The evaluation model of light pollution degree based on Topsis method

Sibei Liu [1], Xinkai Liang [2], Yumeng Yang [3], Changsheng Zhang [4, *]

[1] College of Business Administration, Northeastern University, Shenyang, Liaoning, 110167

[2] College of Science, Northeastern University, Shenyang, Liaoning, 110004

[3] College of Mathematics and Statistics, Huazhong Normal University Wuhan, Hubei, 430079

[4] College of Software, Northeastern University, Shenyang, Liaoning, 110167

* Corresponding author: zhangchangsheng@mail.neu.edu.cn

Abstract. Light pollution is an environmental problem that arises along with the economic development of modern society. To explore the influencing factors of light pollution degree, firstly, the evaluation indicator system was constructed. The system modified by factor analysis, then entropy weight method and multiple linear regression are used to calculate the weight values of factors respectively, and the comprehensive score index of 271 prefecture-level cities in China is obtained by substituting into TOPSIS. And K-Means++ clustering is performed on the scores to derive the grade classification boundary values, thus dividing the degree of light pollution into five criteria. Then the 271 prefecture-level cities in China are divided and visualized by the two rating systems, and the advantages and disadvantages are analyzed by comparing with satellite images. And the DN values were calculated with the composite score series derived from the two models separately to calculate the spearman coefficients, and the results showed a better fit of the multivariate linear TOPSIS. This article applies the superiority rating system of the previous work, selects four representative areas from each of the four scenarios with different levels of light pollution, calculates their comprehensive score index, and adopts the light pollution level classification and cause analysis. The results show that light pollution is very low in conservation land locations, low in rural communities, medium in suburban communities, and high in urban communities.

Keywords: Light pollution, TOPSIS method, multiple linear regression.

1. Introduction

The concept of light pollution was first introduced by experts in the international astronomical community. Astronomers found that the increased brightness of the sky during night lighting in cities had a negative impact on astronomical observations. So, they called this light that enters the environment and hinders their astronomical observations due to night lighting light pollution. Light pollution is an environmental problem that arises along with the economic development of modern society. This phenomenon exists not only at night in large cities, but also in remote places, but its extent varies depending on geographic location, population density, level of urban development, climate, and other factors. Light pollution has become a very important environmental public health problem. It not only endangers human health, threatens traffic safety, but even affects the normal survival of plants and animals.

As the harm of light pollution is multifaceted, and light pollution protection and treatment work has not been included in the agenda of environmental protection work. In order to protect the human body and the sustainable development of the biological environment, it is necessary to study the factors affecting light pollution, to develop criteria for measuring its extent, and to propose intervention strategies. This brings relevance to the study this article conducts below.

Entropy-TOPSIS method, which has a strong objectivity in determining index weights, is not affected by sample size and can accurately reflect the differences among evaluation objects [1]. Therefore, the evaluation strategy combining entropy weighting method and TOPSIS method has been widely applied to the decision-making system containing multiple evaluation indexes. For example, Tian Fujin et al, based on water quality data from 88 monitoring sections in the Xin'an River

basin, used a combination of principal component analysis and entropy weighting method to evaluate the water quality status of the basin [2]. Yang Yujin et al. used Taguchi analysis to identify key factors affecting urban air pollutant emissions and metabolic system health, and combined entropy weight TOPSIS evaluation method to determine the optimal mitigation policy [3]. Rong-Hua Envy et al. used the entropy-weight-TOPSIS method to comprehensively evaluate the functional properties of edible mushroom polysaccharides using in vitro antioxidant activity and hypolipidemic function as evaluation indexes. The quality of edible mushroom polysaccharides was comprehensively evaluated and ranked, and the samples were classified by cluster analysis [4]. From the perspective of capital circulation, Zhang Xiaojie et al. selected 12 financial indicators in four categories of risk: financing, capital recovery, investment and cash flow, and established a quantitative model to evaluate the financial risk by the entropy-TOPSIS method [5]. Salehi et al. applied the entropy-TOPSIS method to the crisis management system of five petrochemical plants to assess and rank their risks at the plant management level, employee level, and technology level, respectively [6].Liu et al. evaluated the carbon market maturity of seven cities in China through the entropy-TOPSIS method in three dimensions, and the study found that the Hubei market ranked the highest and the Chongqing market ranked the lowest [7]. The above study shows that the entropy-weight-TOPSIS evaluation method is not only effective in determining the weight values of each evaluation index when dealing with evaluation problems containing multiple objectives, but also in ranking the evaluation objects in terms of merit. Therefore, in this study, by introducing the entropy-weight-TOPSIS evaluation method, the level of light pollution consisting of key influencing factors determined by factor analysis is evaluated.

To solve this question, two light pollution degree evaluation systems were constructed [8] by multivariate linear TOPSIS and entropy-weighted TOPSIS models [9], and reliability analysis was performed [10]. For the better-performing multivariate linear TOPSIS, Select four specific locations [11], substituted into the evaluation model, scores were calculated, classification was made with reference to the rating system, and reasons were discussed.

2. The evaluation model of light pollution degree based on Topsis method

2.1. Selection of main evaluation indicators

By summarizing and combing the literature related to light pollution factors, it is found that the degree of light pollution may depend on the development level, population, biodiversity, geography, and climate of the site. And it can have an impact on factors such as plant maturity, human biological clocks, motor vehicle accident rates and crime rates. In summary, from the four perspectives of economic development level, urban construction level, population level and climate situation, 18 indicators were specifically selected for analysis, and the indicator system is as figure 1:

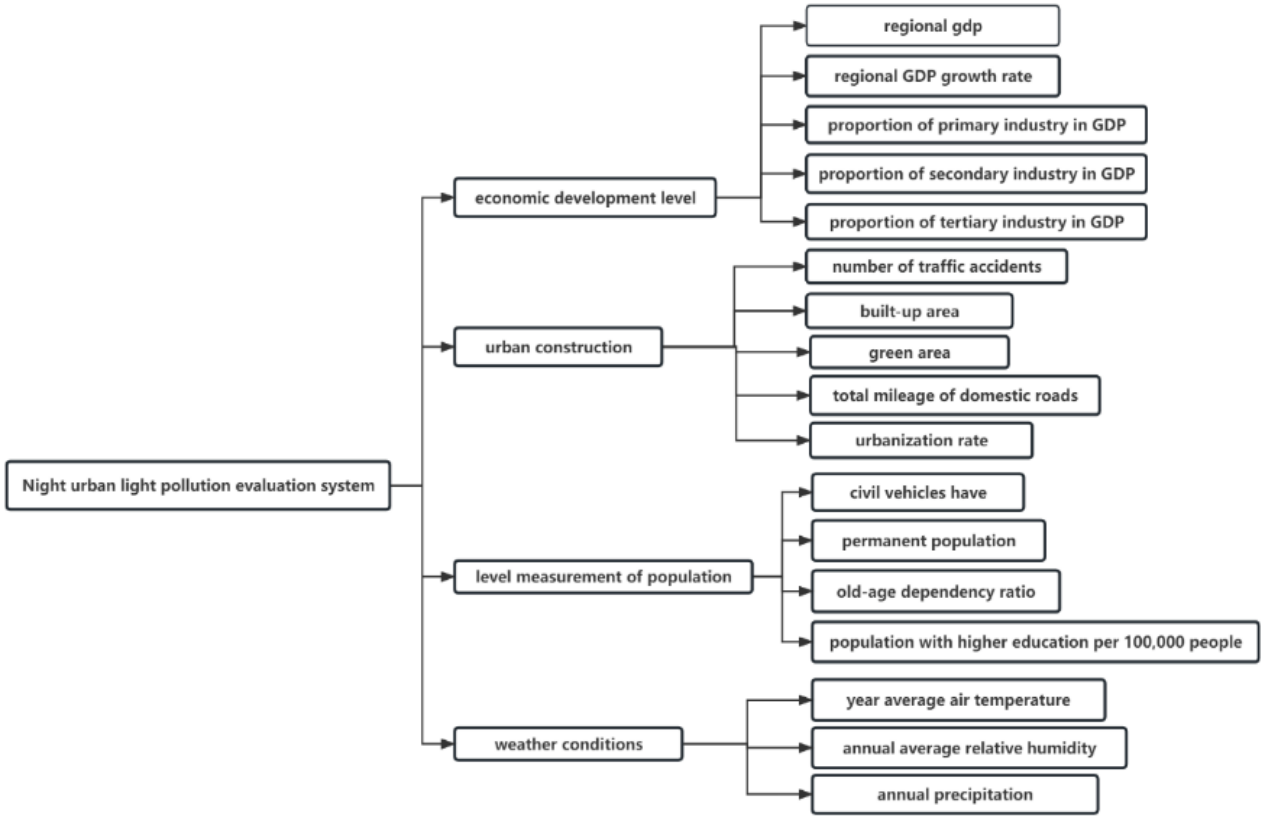

Figure 1. Light pollution evaluation indicator system

2.2. Selection of data

In this paper, the data of the above 18 indicators of 271 prefecture-level cities in China in 2020 were selected through the website of China Bureau of Statistics and China Meteorological Network. The nighttime lighting index data in 2020 were also obtained. The global remote sensing image data of DMSP/OLS source in 2020 are selected here. Here this article use the image DN value to represent the average light intensity, which ranges from 0-63, and this value is also used as an indicator of the light pollution level in this paper.

2.3. Establishment of the evaluation model of light pollution degree

2.3.1. Factor Analysis

The standardized data were subjected to dimensionality reduction and factor analysis as evaluation indicators. The 18 indicators with intricate relationships were synthesized into a smaller number of 8 factors. The factor analysis model building process is as follows.

Assume that the random vector $x=(x1x2,\cdots,xp)'$of size n×p has mean $u=(u1,u2,\cdots up)'$The covariance matrix $\Sigma p\times p=(\sigma ij)$. The general model of the factor analysis is:

$$\begin{cases} x_1 = u_1 + a_{11}f_1 + a_{12}f_2 + \ldots + a_{1m}f_m + \varepsilon_1 \\ x_2 = u_2 + a_{21}f_1 + a_{22}f_2 + \ldots + a_{2m}f_m + \varepsilon_2 \\ \vdots \\ x_p = u_2 + a_{p1}f_1 + a_{p2}f_2 + \ldots + a_{pm}f_m + \varepsilon_p \end{cases} \quad (1)$$

In this model, $f_1, f_2, \cdots, f_m$ are called common factors, $\varepsilon_i (i = 1,2, \cdots, p)$ is called special factor, they are unobservable random variables. Common factors $f_1, f_2, \cdots, f_m$ appear in the expression of each original variable $x_i (i = 1,2, \cdots, p)$,that can be understood as certain characteristics shared by the

original variables (with common influences).Each special factor $\varepsilon_i(i = 1,2, \cdots, p)$appears only in the expression corresponding to the i-th original variable, and it works only on this original variable. The above equation we can write in matrix form as:

$$x = u + Af + \varepsilon \tag{2}$$

Before utilizing factor analysis, this article first performed KMO hypothesis test, Bartlett's ball check test on the data and the results are as table 1.

Table 1. KMO and Bartlett's test results

KMO	Bartlett's test
0.684	.000

In the KMO test, the value of the quantity is about 0.7, which is a large value, and it can be considered that the correlation between the variables is generally strong; the p-value in the Bartlett test is less than 0.05, so the original hypothesis can be rejected, and it is considered that the correlation coefficient cannot be a unit array, indicating that the variables are significantly correlated with each other, which in summary indicates that the original indicators are suitable for factor analysis.

2.3.2. Indicator Weights

1) Entropy method

In order to avoid the interference of human subjective factors, this model uses the entropy weighting method to determine the weights of each factor. The calculation steps are specified as follows:

Establish the original evaluation matrix: with m evaluation objects, n evaluation indicators, and x_{ij} as the i-th city under the j-th indicator(m=271; n=8), the multi-objective decision matrix formed is Eq.(3):

$$X = (x_{ij})_{m\times n} \tag{3}$$

Establish normalized decision matrix: there are four positive and four negative factors among the eight factors of light pollution degree. Therefore, the original values of indicators are homogenized by polarization method to obtain r_{ij}, which can avoid the bias of data analysis.Refer to equation (4) for processing.

$$r_{ij} = \frac{x_{ij}-min(x_j)}{max(x_j)-min(x_j)}; r_{ij} = \frac{max(x_j)-x_{ij}}{max(x_j)-min(x_j)} \tag{4}$$

Construct the weighted decision matrix: multiply the normalized decision matrix with the weights w_j with each indicator to construct the weighted decision matrix equation Z_{ij}, The calculations are as follows:

$$Z_{ij} = (w_j \times r_{ij})_{m\times n} \tag{5}$$

Define entropy e_j:

$$e_j = -\frac{1}{lnm}(\sum_{j=1}^{m} f_{ij} ln f_{ij}) \tag{6}$$

In The formula: m = 271;

$$f_{ij} = \frac{1+r_{ij}}{\sum_{j=1}^{n}(1+r_{ij})} \tag{7}$$

Define entropy weight w_j: The entropy weight of the j-th evaluation index is defined as equation (7), in the formula n=8;

$$w_j = \frac{1-e_j}{m-\sum_{j=1}^{n} e_j} ; \sum_{j=1}^{n} w_j = 1 \tag{8}$$

2) Multiple linear regression method

In this paper, the DN value of nighttime light images is used as an indicator to measure the degree of light pollution, and thus, when determining the indicator weights, a multiple linear regression approach can be innovatively used to estimate the weight values. With m evaluation objects and n evaluation indicators (m=271; n=8), the model is equation (9)

$$DN_i = \alpha + \sum \beta_j x_j + \mu_i \qquad j = 1, 2, 3 \ldots 8 \tag{9}$$

α is a constant term, β is the regression coefficient of each factor, μ_i is a perturbation term.

In this method, the regression coefficient βj of the j-th evaluation index is used as the weight w_j for the solution of TOPSIS method.

2.3.3. Comprehensive evaluation of light pollution level based on TOPSIS method

With $X_{i,j}$denoting the light pollution of 271 prefecture-level cities in China, with i = 1, 2, 3, ..., 271 denoting the 271 prefecture-level cities in China, and j = 1, 2, 3 ... 8 denoting the eight factors after factor analysis, respectively. The weight $W_i$of each factor in the overall program evaluation can be calculated in the previous step, so the linear weighting method can be directly used to determine the weighted light pollution degree data $A_{j,i}$using Equation (10). The specific equation is as follows.

$$A_{j,i} = W_i \cdot X_{i,j} (i = 1,2,3, \ldots ,271; j = 1, \ldots ,8;) \tag{10}$$

Based on the above weighted light pollution level data, the positive ideal solution A^+ for the 8-item factor can be determined according to Equation (11), and the negative ideal solution A^-can be determined according to Equation (12).

$$\begin{aligned} A^+ &= (max(A_{ij})) = [A_1^+, A_2^+, \ldots A_m^+]; \\ A^- &= (min(A_{ij})) = [A_1^-, A_2^-, \ldots, A_n^-] \end{aligned} \tag{11}$$

Determine the distance and closeness of each evaluation object to the ideal solution: the positive ideal solution distance is D_i^+, the negative ideal solution distance is D_i^-, the comprehensive evaluation index is E_i, and the light pollution degree is evaluated according to the magnitude of E_i value. The calculation formulas are as Equation (12):

The TOPSIS model workflow is shown in Figure 2.

$$\begin{gathered} D_i^+ = \sqrt{\sum_{j=1}^{n} (A_{ij}^+ - A_{ij})^2}; D_i^- = \sqrt{\sum_{j=1}^{n} (A_{ij}^- - A_{ij})^2} \\ E_i = \frac{D_i^-}{D_i^- + D_i^+} \end{gathered} \tag{12}$$

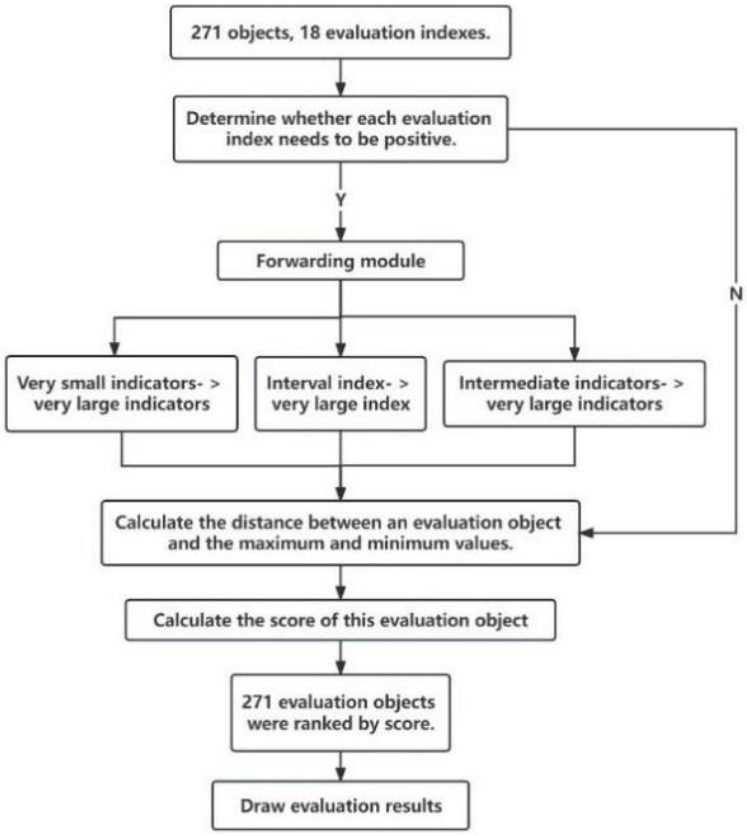

Figure 2. TOPSIS Model workflow diagram

2.4. Results and analysis of light pollution degree evaluation model based on Topsis method

2.4.1. Factor analysis results

The raw test data were standardized using SPSS AU and the correlation coefficient matrix was obtained (Figure 3), from which it can be seen that the correlation coefficient between many variables is greater than 0.5, and the correlation coefficient between built-up area and gross regional product reached 0.85, which indicates that the correlation between several indicators is strong and there is a certain degree of overlap, which is suitable for dimensionality reduction using factor analysis. The eigenvalues, principal component contribution rates and cumulative contribution rates derived from the factor analysis method are shown in Figure 4.

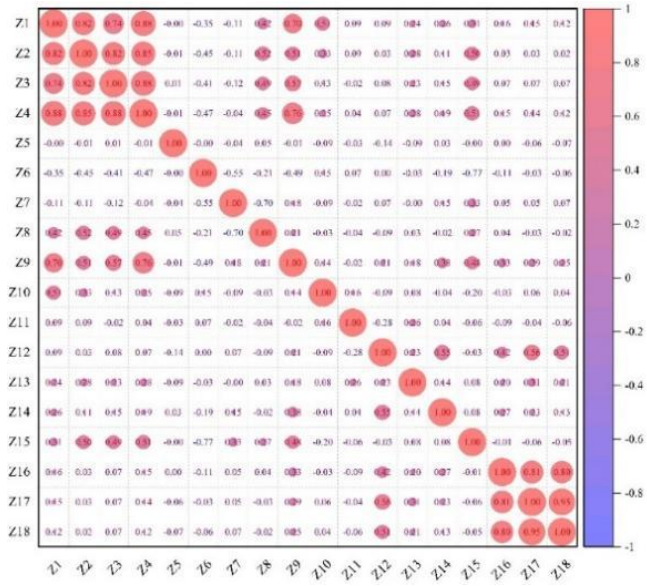

Figure 3. Correlation coefficient matrix

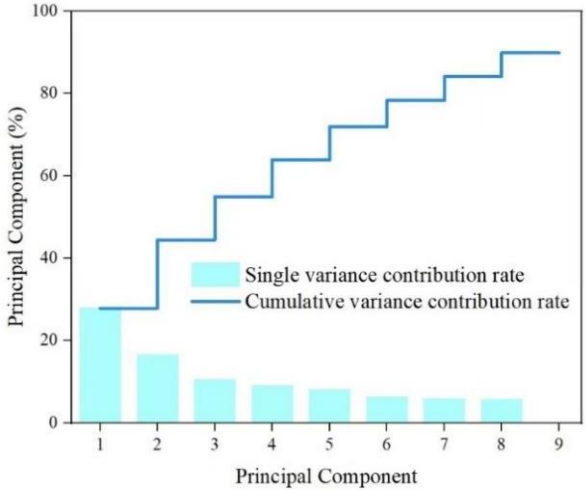

Figure 4. Factor analysis results

According to the factor analysis method, the factors with the squared rotational loadings (λ) greater than 1 are counted as factors. Figure 3 shows that there are 8 factors when λ>1: λ1=5.02, λ2=2.98, λ3=1.893, λ4=1.61, λ5=1.459, λ6=1.136 λ7=1.056, λ8=1.027. The cumulative variance contribution rate is 89.9%. Considering the large number of samples (271) and indicators (18) involved in the evaluation of this study, and the difficulty of extracting the common factors, the cumulative contribution rate of 89.9% is regarded as an acceptable range, which basically contains the main information of the original indicators.

According to the rotated component matrix obtained from factor analysis, factor 1 has high positive loadings on regional population, built-up area, regional GDP, number of enterprises and urbanization rate, which can be interpreted as regional development level factor; factor 2 has high positive loadings on regional average annual temperature, average annual relative humidity and annual precipitation, which can be interpreted as regional humidity and heat factor; factor 3 has high negative loadings on regional secondary industry and high positive loadings on regional tertiary industry. Factor 3 has a high negative load on the secondary industry and a high positive load on the tertiary industry, indicating that the region puts more emphasis on the tertiary industry, i.e. service industry, and does not rely on the secondary industry for development, which can be interpreted as the soft power factor of the region; Factor 4 has a high negative load on the urbanization rate of the region, which can be interpreted as the ruralization factor of the region; Factor 5 has a high positive load on the locomotive ownership and the number of traffic accidents in the region, and the higher locomotive The higher locomotive ownership indicates the higher degree of transportation in the region, and the higher degree of transportation is often the fundamental factor for the increase of traffic accidents, so it can be interpreted as the regional transportation factor; factor 6 has a high positive load on the dependency ratio of the elderly population in the region, and the more serious aging phenomenon indicates that the proportion of young people in the region is less, and the demand for light is lower, so it can be interpreted as the regional population aging factor; factor Factor 7 has a high positive load on the proportion of regional population with education, which can be interpreted as the regional population quality factor; Factor 8 has a high positive load on the regional GDP growth rate, which can be interpreted as the regional economic vitality factor.

2.4.2. Entropy-weighted TOPSIS analysis

1) Entropy method to calculate weighting coefficients

The weights indicate the importance of each indicator in the comprehensive evaluation process, and the final entropy weight is obtained after the calculation of entropy values for the eight factors calculated above. The calculation results are shown in Table 2.

Table 2. Entropy weighting method

Entropy method			
item	information entropy value e	information utility value d	weights (%)
1	0.945	0.055	37.122
2	0.978	0.022	14.45
5	0.985	0.015	10.06
8	0.999	0.001	0.448
3	0.988	0.012	8.024
4	0.999	0.001	0.891
6	0.961	0.039	25.807
7	0.995	0.005	3.198

2) Entropy-weighted TOPSIS construction evaluation model

According to the weighted decision matrix to get the optimal worst solution, and then calculate the distance between each factor and the optimal solution and the worst solution Di + and Di -, and also calculate the proximity to the optimal solution (Ei) for ranking, the larger the Ei value means the better the evaluation result, the higher the ranking, the comprehensive Shenzhen city has the highest degree of light pollution, and Fuxin city has the lowest degree of light pollution.

After getting the light pollution degree score of each city, the K-Means++ clustering algorithm is performed according to the score, four clustering centers are set, and the value corresponding to the final clustering center is taken as the boundary value of the class division, so that the light pollution degree can be divided into five criteria according to the score: very low, low, medium, high and very high. The scoring level criteria are as follows.

E_i In $[0.659214, +\infty)$ is Extremely high; In $[0.49557, 0.659214)$ is High; In $[0.385455, 0.49557)$ is Medium; In $[0.30742, 0385455)$ is Low; In $[-\infty, 0.30742)$ is Extremely low.

2.4.3. Multivariate linear TOPSIS analysis

1) Multiple linear method to calculate weight coefficients

After fitting the factors with multiple linearity, the regression coefficients of each factor were obtained, and the regression coefficients were processed in absolute value before normalization to obtain the weights of each indicator Wj. The calculation results are shown in Table 3. and the model passed the joint significance test, indicating that the model establishment was successful. From the factor regression coefficients, we can judge the factors 1,2,5,8 are positive indicators and 3,4,6,7 are negative indicators.

Table 3. Factor regression coefficients and weights

Factor	Regression coefficient	Wj
1	1.1489	0.4678
2	0.1855	0.4694
3	-0.0232	0.0058
4	-0.9838	0.2489
5	0.2626	0.0664
6	-0.4838	0.1224
7	-0.9283	0.0234
8	0.0864	0.0218

2) Multivariate linear TOPSIS construction evaluation model

The optimal worst solution is also obtained based on the weighted decision matrix, and then the distances Di + and Di - of each factor from the optimal solution and the worst solution are calculated, and the proximity to the optimal solution (Ei) is also calculated for ranking. Guangzhou city has the highest degree of light pollution and Chaoyang city has the lowest degree of light pollution.

After obtaining the light pollution degree scores for each city, the scores were also K-Means++ clustered according to the hierarchical classification algorithm elaborated in the entropy-weighted TOPSIS, and the score hierarchy criteria were obtained as follows:

E_i In $[0.723511, +\infty)$ is Extremely high; In $[0.53945, 0.723511)$ is High; In $[0.46486, 0.53945)$ is Medium; In $[0.409579, 0.46486)$ is Low; In $(-\infty, 0.409579]$ is Extremely low.

2.4.4. Comparative analysis of multivariate linear TOPSIS and entropy-weighted TOPSIS evaluation levels

The above two criteria for classifying light pollution risk levels were derived by multivariate linear TOPSIS model and entropy weight TOPSIS model. To analyze and evaluate the model effect, this article divided the Ei values of 271 prefecture-level cities in China by the two scoring level criteria, and drew a map of light pollution level in China by ArcGIS. Figure 5 shows the map divided according to the evaluation criteria established by multivariate linear TOPSIS, Figure 6 shows the remote sensing image of light pollution in China in 2020 from DMSP/OLS source, and the map divided according to the evaluation criteria established by entropy weight TOPSIS.

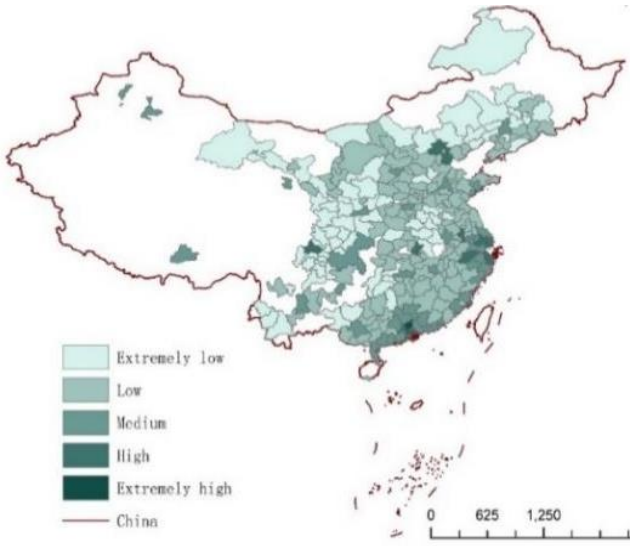

Figure 5. Light Pollution Levels in China

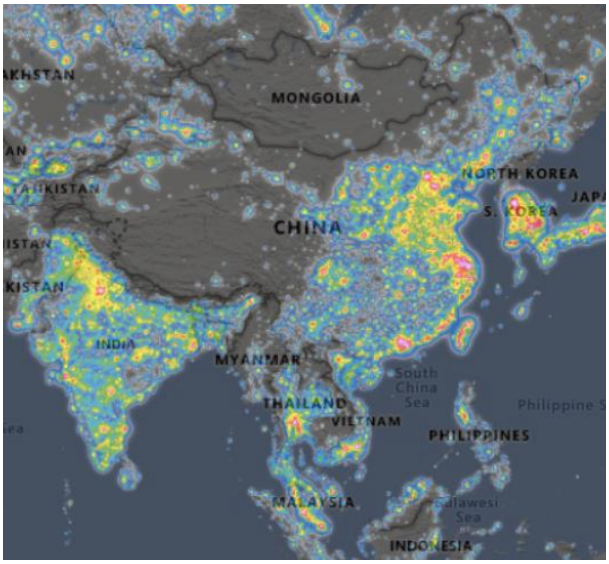

Figure 6. China Light Pollution Map

In Figure 5, it can be roughly seen that Guangzhou and Shenzhen have the highest light pollution level; Shanghai and other cities located in the southeast coastal generation, as well as Beijing and Tianjin, which are located inland, have higher light pollution levels; some inland cities in the south, such as Liuzhou, and cities in the west, such as Taiyuan and Lhasa, have lower light pollution levels, while some cities in northeast and north China, such as Song yuan and Chengde, have the lowest light pollution levels. The evaluation criteria established by multivariate linear TOPSIS classify the light pollution degree and the satellite image with high similarity, which has high credibility. The evaluation model is tentatively considered to be valid.

Shenzhen and Guangzhou are still the areas with the highest light pollution risk level; Beijing, Tianjin and Chongqing are the cities with higher light pollution; the cities in the central abdomen are mostly higher; some cities in the northeast and northwest regions have lower light pollution levels. However, the cities with the highest degree of light pollution are still concentrated in the southern coastal areas, but comparing the satellite image will find that the cities with the highest degree of light pollution in the satellite image are specifically concentrated in the Bohai Bay area, while it does not reflect this important information point, which can be clearly seen through Figure 5. Therefore, it is tentatively concluded that the evaluation criteria established by entropy-weighted TOPSIS to classify the degree of light pollution are also valid, but the accuracy of the model may be inferior to that of multivariate linear TOPSIS.

To further compare and analyze the advantages and disadvantages of the two models, the DN values of the light pollution degree indicators represented by the satellite maps were ranked and the spearman coefficients were calculated with the composite score series derived from the two models, respectively, and the results are shown in Table 4.

Table 4. Correlation coefficients between DN and the scores of the two methods

Relevance	Composite score index (entropy weighting)	Composite score index (regression)
DN value	.570**	.811**

The table 4 shows that the Spearman coefficient of the composite score series calculated by multivariate linear TOPSIS is higher and the model is considered to be a better fit.

2.5. Site-specific evaluation based on multivariate linear TOPSIS

2.5.1. Select Location

Protected land location: Jiuzhaigou County, China

Rural communities: Liuyang City, Hunan Province, China

Suburban Community: Hang County, Zhejiang Province, China
Urban Community: Jinshui District, Henan Province, China

2.5.2. Factor score

Firstly, the raw index data of the four regions were standardized, and then based on the factor score coefficient matrix obtained from the factor analysis in 2.4.1, the factor score coefficient b and the raw index data x were substituted together into the following function f to find out the corresponding 8 factor scores for each region as the basis for the next assessment of the light pollution level.

$$\begin{cases} x_1 = u_1 + a_{11}f_1 + a_{12}f_2 + \cdots + a_{1m}f_m + \varepsilon_1 \\ x_2 = u_2 + a_{21}f_1 + a_{22}f_2 + \cdots + a_{2m}f_m + \varepsilon_2 \\ \vdots \\ x_p = u_p + a_{p1}f_1 + a_{p2}f_2 + \cdots + a_{pm}f_m + \varepsilon_p \end{cases} \Rightarrow \begin{cases} f_1 = b_{11}x_1 + b_{12}x_2 + \cdots + b_{1p}x_p \\ f_2 = b_{21}x_1 + b_{22}x_2 + \cdots + b_{2p}x_p \\ \vdots \\ f_m = b_{m1}x_1 + b_{m2}x_2 + \cdots + b_{mp}x_p \end{cases} \tag{13}$$

The score of the i-th factor can be written as

$$f_i = b_{i1}x_1 + b_{i2}x_2 + \cdots + b_{ip}x_p (i = 1,2,\cdots,m) \tag{14}$$

b_{ij} is the coefficient of the score of the i-th factor corresponding to the j-th variable x_j.

2.5.3. Score and grade of each location

In 2.4.4 the evaluation criteria based on the multivariate linear TOPSIS model was considered more reasonable through visualization and spearman coefficient analysis, so in this problem this article chose the weight values calculated from the multiple linear regression of DN and 271 prefecture-level cities in China to bring into the TOPSIS model to calculate the composite score index, as shown in Table 5 below.

Table 5. Composite score index by location

Index Value	Positive ideal solution distance (D+)	Negative ideal solution distance (D-)	Overall Score Index	Rating
Jinshui District	0.53591176	0.81659831	0.60376505	1
Hang County	0.58465977	0.62677664	0.51738303	2
Liuyang City	0.6743678	0.52389746	0.43721326	3
Jiuzhaigou County	0.92141091	0.35298828	0.27698408	4

Corresponding to the evaluation levels derived from multivariate linear TOPSIS, the combined score indices of the four locations showed that the light pollution level in Jinshui District was high; the light pollution level in Hang County was medium; the light pollution level in Liuyang City was low, and the light pollution level in Jiuzhaigou was extremely low.

Jinshui District is an urban community with a large resident population, high population density, high level of economic development, and the existence of many large commercial communities in the city, a large number of colored LED lights in the commercial area will inevitably project a large amount of light into the night sky. The formation of local glare and light pollution phenomenon.

Hangzhou County is a suburban community, the resident population is smaller than the urban area, and the level of economic development is lower than that of urban communities, but some large

industrial enterprises are currently affected by the policy to move out to the suburbs, so the degree of industrialization is high, and the particulate matter emitted by industrial enterprises will reflect light and intensify light pollution, so the degree of light pollution in Hangzhou County is still at a medium level.

Liuyang City is a rural community with low population density, high proportion of primary industry, few commercial communities and industrial enterprises, and low urbanization rate. And the green area is large, which has a shading effect and reduces the transmission of light to the sky, thus reducing light pollution, so its light pollution level is at a low level.

Jiuzhaigou County is a protected land location, and the government has extremely strict control over the population flow, surrounding industrial and commercial areas, and vehicles driving on the surrounding roads, so the brightness of the surrounding area will not be too high under protection, and the emission of particulate matter is reduced, which also reduces the spread of light to the sky.

3. Conclusion

In order to evaluate the light pollution level of a region, this paper first constructs an evaluation index system. The entropy weight method and multiple linear regression method were used to calculate the weight values respectively, and the comprehensive score index of 271 prefecture-level cities in China was obtained by substituting into TOPSIS. The scores were also clustered by K-Means++ to derive the rank classification boundary values, thus classifying the degree of light pollution into five criteria. Then the 271 prefecture-level cities in China are divided and visualized by the two rating systems, and their advantages and disadvantages are analyzed by comparison with satellite images. The DN values were also calculated separately using the composite score series derived from the two models to calculate the spearman coefficients, and the results showed that the multivariate linear TOPSIS was a better fit.

In addition, the model was applied to four specific scenarios in this paper, and the factor scores were calculated for each region of each different specific scenario, then substituted into the evaluation model to calculate the total score and classified with reference to the scoring system. The results show that light pollution is very low in conservation land locations, low in rural communities, medium in suburban communities, and high in urban communities.

References

[1] Yang YZ, Zhang Q, Wu LY. Entropy-based TOPSIS supplier selection method[J]. Journal of Beijing University of Technology, 2006, 26 (1): 31 - 35.

[2] Tian Fujin, Ma Qingshan, Zhang Ming, Tang Zhimin. Evaluation of water quality in Xin'an River basin based on principal component analysis and entropy weight method [J/OL]. Zhongguo Geology: 1-14 [2023-03-02]. http://kns.cnki.net/kcms/detail/11.1167.P.20221020.1804.006.html.

[3] Yang YJ. Ecological input-output-analysis model for air pollution mitigation strategies in Fujian Province[D]. Xiamen Institute of Technology, 2022. DOI: 10.27866/d.cnki.gxlxy.2022.000003.

[4] Envy R. H., Pu D. W., Fan Z. Luan, Liu R. Evaluation of polysaccharide activity of 10 edible mushrooms based on principal component analysis combined with entropy TOPSIS method [J/OL]. Modern Food Science and Technology:1-10[2023-03-02]. DOI: 10.13982/j.mfst.1673-9078.2023.5.0710.

[5] Zhang Xiaojie. Research on the evaluation and prevention of financial risks of long-term rental apartments based on entropy TOPSIS method[D]. Guangxi University, 2022. DOI: 10.27034/d.cnki.ggxiu.2022.001712.

[6] Salehi V, Zarei H, Shirali G, et al. An entropy-based TOPSIS approach for analyzing and assessing crisis management systems in petrochemical industries[J]. Journal of Loss Prevention in the Process Industries, 2020, 67: 104241.

[7] Liu X F, Zhou X X, Zhu B Z, et al. Measuring the maturity of carbon market in China: An entropy-based TOPSIS approach [J]. Journal of Cleaner Production, 2019, 229: 94 - 103.

[8] Luo Zhenqing, Su Hang, Wang Zhuoli, Yang Biao. Classification of dynamic light pollution in urban lighting planning and nighttime light environment [J]. Journal of Lighting Engineering, 2022, 33 (04): 193 - 202.

[9] Chen Hongfang, Gao Yi, Liu Lixia. A comprehensive evaluation method of graduation requirement achievement based on entropy weight method and TOPSIS method [J]. Heilongjiang Education (Theory and Practice), 2023 (02): 58 - 60.

[10] Yu, O., Xue, I. Han. A comprehensive evaluation of airline safety management capability based on entropy weight TOPSIS [J]. Project Management Technology, 2023, 21 (02): 101 - 105.

[11] Feng K, Dai Shujian, Hao Luoxi. A preliminary investigation on the evolution characteristics of light pollution based on VIIRS images in four cities in China [J]. Journal of Lighting Engineering, 2022, 33 (04): 172 - 185.