disturbance and development occurred from 2000 to 2020, to develop a core metropolitan area centered on Kunming, and this may have contributed to the relatively weak EH in Kunming. The deterioration of EH in Qujing was significantly higher than in other districts, which is consistent with the results of previous studies. For example, in evaluating the vulnerability of regional urban agglomerations, Junkai (Junkai and Jiangang 2020) found that the EH of Qujing was significantly more vulnerable than that of neighboring districts due largely to Qujing’s focus on the coal and tobacco industries which caused a lot of pollution.

Spatial autocorrelation of EH

The spatial correlations among different units of ecosystem health in Yunnan Province were summarized by the global Moran’s I index and local spatial autocorrelations. The global spatial autocorrelation characterized the spatial distribution of EH within the entire Yunnan province, reflecting the interconnectedness and dependence among districts. The lowest value of the Moran’s I index in 2000 was 0.29. In 2010 and 2020, the Moran’s I index was greater than 0.4 at a 99% confidence level (P = 0.009), indicating that the levels of EH in the region had a significant positive spatial correlation and a clustered distribution. From 2000 to 2020, the degree of agglomeration gradually increased, showing that districts with high EH levels were clustered together, and vice versa.

The global Moran’s I index reflects the significant positive spatial correlations of the ecosystem health among the districts in Yunnan Province in general but it cannot clarify the location of aggregation of a specific unit. The local spatial autocorrelation analysis reflects the aggregation type of districts and the spatial correlation of a unit with the surrounding units. Figure 7 shows that the high-high cluster type, which has a better EH level for itself and neighboring districts, occupies the most area in Yunnan Province by 2020. The low-low type areas represented by Kunming and Qujing decreased over time from 2000, and the high-high type represented by northwestern and southeastern Yunnan Province increased, which indicates that as the degree of EH improved it produced a better diffusion effect and led to improvement of ecological health in the surrounding areas. This phenomenon is mainly due to the region’s own efforts and the radiation of districts with high EH, indicating that the

![Figure 7. Spatial autocorrelation of ecosystem health in Yunnan Province during 2000–2020.](image-url)
ecological protection and promotion policies in the northwest and southeast of Yunnan Province have achieved good results.

Although the EH levels of different regions in Yunnan Province presented a positive correlation overall, spatial heterogeneity was observed. The area of high-low outlier type (which has a good level of EH but the surrounding units are the opposite) increased significantly. This type is highly unstable owing to the influence of spatial polarization, and it easily changes into the low-low type under the influence of its surrounding areas. This phenomenon occurred because Puer City (which is adjacent to Yuxi and Chuxiong) has more than 67% forest cover and is one of the richest biodiversity areas in the country with a good level of ecosystem health (5), while Kunming and Qujing have an average or relatively weak level of ecosystem health (3 and 2, respectively) due to high urbanization and the development of polluting industries such as coal. Thus, the EH of Yuxi and Chuxiong is influenced by cross-regional radiation from the units on both sides, and the degree of ecological health fluctuates and fluctuates. Zhaotong is in a similar situation. The high-low outlier type shows asynchronous development of ecosystem health and socio-economic transformation, and lack of communication between strong and weak units. Thus, strengthening inter-city ecological links and cooperation, reducing spatial differences in EH, and promoting synergistic regional development policies are recommended priorities for the future ecological development of these three units.

Conclusions

Achieving an integrated assessment of the health status of the spatial mosaic of ecosystems on a regional scale is vital for current ecosystem management. However, linear superposition, limited indicator selection, and artificial determination of indicator weights ignore the complexity of ecosystem assessment. In this study, we applied the GA-BPANN model to a regional EH assessment, taking Yunnan Province as an example, and aimed to improve the scientific and rational nature of the assessment while accounting for the nonlinear characteristics of ecosystems. The results show the following: a) the model can continuously optimize the gradient of the loss function between the input and output values to dynamically simulate the relationship between the influencing factors and, thus, has a strong nonlinear mapping ability. It has great advantages over traditional EH evaluation methods for targeting such a complex nonlinear mapping relationship. b) the model can make an overall and reasonable evaluation of the complex system of regional EH with limited evaluation indicators. This makes the model a feasible and reliable option in the practical application of incomplete details.

In the assessment of EH in Yunnan, economic pressure was found to be the dominant factor in the decline of EH. The impact and performance of this factor were analyzed. The regional EH levels in Yunnan Province over 20 years were quantified, and their spatial distribution was visually represented. c) We found that as economic pressure increased, the rate of growth in EH decreased, and the spatial heterogeneity of units increased. This reflects unstable ecological protection and low synergy of regional development in some areas. With the expansion of real sample data in the future and constant updating of the model, a dynamic monitoring system for EH in Yunnan Province can be established. The results of such a model can reflect the implementation status of environmental protection and urban development policies in real-time, providing a scientific basis for the formulation of policies for regional ecological protection and management. This study provides a methodological exploration for assessing the spatial mosaics of different ecosystems on a regional scale.

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Credit authorship contribution statement

Yuze Li: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing – original draft preparation, Writing - Review & Editing, Visualization. Yuanxiang Wu: Writing - Review & Editing, Funding acquisition, Supervision. Xiaoguang Liu: Project administration.

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