

Revealing the Risks of Light Pollution and Regional Governance Strategies

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Abstract. Light pollution impacts various environmental and human health aspects, necessitating a robust quantitative analysis for effective abatement. This investigation entailed an extensively systematic exploration of light pollution levels across 31 Chinese provinces and four earmarked zones, excluding Hong Kong, Macau, and Taiwan. We introduced a two-tier comprehensive examination index for light pollution utilizing the entropy weighting method-based TOPSIS model, generating a light pollution rating for each region. Coupled with a multitude of factors, specific abatement protocols were devised. Cluster analysis aided the demarcation of the regions into different risk levels, thus facilitating tailored interventions. Outcomes revealed that Shennongjia Scenic Area exhibited minimal light pollution, offering an excellent model for intervention strategy efficacy. Conversely, Hongqiao District in Shanghai suffered severe light pollution, warranting urgent interventional measures. Prioritizing urban lighting management, ensuring safety, and maintaining ecological protection emerged as the most effective strategies, underscoring the potential for tangible improvements in the management of light pollution.

Keywords: Light Pollution, TOPSIS, Cluster Analysis, Interventional Measures.

1. Introduction

Against the backdrop of increasing global urbanization, the increase in artificial light sources has exacerbated the light pollution problem, which has a wide range of impacts on ecosystems and human health. Although Yinghua Li et al^[1] quantitatively evaluated the light pollution risk by applying the TOPSIS comprehensive evaluation algorithm and decision tree method, Mengmeng Jiang^[2] combined the entropy weighting method and the TOPSIS method to comprehensively evaluate the light pollution risk in different regions, and Xianghe Liu and Zhengrui Zhang^[3] analyzed the influencing factors of light pollution in buildings and proposed corresponding interventions, these studies provide an important theoretical basis for the risk assessment and prevention and control strategies of light pollution. However, these studies have mainly focused on the development of evaluation methods and the application in specific areas or scenarios, with less consideration of the specific impacts of light pollution on different ecological and social environments and how to implement effective management measures in a wider context.

Therefore, this study aims to build on existing research by considering aspects that have not been adequately considered by other scholars, such as the impacts of light pollution on biodiversity, the long-term effects on human health, and the implementation of risk assessment and management measures at different types of sites, ranging from protected areas to urban areas. We propose an updated and optimized quantitative model that not only includes a more comprehensive system of evaluation indicators, but also incorporates the latest data and modular advances to improve the accuracy and efficiency of evaluation and management. In this way, we expect to provide more effective strategies and solutions for light pollution risk management and intervention. (Data sources: <https://www.stats.gov.cn/sj/ndsj/2023/indexch.htm>)

2. TOPSIS Model Based on Entropy Weight Method

2.1. Data Preprocessing

This paper establishes a universally applicable multi-indicator evaluation system for determining the level of light pollution at a given location. This paper focuses on light pollution levels in 31 provinces in China (except Hong Kong, Macau and Taiwan). From the five dimensions of light pollution causes, economic, social, health and ecology, 25 indicators were selected and the entropy-based TOPSIS model was used to evaluate and classify the light pollution level of a site. Finally, the evaluation system is applied to four types of areas, namely, protected land, rural areas, suburban areas and urban communities, to obtain three effective intervention strategies.

This paper selected 5 indicators to assess the level of Light Pollution. They are the causes of Light Pollution x_1 , Economic Aspects x_2 , Health Dimension x_3 , Social Level x_4 and Ecological Level x_5 .

Then, on the basis of these 5 indicators, this paper refines the relevant secondary indicators, which are 25 in total: Number of urban streetlights y_1 , Light Pollution Level y_2 , Light intensity at night y_3 , GDP per capita y_4 , Electricity consumption y_5 , Total retail sales of consumer goods y_6 , Population density y_7 , Total export amount y_8 , Urban villages & industrial & mining land y_9 , Number of hospital ophthalmology beds y_{10} , Number of hospital dermatology beds y_{11} , Sleepiness index y_{12} , Number of ophthalmologic emergencies y_{13} , Number of dermatologic emergencies y_{14} , Incidence of infectious diseases y_{15} , Crime rate y_{16} , Number of traffic accidents y_{17} , Emissions of nitrogen oxides from exhaust gases y_{18} , Rate of forest cover y_{19} , Soil erosion rate y_{20} , Average annual temperature y_{21} , Protected land area y_{22} , Measured quantity of rain y_{23} , Quantity of cloud y_{24} , Number of wildlife species y_{25} .

Since the entropy weighting method requires the use of normalized data after removing the effect of scale, and the evaluation of the degree of light pollution also requires the normalization of data. In this study, the attributes of 25 indicators were obtained through literature search^[4], this paper transforms all the indicators into very large indicators (the larger the value is, the more serious the degree of light pollution is), and the specific transformation method is as follows:

(1) Very Small Indicators into Very Large Indicators

For very small indicators y_n , i.e., the smaller the value of y_n , the more severe the level of light pollution. To transform it into a very large indicator, simply do the translation transformation $y'_n = M_n - y_n$, where $M_n = \max_{1 \leq m \leq 31} \{y_{mn}\}$ transforms the very small indicator y_n into a very large one.

(2) Intermediate Indicators into Very Large Indicators

For an intermediate type indicator series $\{y_n\}$, this study take the optimal value to be the median y_{best} in the same indicator data, then the normalization formula is as follows:

$$M = \max\{|y_n - y_{best}|\}, y'_n = 1 - \frac{|y_n - y_{best}|}{M} \quad (1)$$

(3) Standardize Normalized Data

For the positively normalized data, this study also need to carry out standardization, which is to remove the influence of the scale, the standardization process also needs to determine whether it is a non-negative matrix, non-negative standardized matrix specific transformation method is shown below: Existing $m = 31$ provinces to be evaluated, n ($n = 2, 3, 6$ or 8) evaluation indicators (have been forwarded) constitute the forwarding matrix Y' as follows:

$$\begin{bmatrix} y'_{11} & y'_{12} & \cdots & y'_{1m} \\ y'_{21} & y'_{22} & \cdots & y'_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ y'_{n1} & y'_{n2} & \cdots & y'_{nm} \end{bmatrix} \quad (2)$$

Then, the matrix standardized for this normalized data is denoted as Z, and each element in Z:

$$z_{ij} = y'_{ij} / \sqrt{\sum_{i=1}^m (y'_{ij})^2} \quad (3)$$

For the presence of negative numbers in the normalized matrix, it is necessary to use another normalization method for Y' to obtain the Z matrix with the normalization formula:

$$z_{ij} = \frac{y'_{ij} - \min\{y'_{1j}, y'_{2j}, \dots, y'_{mj}\}}{\max\{y'_{1j}, y'_{2j}, \dots, y'_{mj}\} - \min\{y'_{1j}, y'_{2j}, \dots, y'_{mj}\}} \quad (4)$$

2.2. Entropy Weighting Method for Determining Weights

By searching the literature, the following weights were obtained for the impacts of light pollution on five aspects: economic, health, social and ecological. The weightings are shown in Table.1.

Table.1. Weighting of the five aspects

Evaluation Indicators:	Causes of Light Pollution	Economic Aspects	Health Dimension	Social Level	Ecological Level
Weights:	0.55021	0.01115	0.00630	0.21219	0.22015

Next, the 25 evaluation indicators are divided into five parts, and then the weights corresponding to the 25 indicators are calculated in five times using the entropy weighting method, where the weight of the i th sample under the j th indicator is first calculated and used as the probability used in the relative entropy calculation. Now, there are $m=31$ provinces, n ($n=2, 3, 6$, or 8) evaluation indicators, and a non-negative normalized matrix Z with data preprocessing.

(1) Calculate the Probability Matrix P

The formula for each element P_{ij} in P is as follows:

$$p_{ij} = z_{ij} / \sum_{i=1}^n z_{ij} \quad (5)$$

(2) Calculation of Entropy Weights

The information entropy and information utility value of each indicator are calculated and normalized to get the entropy weight of each indicator. For the j th indicator, its information entropy is calculated as:

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^m p_{ij} \ln(p_{ij}) \quad (j = 1, 2, \dots, n) \quad (6)$$

For the information utility value, the larger the information utility value, the more information it corresponds to, so he is defined as: $d_j = 1 - e_j$. Finally, normalizing the information utility values gives the entropy weights for each internal quantity:

$$\omega_j = d_j / \sum_{j=1}^m d_j \quad (j = 1, 2, \dots, m) \quad (7)$$

The results of the entropy weighting method of light pollution level evaluation indicators are shown in Table.2, the top three primary indicators with the highest weights affecting the risk level of

light pollution are the causes of light pollution, the social and ecological aspects, and the top five secondary indicators are the number of urban streetlights, the intensity of lights at night, the number of traffic accidents, the crime rate, and the rate of water and soil erosion. These five indicators contribute a weight of 0.80367.

Table.2. Weighting and ranking of 25 indicators

Indicator number	Weight	Combined Weight	Ranking	Indicator number	Weight	Combined Weight	Ranking	Indicator number	Weight	Combined Weight	Ranking
y_1	0.6839	0.3763	1	y_{10}	0.1863	0.0012	20	y_{19}	0.1549	0.0341	8
y_2	0.0016	0.0009	21	y_{11}	0.1935	0.0012	18	y_{20}	0.1916	0.0422	5
y_3	0.3144	0.1730	2	y_{12}	0.1023	0.0006	22	y_{21}	0.1267	0.0279	10
y_4	0.0449	0.0005	23	y_{13}	0.1990	0.0013	17	y_{22}	0.0349	0.0077	12
y_5	0.1376	0.0016	16	y_{14}	0.2676	0.0017	15	y_{23}	0.1278	0.0281	9
y_6	0.1908	0.0022	14	y_{15}	0.0513	0.0003	25	y_{24}	0.1585	0.0349	6
y_7	0.0343	0.0004	24	y_{16}	0.2768	0.0587	4	y_{25}	0.0424	0.0093	11
y_8	0.4864	0.0056	13	y_{17}	0.7232	0.1535	3				
y_9	0.1059	0.0012	19	y_{18}	0.1633	0.0346	7				

2.3. TOPSIS Model

The score was calculated using the TOPSIS model based on the combined weights determined by the entropy weighting method, normalized and standardized data. The maximum value Z^+ and the minimum value Z^- are first defined as follows:

$$Z^+ = (Z_1^+, Z_2^+, \dots, Z_n^+) \quad (8)$$

$$= (\max\{z_{11}, z_{21}, \dots, z_{m1}\}, \max\{z_{12}, z_{22}, \dots, z_{m2}\}, \dots, \max\{z_{1n}, z_{2n}, \dots, z_{mn}\})$$

$$Z^- = (Z_1^-, Z_2^-, \dots, Z_n^-) \quad (9)$$

$$= (\min\{z_{11}, z_{21}, \dots, z_{m1}\}, \min\{z_{12}, z_{22}, \dots, z_{m2}\}, \dots, \min\{z_{1n}, z_{2n}, \dots, z_{mn}\})$$

Then the distance D_i^+ from the maximum value and the distance D_i^- from the minimum value of the i th ($i = 1, 2, \dots, m$) evaluation object are defined as follows:

$$D_i^+ = \sqrt{\sum_{j=1}^n \omega_j (Z_j^+ - z_{ij})^2} \quad (10)$$

$$D_i^- = \sqrt{\sum_{j=1}^n \omega_j (Z_j^- - z_{ij})^2} \quad (11)$$

Then, calculate the score for the i th ($i = 1, 2, \dots, m$) evaluator:

$$S_i = D_i^- / (D_i^+ + D_i^-) \quad (12)$$

Obviously $0 \leq S_i \leq 1$, and the larger S_i is the smaller D_i^+ is, i.e., the closer it is to the maximum value.

2.4. Cluster Analysis

The study used the K-means clustering algorithm, which iteratively optimizes the location of the centroid of each class cluster by reducing the total distance of the samples within the class from the center until the termination condition is met. In selecting the optimal number of clusters, this paper uses the elbow rule to assess the effect of the number of clusters on the overall degree of cohesion to determine the number of class clusters and maximize the accuracy of class clustering.

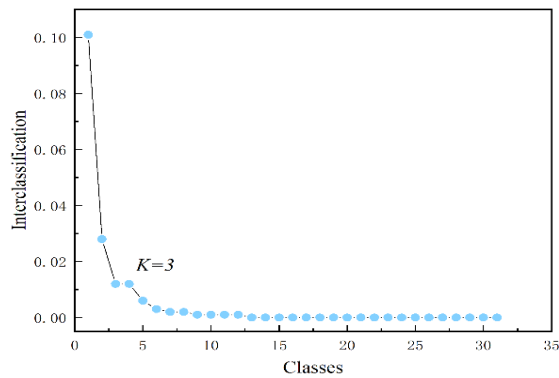


Fig 1. Clustered Elbow Chart

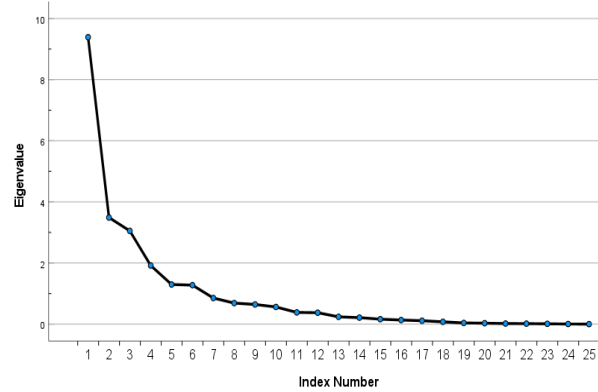


Fig 2. Gravel Chart

As shown in Fig 1, choosing K=3 as the number of clusters can achieve a better balance between the aggregation effect and the computational complexity, which is a more reasonable strategy for choosing the number of clusters.

Based on the spectrogram, the classification of 31 provinces was obtained and their light pollution levels^[5] were categorized as high (4 provinces), medium (8 provinces) and low (19 provinces).

Based on the classification and the light pollution scores calculated by the TOPSIS model in different categories, this study rates the light pollution risk level of the provinces whose light pollution scores are within the interval $[0, 0.3]$ as low, and the provinces within the interval $(0.3, 0.5]$ as medium, and the provinces within the interval $(0.5, 1]$ as high.

3. Assessing Light Pollution Levels in Four Types of Areas

3.1. Application of The Indicator System and The TOPSIS Model

To comprehensively evaluate the risk of light pollution and examine its specific impacts in different types of areas, this paper selects the following four representative areas as research objects based on the title's definition of four different types^[6]: Shennongjia Scenic Area, White Deer Plain Area, Haidian District, and Hongqiao District in Shanghai.

According to the data collected from the 25 indicators of the selected four areas and the comprehensive weights determined in the previous paper, this paper uses the TOPSIS model based on the entropy weighting method to calculate the scores of light pollution levels of these four areas as shown in Table.3. According to the interval of the light pollution levels obtained in the previous paper, we can rate Shennongjia Scenic Area as low, White Deer Plain Area and Beijing Haidian Area as medium, and Shanghai Hongqiao Area light pollution level as high. level is rated as high.

Table.3. Assessment results of light pollution levels in four diverse types of areas

Provinces	Scores	Light Pollution Level Rating
Shennongjialin	0.259903	lower
White Deer plains region	0.361325	medium
Beijing Haidian District	0.446242	medium
Shanghai Hongqiao District	0.740455	high

3.2. Interpreting the Results

Shennongjia Scenic Area scored 0.259903, a low score indicating that its light pollution is relatively mild, and thus the area is categorized as "mildly light-polluted". This is in line with the nature of the area as a natural forestry reserve, with lush natural vegetation and relatively little artificial lighting, keeping the night sky in a more natural state^[7].

The scores for the White Deer Plain and Beijing Haidian District are 0.361325 and 0.446242 respectively, both in the middle range, and they are categorized as "moderately light-polluted areas". This means that although there is significant artificial lighting, light pollution is not particularly severe. Such areas require proper monitoring and management to prevent light pollution from worsening.

Shanghai Hongqiao, with a score of 0.740455, scored higher than the other areas with significant levels of light pollution, and was therefore rated as a "severely light-polluted area". The result reflects the increase in artificial light due to regional development, transportation hubs and commercial concentration, and calls for proactive measures to mitigate the effects of light pollution.

4. Intervention Strategies Using Factor Analysis

4.1. Factor Analysis

To comprehensively assess the risk level of light pollution in different locations^[8], this study used factor analysis to extract the main influencing factors from many indicators. Data preprocessing included descriptive statistics and correlation tests to ensure that sufficient correlations existed between variables. The suitability of the data was verified by KMO and Bartlett sphericity tests.

(1) KMO and Bartlett's Test of Sphericity

In this paper, the selected indicators are first analyzed by SPSS software, and the results show that the KMO sample fitness is 0.979, which is much higher than the benchmark value of 0.6 that is usually considered suitable for factor analysis, and at the same time, according to the test of Bartlett's sphericity, it indicates that the sample data are very suitable for factor analysis. The results are summarized in the Table.4:

Table.4. KMO and Bartlett's test of sphericity

KMO Quantity of Sample Suitability		0.979
Rough Chi-square		841.171
Bartlett's test of sphericity	Degrees of Freedom	300
Significance		0.0001

(2) Number of Factors to Be Determined

After the KMO and Bartlett's test of sphericity indicated that the data were suitable for factor analysis, the paper further determined the number of factors that should be included in the analysis.

Table.5. Total Variance Explained

Component	Extract the sum of the squares of the loads			Rotational load sum of squares		
	Total	Percentage of variance	Accrue %	Total	Percentage of variance	Accrue %
1	9.391	37.565	37.565	7.834	31.338	31.338
2	3.489	13.956	51.521	4.107	16.428	47.766
3	3.051	12.206	63.727	2.865	11.458	59.224
4	1.918	7.673	71.400	2.639	10.558	69.782
5	1.298	5.192	76.592	1.490	5.960	75.742
6	1.277	5.108	81.700	1.490	5.958	81.70

Combining the results of the analysis of the total variance explained Table.5 and the Fig 2, it was determined that it would be most appropriate to include 6 factors ($N = 6$). These 6 factors, while

they are located before the inflection point on the gravel plot, indicate that they play a key role in explaining the variance of the raw data.

(3) Determine The Component Matrix & Named Factors^[9]

Factor I - Urbanization and Sanitation Demand Factor: Aggregates indicators such as electricity consumption (0.930), urban villages and industrial and mining land (0.891), which highly maps the integrated impact of urbanization process on energy consumption, land planning and lighting demand. Factor II - Natural Environment and Climate Factor: Combined with the characterization of precipitation depth (0.860) and forest cover (0.833), it carefully depicts the possible contribution of natural meteorological conditions and environmental quality to light pollution.

Factor III - Economic Development Factor: Centered on GDP per capita (0.728) and total exports (0.704), it reveals an economic perspective on the correlation between regional economic vitality and light pollution.

Factor IV - Public Health Indicator Factor: Closely linked to the incidence of infectious diseases (0.855) and dermatology medical service indicators, reflecting the health effects of light pollution and the potential impact on medical resources.

Factor V - Population and quality of life factor: Combining population density (0.887) and sleep index (0.756), reflecting the interaction between population distribution and nighttime light impacts.

Factor VI - Nighttime Lighting Intensity Factor: A single indicator, Nighttime Lighting Intensity (0.891), serves as the main component in evaluating this factor, clearly defining the direct impact of lighting intensity on light pollution risk levels.

4.2. Three Intervention Strategies

(1) Intervention Policy I: Urban Lighting Management Improvement

Retrofit existing urban street lighting^[10] by reducing the number of streetlights to reduce energy consumption and decrease light pollution caused by lighting. Implement strict lighting design standard. Strengthen traffic lighting safety guidelines to match light intensity with traffic requirements to reduce nighttime driving accidents.

(2) Intervention Policy II: Urban Safety and Lighting Standards

Integrate urban planning to provide appropriate and more efficient lighting for high crime areas while reducing non-essential over-lighting. Increase crime suppression rates through additional surveillance and increased intensity of nighttime patrols, as well as improve residents' sense of security through community lighting programs.

(3) Intervention Policy III: Ecological Conservation and Land Management

Optimize urban industrial and mining land use planning, implement green lighting policies, limit the impact of lighting on natural areas, and protect ecosystems from light pollution. Strengthen vegetation restoration and water conservation projects in erosion-sensitive areas to reduce the aggravation of light pollution by land degradation.

5. Controlled Modeling of Indicators for Two Regions

5.1. Controlled Experiments

Changes in light pollution scores were observed by varying the raw data for these indicators, e.g., by reducing 100,000 city streetlights or by decreasing the nighttime light intensity by 5lux each time. A total of 10 charts, one for each indicator in each region, have been produced to visualize the trend of light pollution scores during successive adjustments. This paper shows Score maps for only the two indicators that have the greatest impact on the two regions. As in Fig 3 and Fig 4.

(1) Shennongjia Scenic Area Intervention Policy

In the Shennongjia Scenic Area, it is particularly important to implement intervention policy III: ecological protection and land management. Through a series of controlled experiments, this study learned that when the soil erosion rate was reduced to 5.8%, the light pollution level score was significantly reduced to 0.190. This effect indicates that strengthening ecological protection and

optimizing land management are crucial for reducing light pollution in this scenic area, and the effectiveness is confirmed. The relevant values are specified in Fig 3:

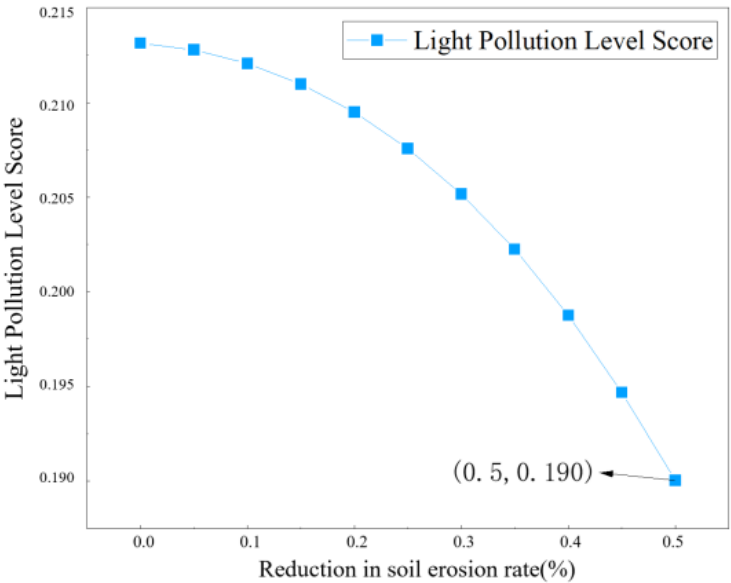


Fig 3. Score map of Shennongjia Scenic Area when changing the rate of soil erosion

(2) Shanghai Hongqiao District Intervention Policy

In Hongqiao District, Shanghai, the effect of Intervention I: Urban Lighting Management Improvement is more prominent. Our analysis shows that when the number of streetlights in the city is reduced to 309,000, the light pollution score is reduced to 0.442. Adjusting traffic lighting and optimizing safety standards will also help reduce nighttime accidents, with the light pollution score dropping to 0.512 when the number of accidents is reduced to less than 500, as shown in Fig 4:

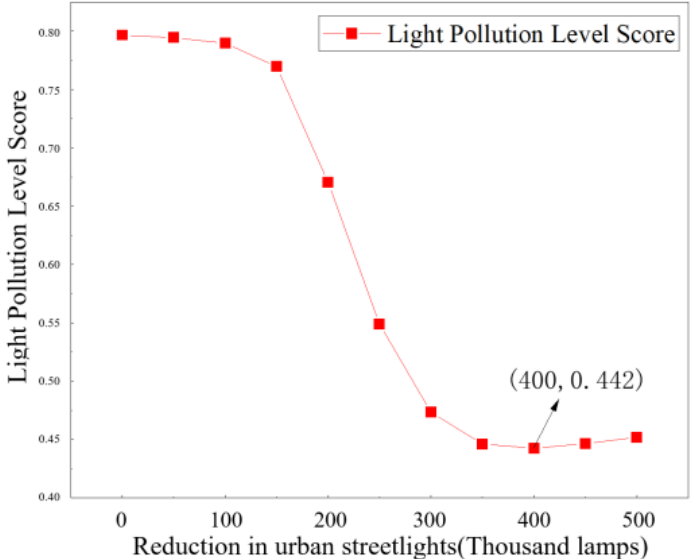


Fig 4. Score map of Shanghai Hongqiao District when changing the number of city street lights

6. Conclusions

In this study, a series of data analysis methods were used to develop Through these methodological tools, we developed a widely used indicator system, namely the Light Pollution Level II Comprehensive Assessment Indicator System, which in turn succeeded in comprehensively assessing the light pollution situation in four different types of areas. The results of the model application show that light pollution levels are influenced by a variety of factors, and three management strategies are finally proposed.

References

- [1] Li Yinghua, Xie Jingya, Gu Huayu, et al. Design of Mathematical Models for Assessing Light Pollution Risk and Strategy Evaluation [J]. *Software*, 2023, 44(8): 133-138.
- [2] Jiang Mengmeng. Evaluation of Light Pollution Risk Level Based on Entropy Weight Method and TOPSIS Method [J]. *Lighting & Light Source*, 2023, (6): 40-42.
- [3] Liu Xianghe, Zhang Zhengrui. Influencing Factors and Intervention Strategies for Architectural Light Pollution [J]. *Lighting & Light Source*, 2023, (6): 36-39.
- [4] Luo Zhenqing, Su Hang, Wang Zhuoli, et al. Urban Lighting Planning and Dynamic Light Pollution Grading in Nighttime Light Environment [J]. *Journal of Lighting Engineering*, 2022, 33(4): 193-202.
- [5] Wang Kuan. On the Value of Natural Night and Its Realization - An Analysis of a New Path for Light Pollution Control [J]. *Communications in Natural Dialectics*, 2023, 45(12): 80-87.
- [6] Li Yinghua, Xie Jingya, Gu Huayu, et al. Design of Mathematical Models for Assessing Light Pollution Risk and Strategy Evaluation [J]. *Software*, 2023, 44(8): 133-138 (Duplicate entry, possible citation error).
- [7] Wang Dongxu, Ma Long, Jiao Zhilin, et al. Analysis and Prevention Strategy Study of Light Pollution Degree Based on Entropy Weight-TOPSIS Method [C] // CPC Shenyang Municipal Committee, The Government of Shenyang. Proceedings of the 20th Shenyang Science and Academic Annual Conference - Second Prize Papers. College of Civil Engineering, College of Science and College of Transportation & Surveying Engineering, Shenyang Jianzhu University, 2023: 6.
- [8] Xiong Ruiyu, Chen Zheng. A Review of the Impacts of Night-time Light Pollution on All Health and Key Thresholds [J]. *Chinese Landscape Architecture*, 2023, 39(2): 32-37.
- [9] Huang Ruixue, Guo Yijiao, Zhang Dingling, et al. Current Status and Suggestions of Nighttime Light Pollution in Main Urban Residential Areas of Chongqing [J]. *Lighting & Light Source*, 2022, (11): 5-7.
- [10] Wang Zhide, Yuan Jingyu, Yao Sheng, et al. Research Status of Light Pollution Caused by Artificial Lighting at Night [J]. *ZHAOMING GONGCHENG XUEBAO*, 2021, 32(03): 94-99.