Assessing Urban Ecosystem Health in Diverse Climate Zones: A Hybrid Model Approach for Regional Sustainability

Haiyan Huang[12] Yuesheng Huang[2] Jiayin Liu[2] Zhuoyi Chen[2]

1.Research Center of the Economy of the upper Reaches of Yangtze River, Chongqing Technology and Business University, China, 400067;

2.Guangdong Polytechnic Normal University, China, 510665;

Abstract: Ecosystem health is a necessary condition for the survival and development of the population in the settlement system and the basis for regional sustainable development. Ecosystem health assessment is one of the hot topics in ecological research. This study analyzed the multidimensional factors of the ecosystem in six typical provinces with large populations in different climate zones from 2013 to 2021, Its innovation lies in the ingenious integration of multiple mathematical models and algorithms, the use of descriptive statistical analysis, principal component analysis, T-SNE weight solution and other methods, combined with a comprehensive evaluation scheme based on DDP dynamic programming and T-S fuzzy neural network, to achieve a comprehensive and accurate evaluation of the urban ecosystem. The study shows that the forest ecosystem index, water resource ecosystem index, and atmospheric ecosystem index are highly correlated with urban ecological health. At the same time, the ecological ecological assessment results of different provinces vary greatly, and it is necessary to set up optimized system management according to local conditions.

Keywords: Urban ecosystem; T-SNE GCC-PHAT dynamic programming; T-S fuzzy neural network; Provincial differences

DOI:10.69979/3041-0843.25.01.033

1. Introduction

With the acceleration of China's modernization process, the pace of urbanization is increasing, bringing unpr ecedented changes to urban ecosystems. This transformation has not only reshaped the face of cities, but also posed serious challenges to the health and sustainability of ecosystems [1]. The health of urban ecosystems in th e context of urban expansion and population explosion has become a focus of attention for policy makers and environmental scientists, and its importance cannot be overstated. In the context of new urbanization, the coordi nated development of urban agglomerations has become a key factor in promoting sustainable development [2]. Faced with the complexity and dynamics of modern urban landscapes, traditional assessment methods may be o ut of their reach. Therefore, there is an urgent need for innovative, comprehensive and accurate assessment too ls that can provide insights that are instructive for urban planning and management.

Ecosystem health assessment is an important indicator of a region's ecosystem stability and potential for sus tainable development [3-6]. It comprehensively evaluates the internal structural stability of ecosystems, their ability to self-regulate, their resilience in the face of adversity, and the services needed to support human activities [7]. Currently, this assessment method has played an important role in the initial evaluation and impact assessment in the fields of ecological restoration, urban planning and urban renewal [8,9].Luo et al. [10] provided us with the trends, problems and future directions of urban health impact assessment research through systematic evaluation and bibliometric analysis.Peng et al. [11] provided us with the trends, problems and future directions of urban h ealth impact assessment research by combining ecosystem services with landscape pattern combined with landsc ape pattern to assess the health of urban ecosystems.Yang et al [12] demonstrated the progress of ecosystem he alth research by using the visualization research method of CiteSpace.

In the field of ecosystem assessment, many experts in econometric analysis have summarized the research results in depth using traditional methods.Tett et al [13] proposed a framework for assessing the health of marine ecosystems.O'Brien et al [14] systematically analyzed the temporal and spatial distributions of ecosystem assessment studies and explored the methods of assessing the health of freshwater and estuarine ecosystems. Li et al [15] utilized remote sensing techniques to assess ecosystem health from a dynamic spatial and temporal scale and looked at the opportunities and challenges for future development, while Su et al [16] provided a picture of the development of urban ecosystem health assessment. Although these studies provide us with valuable insights, many of the analyses have limitations and some of them appear outdated. Therefore, we urgently need more in-depth and comprehensive studies to fill this gap, to promote the innovation and application of ecosystem assessment methods, and to provide a solid scientific foundation for realizing sustainable management of ecosystems. The development of hybrid modeling approaches, such as integrating Emergy and LCA, has provided new perspectives for assessing the sustainability of urban systems [17-20].Wang et al [21] conducted an in-depth review of both EMA and LCA approaches and proposed a coupling development strategy to fully utilize the potential and advantages of each approach.The combination of LCA with intelligent body-based modeling (ABM) provides a behavior-driven modeling provides new avenues [22-25].

The impact of urbanization on urban ecological health has been the focus of many researchers.Xiao et al [26] assessed the ecological health of mountains in southwest China by quantifying the importance of ecosystem services, revealing a negative correlation between urbanization and ecological health.A study by Wang et al [27] pointed out that the city of Zhuhai, China, has experienced ecological degradation since 1999, with a Urbanization was negatively correlated with ecological health.Cheng et al [28] assessed the ecological health of the Haihe River Basin using a number of indicators, and found that cultivated land area, per capita GDP, and population density were inversely correlated with river ecological health. With insufficient data, Van Niekerk et al [29] applied five indices to explore the main pressures between urbanization and ecological health, while Styers et al [30] used landscape indices and urbanization parameters to assess ecological health. Maintaining optimal ecological health is essential for resource adequacy and ecological development. However, the assessment of environmental loads in urban environments has often neglected the coupled relationship between rapidly growing cities and environmental loads, especially the study of spatial heterogeneity and sensitivity to multiple anthropogenic pressures. Therefore, we need to address this challenge by using integrated and quantitative techniques to analyze the spatial heterogeneity and sensitivity of urban ecosystem health.

This study demonstrates significant superiority in the field of urban ecosystem assessment, and its innovation lies in the skillful integration of multiple mathematical models and algorithms. We adopt advanced techniques such as descriptive statistical analysis, principal component analysis, and T-SNE weights solving, combined with a comprehensive assessment scheme based on DP dynamic planning and T-S fuzzy neural network, to realize a comprehensive and accurate assessment of urban ecosystems. This method not only makes a breakthrough in improving the accuracy and stability of assessment, but also plays an important role in providing scientific decision support for urban planning and management.

The research of this project fills the possible limitations and obsolescence of existing traditional evaluation methods. Approach enables a deeper understanding and analysis of the complexity and dynamics of urban ecosystems, providing new tools and perspectives for policy makers and environmental scientists. In addition, the results of this study are important for promoting ecological civilization and sustainable urban development. This study not only provide a new assessment tool, but also present a fresh perspective to promote a comprehensive understanding and effective management of urban ecosystem health and sustainability issues. Through this approach, can better identify and solve the problems that arise in the process of urbanization and contribute to the achievement of long-term sustainable urban development.

2. Materials and Methods

2.1. Research framework

(1) This paper analyzes and extracts features from multidimensional data of urban ecosystems. By using stati stical analysis and other methods, key features and potential laws are discovered, which can help us better und erstand the complexity and changing trends of urban ecosystems. Secondly, this paper uses the t-SNE algorithm to reduce the dimension and visualize the urban ecosystem data. t-SNE can map high-dimensional data to low-di mensional space, showing characteristics such as data clustering, distribution and similarity. Through t-SNE dimens ionality reduction and visualization, the correlation between different indicators in urban ecosystems can be intuit ively displayed.

(2) The various indicators of urban ecosystems are comprehensively evaluated and weighted. The weights of indicators are determined by principal component analysis, and fuzzy comprehensive evaluation methods are us ed in combination with intelligent algorithms to evaluate them, providing a comprehensive and comprehensive ur ban ecosystem health assessment framework.

(3) This paper uses a variety of machine models and intelligent algorithms to establish a prediction model t o predict the future changing trends of urban ecosystems. By using historical data and related features, the mac hine learning model is trained and the development of urban ecosystems under different intervention measures i s predicted.

(4) The mathematical model and intelligent algorithm are combined with the concept of Chinese modernizat ion to provide scientific support for the health assessment and optimal management of China's urban ecosystem s. Through in-depth analysis of the characteristics, relationships and evolution laws of urban ecosystems, and pro posing optimization strategies and measures.

2.2. Description of symbols

S/N	SYMBOL	EXPLAIN
1	$p_{j\|i}$	Conditional probability between data points
2	$H(P_i)$	Shannon entropy
3	c_j^i	Membership Center
4	b_j^i	Membership width
5	k	Input parameter
6	A_j^i	Fuzzy set
7	Y_t	Original time series
8	P	Lag order

2.3. Data statistics

2.3.1. Data sources

The data for this study mainly comes from the National Bureau of Statistics (http://www.stats.gov.cn/). From 2013 to 2021, typical representatives of provincial administrative regions with large base populations in six diffe rent climate zones in China (Guangdong, Henan, Hebei, Shanxi, Beijing, and Shanghai) were selected for ecosyste m assessment and analysis.

2.3.2. Data statistics

(1) Normalize the data. Data normalization is a common data preprocessing technique that aims to unify t he data scales between different features and eliminate the dimensional differences between features for better data analysis and modeling. Linearly map the data to the range of [0, 1] to ensure that the influence weight of each feature on the model is relatively balanced, avoid excessive or insufficient influence of some indicators on the model results, and improve the stability and accuracy of the model.

Correlation analysis of data. By calculating the Pearson correlation coefficient, we can get the correlation be tween variables and visualize it as a heat map, which can more intuitively observe the relationship between vari ables. The calculation formula of the Pearson correlation coefficient is as follows:

$$r = (\Sigma((X - X_m ean) * (Y - Y_m ean)))/(sqrt(\Sigma((X - X_m ean)^2)) * sqrt(\Sigma((Y - Y_m ean)^2))) \quad (1)$$

Principal component analysis is used to reduce the dimension of data. Component analysis is a linear transf ormation technique that achieves data dimensionality reduction by projecting the original data into a new coordi nate system. The basic idea is to obtain the main features by finding the maximum variance in the projection d irection.

First, the original data is decentralized, that is, each variable is subtracted from its mean to obtain a decen tralized data matrix. Let X be a matrix composed of n random variables, each random variable is sampled m ti mes, and the covariance matrix of the decentralized data matrix is calculated:

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_n \end{bmatrix} = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1m} \\ X_{21} & X_{22} & \cdots & X_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ X_{n1} & X_{n2} & \cdots & X_{nm} \end{bmatrix} \tag{2}$$

$$Y = \begin{bmatrix} X_{11}-E(X_1) & X_{12}-E(X_1) & \cdots & X_{1m}-E(X_1) \\ X_{21}-E(X_2) & X_{22}-E(X_2) & \cdots & X_{2m}-E(X_2) \\ \vdots & \vdots & \ddots & \vdots \\ X_{n1}-E(X_n) & X_{n2}-E(X_n) & \cdots & X_{nm}-E(X_n) \end{bmatrix} \tag{3}$$

$$\begin{aligned} C &= \mathrm{cov}(Xi，Xj) \\ &= \begin{bmatrix} E\{(X_1-u_1)(X_1-u_1)\} & E\{(X_1-u_1)(X_2-u_2)\} & \cdots & E\{(X_1-u_1)(X_n-u_n)\} \\ E\{(X_2-u_2)(X_1-u_1)\} & E\{(X_2-u_2)(X_2-u_2)\} & \cdots & E\{(X_2-u_2)(X_n-u_n)\} \\ \vdots & \vdots & \ddots & \vdots \\ E\{(X_n-u_n)(X_1-u_1)\} & E\{(X_n-u_n)(X_2-u_2)\} & \cdots & E\{(X_n-u_n)(X_n-u_n)\} \end{bmatrix} \\ &= E(YY^T) \end{aligned} \tag{6}$$

2.3.3. Solution of indicator weights

(1) Weight solution based on T-SNE algorithm

In order to effectively analyze the classification rules of different indicators, we decided to fuse the plane p arameters here. In order to analyze the impact of multiple indicators on the degree of characteristics, the T-SNE algorithm is used to first find the weight of each indicator for the risk score. First, the high-dimensional Euclid ean distance between data points can be converted into conditional probabilities representing similarities using ra ndom neighbor embedding (SNE). Weight adjustment based on GCC-PHAT and multi-frame weighted smoothing o ptimization method.The ultimate optimization goal is to get the value of the loss function as small as possible. Here we consider two extreme cases, that is, when the value of the loss function is 1, and when the value of the loss function reaches infinity. Through the comparison and analysis of these two cases, we finally get the to tal weight adjustment function that meets the model requirements as follows:

$$\begin{aligned} J(w,b) &= \mathrm{frac1msum}_{i=1}^{m} L(t(i)-y(i)) \\ &= -\,\mathrm{frac1msum}\, m_{i=1}^{m}\ [y(i)\log t(i) + (1-y(i))\log(1-t(i))] \end{aligned} \tag{4}$$

2.3.4. Urban Ecosystem Health Assessment Program Model

(1) Classification of influencing factors based on T-SNE algorithm. In order to analyze the impact of multiple indicators on the degree of features, the T-SNE algorithm is used to first find the weight of each factor for th e risk score. First, the high-dimensional Euclidean distance between data points can be converted into conditiona l probabilities representing similarities using Stochastic Neighbor Embedding (SNE). Optimal evaluation scheme b ased on DDP dynamic programming. Considering that the threshold conditions of the plane parameters have cha nged to a certain extent, we need to readjust the planning objectives and then solve a truly suitable evaluation model.

Where J denotes the loss case during the propagation of the influence factor and L denotes a summing ca se. The first equation term after the equal sign is the sum value[16] . Our aim is to find a set of suitable influ ence matching processes to minimize the value of the objective function. For the objective function of a nonline ar system, we reduce it to:

$$J = \frac{1}{2} x_N^T W_N x_N + w_N x_N + \sum_{k=1}^{N-1} \left(\frac{1}{2} x_k^T W_k x_k + R_k u_k \right) + w_K x_K + r_k u_k \tag{5}$$

which contains the positive definite and positive definite transit cost weighting matrices.V denotes the optim al evaluation mode and Q represents the amount of virtual evaluation for the iterative process, and these two variables will be accumulated progressively at the time step. When conforming to the computational description of the optimal strategy and utilizing the optimality principle, then using the recurrence relation can be expressed as:

$$J = \min Q_k^* = \min\left(\sum_{k=1}^{N-1} \frac{1}{2} x_k^T W_k x_k + w_K x_K + \frac{1}{2} u_k^T R_k u_k + r_k u_k + V_k^*(f(x,u))\right) \quad (6)$$

When such a process of synthesizing the loss of influencing factors with the environmental assessment is co nsidered as an iterative updating process, this is the classical Differential Dynamic Programming DDP algorithm[17]

When such a process of synthesizing the loss of influencing factors with the environmental assessment is consi dered as an iterative updating process, this is the classical Differential Dynamic Programming DDP algorithm[17] .

Since the dynamical system is presenting a nonlinear relationship when the initial change process, V is subject to a kind of partial approximation:

$$V_k(x+\delta x, u+\delta u) \approx Q_k(x,u) \quad (7)$$

The total impact factor Q is approximated:

$$Q_k(x+\delta x, u+\delta u) \approx Q_k(x,u) + \frac{1}{2}\begin{bmatrix}\delta x\\ \delta u\end{bmatrix}^T \begin{bmatrix}Q_{xx} & Q_{ux}\\ Q_{xu} & Q_{uu}\end{bmatrix}\begin{bmatrix}\delta x\\ \delta u\end{bmatrix} + \begin{bmatrix}Q_x\\ Q_u\end{bmatrix}\begin{bmatrix}\delta x\\ \delta u\end{bmatrix} \quad (8)$$

The matrix is a matrix block form and Q is a vector form of the gradient. If the matrices and gradients ar e computed directly according to the above transit cost equations, it is the so-called classical algorithm of differ ential dynamic programming.

3. Optimization of the final evaluation scheme based on T-S fuzzy neural network

Considering the problem of selecting the optimal ecological environment assessment scheme for model eval uation design, so we add the rating algorithm based on dynamic programming, therefore, this paper constructs t he T-S fuzzy neural network, which combines the fuzzy logic and neural network to better utilize the strengths of both.[18] The T-S fuzzy neural network is mainly divided into input layer, fuzzification layer, fuzzy rule calculat ion layer and output layer. The fuzzification layer uses the affiliation function to fuzzify the input layer to get th e fuzzy affiliation value, and the fuzzy rule calculation layer uses the fuzzy concatenation formula to calculate th e fuzzy value.\For the inputs y=[y2, y3,... ,yn], the affiliation degree of each input variable yk is calculated accor ding to the fuzzy rule as:

$$uA_j^i = \frac{\exp(-\left(x_j - c_j^i\right)^2}{b_j^i} \qquad j = 1,2,\cdots,k; i = 1,2\cdots,n \quad (9)$$

Where c and b are the center and width of the affiliation function, respectively; k is the input parameter; and n is the number of fuzzy subsets. The fuzzy operator used in the fuzzy calculation of each affiliation is the concatenation operator, i.e.:

$$\omega^i = uA_j^1(x_1) * uA_j^2(x_2) * \cdots * uA_j^k(x_k) \quad (10)$$

$$y^i = \sum_{i=1}^n W^i\left(p_0^i + p_1^i x_1 + \cdots + p_k^i x_k\right) / \sum_{i=1}^n \omega^i \quad (11)$$

Here yi is the evaluation result. Eventually, we determine the environmental assessment index of the selecte d city from the results of the calculation.

4. Results and Analysis

4.1. Data preprocessing results and analysis

4.1.1. Result of normalize the data

Before performing descriptive statistics on the data, a missing value test was performed on the data set, an d it was found that there were no missing values in the data. The missing value test results are as follows:

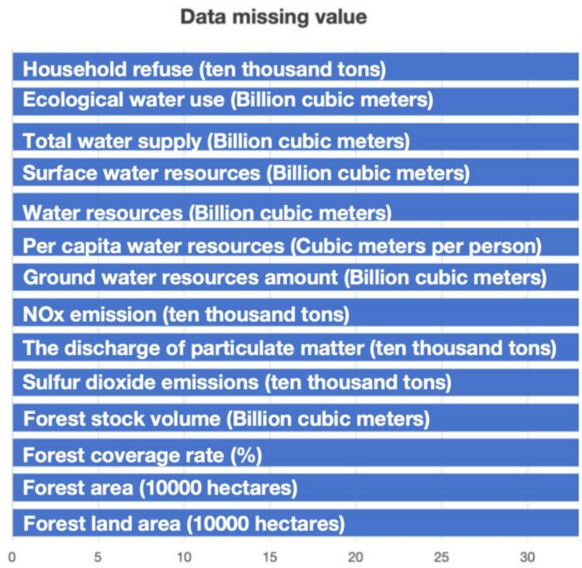

Figure 1 Data missing value detection diagram

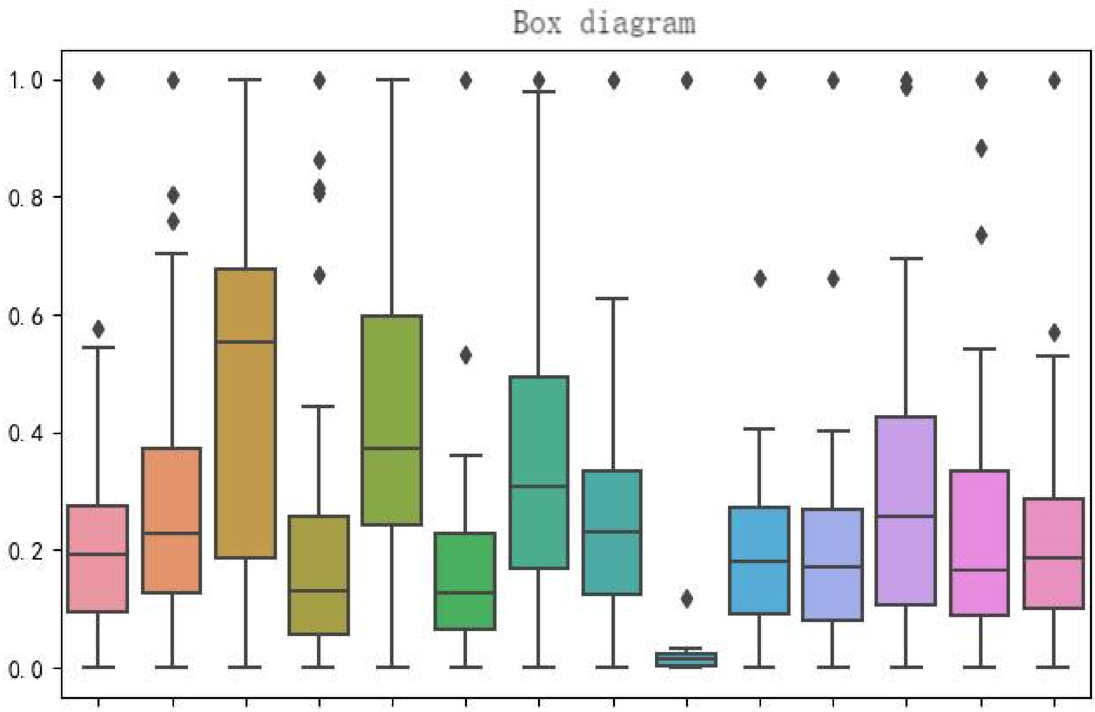

Figure 2 Data box plot

Figure 3 shows the distribution, outliers and abnormal values of data such as forest land area, forest covera ge, water resources and groundwater resources, which helps to understand statistical information such as the me dian, quartiles and extreme range of the data, and detect whether there are abnormal values in the data. I f there are abnormal values, they are processed: the median of the data is used to replace the abnormal value s.

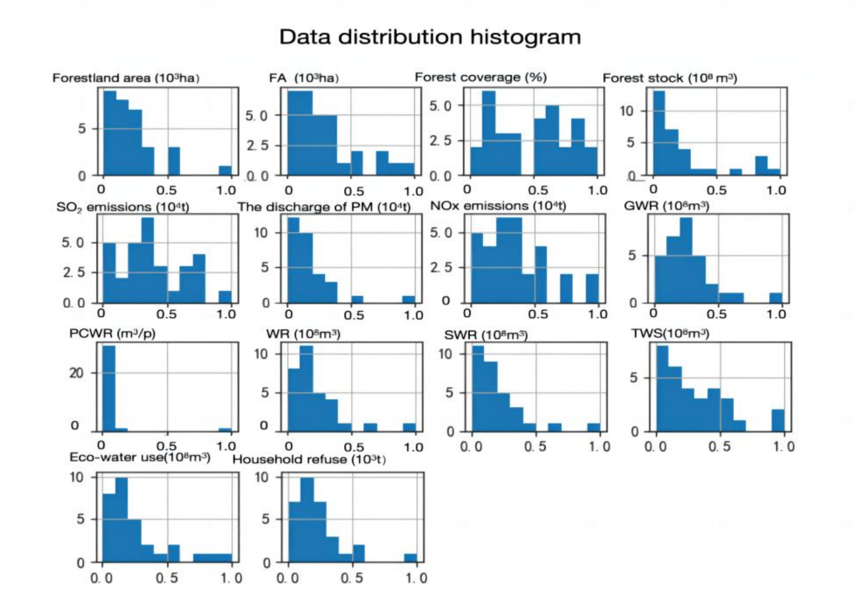

Figure 3 Data distribution histogram

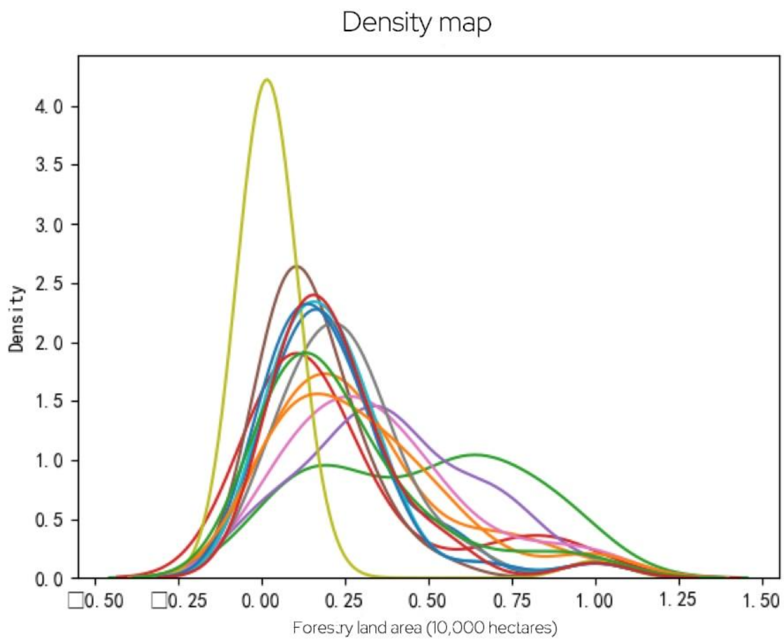

Figure 4 Data distribution density diagram

The histogram shows the distribution of data, reflecting the concentration and skewness of the data; the pr obability distribution diagram reflects the probability density distribution of the data, which can intuitively and cl early understand the overall shape and peak position of the data.

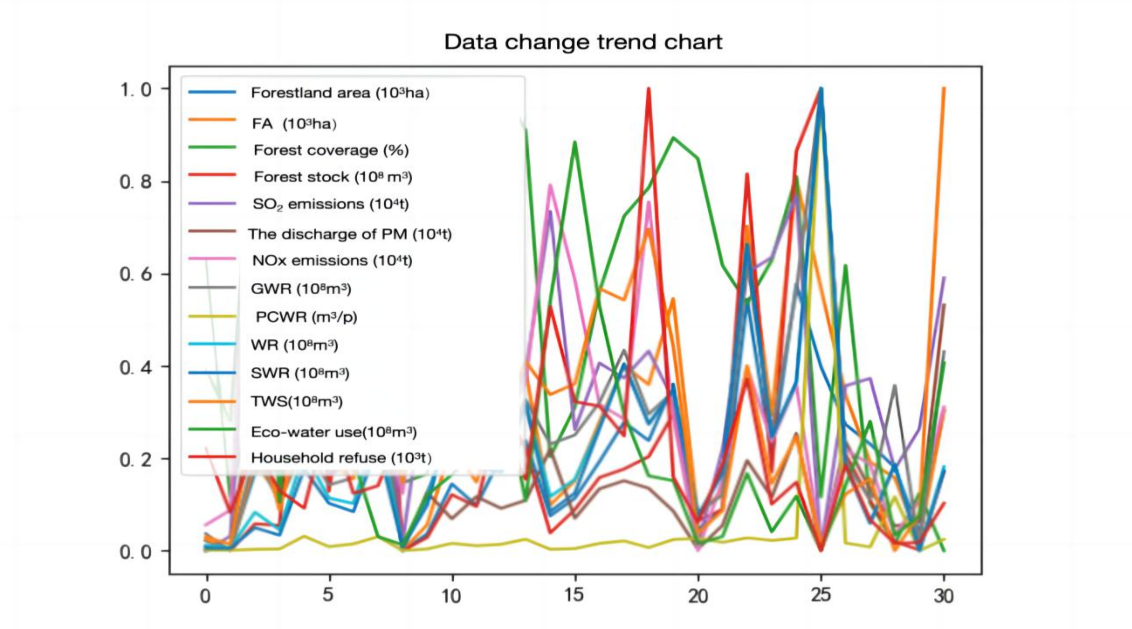

Figure 5 Data change trend chart

The above visualization analysis charts can intuitively analyze the distribution of data, the relationship betwe en indicators, and the existence of outliers. By observing charts such as box plots, histograms, and scatter plots, relevant information such as the central tendency, degree of dispersion, skewness, and anomalies of the data c an be found, and the data can be processed accordingly to facilitate subsequent modeling.

4.1.2. Result of correlation analysis of data

This study calculated the Pearson correlation coefficient between each variable, and then plotted the value of the correlation coefficient in a heat map, using the depth of color to indicate the strength of the correlation.

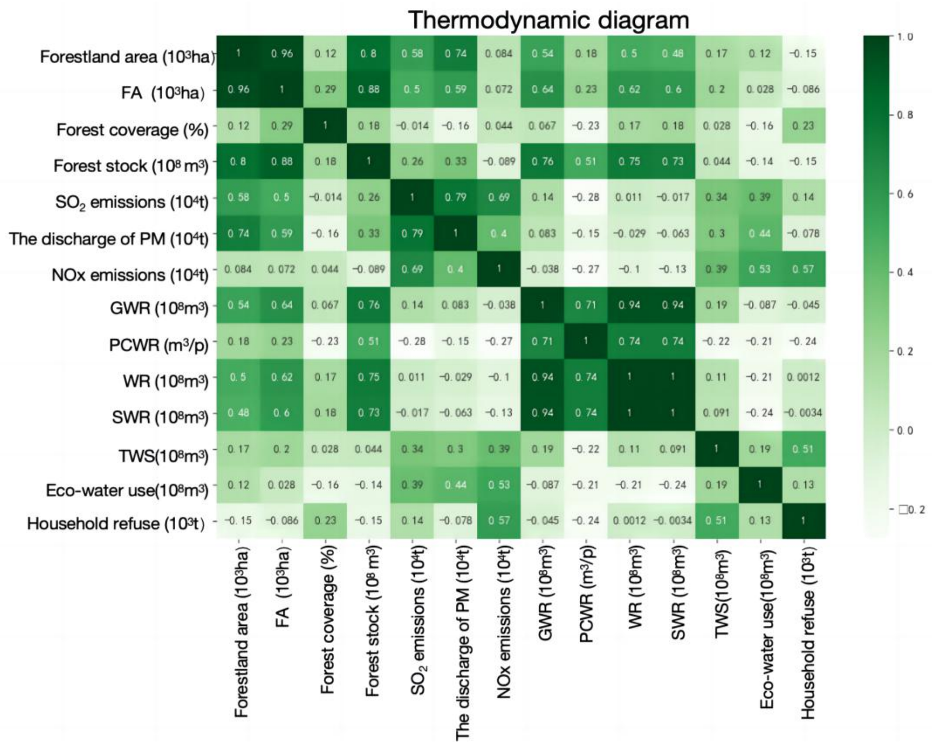

Figure 6. Heat map of correlation coefficients of various indicators

By observing the color intensity of the heat map, we can find the positive and negative correlations and strengths between indicators such as forest land area, forest coverage, water resources, and groundwater resources.

In summary, the preprocessing of the data set provides a data foundation and basis for the construction of the fuzzy comprehensive evaluation model. Based on the relevant results such as descriptive statistics, fuzzy evaluation indicators and membership functions can be designed, and a fuzzy comprehensive evaluation model can be established. The fuzzy evaluation results of each indicator are integrated through fuzzy logic operations to obtain the final evaluation results, which is also convenient for further improvement and optimization of the model.

4.1.3. Result of principal component analysis is used to reduce the dimension of data

Visual analysis can reveal the main patterns and relationships in the data, providing valuable information for the study of forestry and environmental issues.

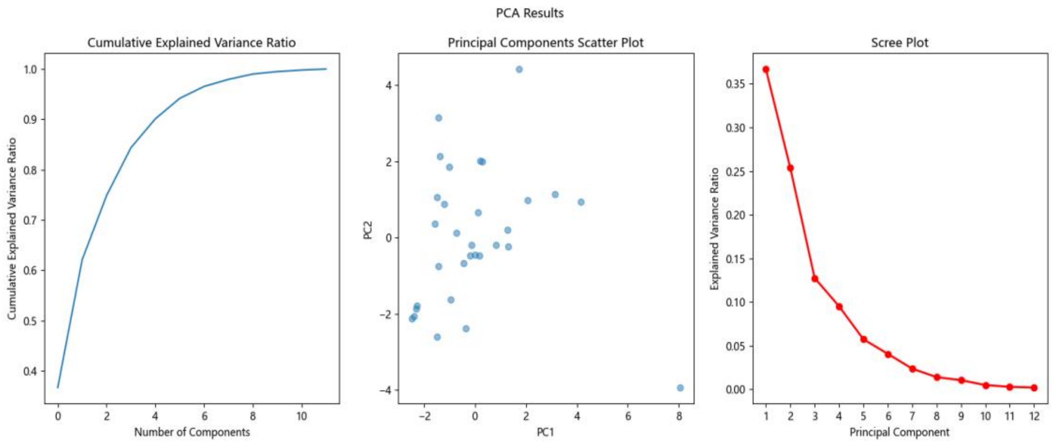

Figure 7 Dimensionality reduction results

PCA can extract the main patterns and relationships in the data, and achieve effective dimensionality reduction and visual analysis of the data. After dimensionality reduction, the data indicators selected are 12 typical representative results, including total water supply, total ecological water use, forest area, forest coverage, sulfur dioxide emissions, and particulate matter emissions.

5. Discussion

Different factors have different impacts on the ecological environment. In order to determine the best solution for the optimal urban ecosystem, this study used advanced technologies such as descriptive statistical analysis, principal component analysis, and T-SNE weight solution, combined with a comprehensive evaluation scheme based on DP dynamic programming and T-S fuzzy neural network, to achieve a comprehensive and accurate evaluation of the urban ecosystem.

5.1 weight solution based on T-SNE algorithm

After embedding t-SNE into two-dimensional space, we can see that the category information between data points is preserved. Then we can get the weight relationship of each factor:

Table 1 Results of t-SNE factor weights

INDEX	E-value	D-value	Weight (%)
Total water supply	0.895	0.105	7.45
Total ecological water consumption	0.871	0.129	8.627
Water resources per capita	0.487	0.513	33.176
Surface water resources	0.885	0.115	8.054
Total water resources	0.896	0.104	7.264

Forest area	0.991	0.009	6.864
Groundwater resources	0.918	0.082	5.816
Forest coverage	0.936	0.064	4.543
Forest volume	0.832	0.168	12.305
Sulfur dioxide emissions	0.974	0.029	2.519
Particulate emissions	0.984	0.016	0.874

Afterwards, the fused metrics are subjected to a Fi mapping exercise, which ultimately results in the degree of Fi for the different metrics.

5.2 weight adjustment based on GCC-PHAT and multi-frame weighted smoothing optimization

The adjusted weights as follow:

Table 2 Table of data weights for each indicator

Item	Information entropy value e	Information utility value d	Weighting(%)
Total water supply	0.897	0.103	7.01
Total ecological water consumption	0.873	0.127	8.622
Water resources per capita	0.484	0.516	35.137
Surface water resources	0.882	0.118	8.058
Total water resources	0.894	0.106	7.244
Forest area	0.899	0.101	6.864
Groundwater resources	0.915	0.085	5.816
Forest coverage	0.933	0.067	4.543
Forest volume	0.83	0.17	11.555
Sulfur dioxide emissions	0.969	0.031	2.083
Particulate emissions	0.987	0.013	0.877
NOx emissions	0.968	0.032	2.192

6. Conclusion and Suggestions

This paper establishes urban ecosystem indicators through t-SNE and GCC-PHAT algorithms. Through data di mensionality reduction, the main components, i.e. the main evaluation indicators, are forest ecosystem index, wa ter resource ecosystem index, and atmospheric ecosystem index. Therefore, urban ecological management should focus on these three ecosystems, such as actively protecting forest resources, maintaining forest carbon sinks, s aving and protecting water resources, rationally allocating water resources, and actively purifying the air. In the c orrelation analysis of indicators in this paper, it can be seen that there is a certain correlation between the indi cators, so the protection of various ecosystems must complement each other to achieve the best effect.

Based on DDP dynamic programming combined with T-S fuzzy neural network, this paper establishes an urb an ecosystem health assessment model for each city. Through our model, we have calculated the total scores of Beijing, Shanghai, Guangdong, Henan, Hebei, and Shanxi Province. It can be seen that the urban ecosystems of Beijing and Shanghai still need to be strengthened. By consulting the information, we found that the air polluti on in Beijing and Shanghai is relatively serious, so we must prescribe the right medicine to improve the entire urban ecosystem

REFERENCES

[1]Hu, W.; Liu, J. The Coupling and Coordination of Urban Modernization and Low-Carbon Development. Sustainability 2023, 15, 14335. https://doi.org/10.3390/su151914335.Yan, M., Zhao, J., Yan, S. et al.

[2]Coupling coordination of new urbanization in Chinese urban agglomeration—characteristics and driving factors. Environ Sci Pollut Res 30, 117082–117095 (2023). https://doi.org/10.1007/s11356-023-27469-1.

[3]Ran, C., Wang, S., Bai, X., Tan, Q., Wu, L., Luo, X., ... & Lu, Q. (2021). Evaluation of temporal and spatial changes of global ecosystem health. Land Degradation & Development, 32(3), 1500-1512.

[4]ao, R., Liu, Y., Fei, X., Yu, W., Zhang, Z., & Meng, Q. (2019). Ecosystem health assessment: A comprehensive and detailed analysis of the case study in coastal metropolitan region, eastern China. Ecological indicators, 98, 363-376.

[5]Su, M., Fath, B. D., & Yang, Z. (2010). Urban ecosystem health assessment: A review. Science of the total environment, 408(12), 2425-2434.
[6]Tolstykh, T., Gamidullaeva, L., Shmeleva, N., & Lapygin, Y. (2020). Regional development in Russia: An ecosystem approach to territorial sustainability assessment. Sustainability, 12(16), 6424.
[7]Qiao, W.Y.; Huang, X.J. The impact of land urbanization on ecosystem health in the Yangtze River Delta urban agglomerations, China. Cities 2022, 130, 103981.
[8]Ren, Y.; Zhang, F.; Li, J.; Zhao, C.; Jiang, Q.; Cheng, Z. Ecosystem health assessment based on AHP-DPSR model and impacts of climate change and human disturbances: A case study of Liaohe River Basin in Jilin Province, China. Ecol. Indic. 2022, 142, 109171.
[9]Abbaszadeh Tehrani, N.; Mohd Shafri, H.Z.; Salehi, S.; Chanussot, J.; Janalipour, M. Remotely-Sensed Ecosystem Health Assessment (RSEHA) model for assessing the changes of ecosystem health of Lake Urmia Basin. Int. J. Image Data Fusion 2022, 13, 180–205.
[10]Luo, W., Deng, Z., Zhong, S., & Deng, M. (2022). Trends, issues and future directions of urban health impact assessment research: a systematic review and bibliometric analysis. International Journal of Environmental Research and Public Health, 19(10), 5957.
[11]Peng, J., Liu, Y., Wu, J., Lv, H., & Hu, X. (2015). Linking ecosystem services and landscape patterns to assess urban ecosystem health: A case study in Shenzhen City, China. Landscape and Urban Planning, 143, 56-68.
[12]Yang, H.; Shao, X.; Wu, M. A Review on Ecosystem Health Research: A Visualization Based on CiteSpace. Sustainability 2019, 11, 4908. https://doi.org/10.3390/su11184908.
[13]Tett, P.; Gowen, R.; Painting, S.; Elliott, M.; Forster, R.; Mills, D.; Bresnan, E.; Capuzzo, E.; Fernandes, T.; Foden, J. Framework for understanding marine ecosystem health. Mar. Ecol. Prog. Ser. 2013, 494, 1–27.
[14]O' Brien, A.; Townsend, K.; Hale, R.; Sharley, D.; Pettigrove, V. How is ecosystem health defined and measured? A critical review of freshwater and estuarine studies. Ecol. Indic. 2016, 69, 722–729.
[15]Li, Z.; Xu, D.; Guo, X. Remote sensing of ecosystem health: Opportunities, challenges, and future perspectives. Sensors 2014, 14, 21117–21139.
[16]Su, M.; Fath, B.D.; Yang, Z. Urban ecosystem health assessment: A review. Sci. Total Environ. 2010, 408, 2425–2434.
[17]Londoño, N. A. C., Velásquez, H. I., & McIntyre, N. (2019). Comparing the environmental sustainability of two gold production methods using integrated Emergy and Life Cycle Assessment. Ecological Indicators, 107, 105600.
[18]Li, T., Song, Y. M., Li, A., Shen, J., Liang, C., & Gao, M. (2020). Research on green power dispatching based on an emergy-based life cycle assessment. Processes, 8(1), 114.
[19]Santagata, R., Zucaro, A., Fiorentino, G., Lucagnano, E., & Ulgiati, S. (2020). Develo** a procedure for the integration of Life Cycle Assessment and Emergy Accounting approaches. The Amalfi paper case study. Ecological Indicators, 117, 106676.
[20]Falahi, M., & Avami, A. (2020). Optimization of the municipal solid waste management system using a hybrid life cycle assessment–emergy approach in Tehran. Journal of Material Cycles and Waste Management, 1-17.

Fund: This work was supported by Humanities and Social Science Fund of Guangdong Province (Grant No. GD24CYJ45)