Construction of A Light Pollution Evaluation System Based on Subjective and Objective Integration Empowerment

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Abstract. To address light pollution, this study presents an evaluation model designed to precisely quantify the extent of light pollution at a given location. The proposed model utilizes the Analytic Hierarchy Process and Entropy Weight Method (AHP-EWM) to conduct a combined weighted analysis of relevant indicators. Additionally, the Grey Comprehensive Evaluation Model (GCEM) is introduced to establish a broadly applicable measurement system. To demonstrate the model's effectiveness, it is applied to specific cities, with comprehensive explanations provided.

Keywords: Light pollution, AHP-EWM, GCEM.

1. Introduction

As urbanization and human activities continue to expand, environmental pollution has become a significant issue worldwide. Among various types of pollution, light pollution, which is often overlooked, poses significant risks to public health and safety. According to a report, around two-thirds of the global population is exposed to light pollution. An endocrinologist at the University of Texas Health Science Center, Dr. Russell Leiter, has emphasized that light is a drug, and its misuse can have severe health consequences. To mitigate the negative effects of light pollution, local governments, and social groups have initiated several interventions. Therefore, there is a pressing need to develop a universally applicable metric to evaluate the effectiveness of intervention policies and to assess the degree of light pollution risk at a specific location.

2. Establishment of an evaluation system model

2.1. Selection of evaluation system model indicators

2.1.1 Direct factors

The most direct way to determine the level of light pollution risk in an area is to measure the area's light pollution index, which combines three factors [1]:

Artificial light intensity: Measures the intensity of artificial light emitted from outdoor light sources and is the strongest indicator of light pollution levels.

Sky brightness: This factor measures the brightness of the night sky caused by the scattering of artificial light sources and natural light such as the moon and stars. The brightness of the night sky accurately reflects the overall brightness effect of artificial light.

Spatial extent: Light pollution in an area is not only related to brightness and intensity but also to the extent of light pollution. Spatial extent is a factor used to measure the extent of light pollution in an area, which can be visually seen from the real-time global light pollution distribution map.

2.1.2 Indirect factors

In addition to the immediate factors mentioned above [2], we specifically defined the indicators affecting light pollution as the local development level, population size, geographical location, climate, and biodiversity, and selected the following secondary indicators to explain. Let's call it the indirect factor is shown in Table 1.

Table 1. Indirect factor measures

Indirect factor	index
Developmental level	GDP per capita
	Urbanization rate
	Motor vehicles
	Urban built-up area
	Electricity consumption
Population	Population
	The proportion of the urban population
Geographic position	Elevation
	Longitude and latitude
Climate	Temperature
	Rainfall capacity
Biodiversity	Mclntosh index
	Mclntosh balance degree

The following Figure 1 is a display diagram of the organizational framework of subjective weights and objective weights.

Figure 1. Direct factors and Indirect factors

2.2. Determination of model weights

By looking at the data, we found that measuring the risk of light pollution in an area is not limited to the local level of development but is also related to population, geographical location, and even climate and biodiversity [3]. Therefore, the core of the classification of light pollution levels lies in how to weigh each index. The subjective weighting method may cause the weight to be influenced too much by human factors. However, objective empowerment may be too mechanized and lack humanistic feelings, resulting in inaccurate weight determination [4].

Therefore, we create a new evaluation system model, which will use the subjective weighting method "improved Analytic Hierarchy Process (AHP)" and the objective weighting method "entropy weight method" to integrate new weights based on the moment estimation. This method has the characteristics of taking into account the subjective importance of events, the internal connection of each index, and the gradual change of weights over time. On this basis, the grey comprehensive evaluation method is further used to classify the event hazard level.

2.2.1 Subjective weighting assignment

The improved analytic hierarchy process (AHP) [5] is to regard the problem to be studied as a large system affected by a variety of factors and then decomposes the interrelated and restrictive factors into several levels. The weight of different schemes is obtained by analyzing each level.

2.2.2 Objective weight assignment

The basic idea of determining objective weight by entropy weight method is to determine objective weight according to the variability of the index. Generally speaking, the smaller the information entropy of an index is, the greater the variation degree of the index value, the more information it provides, the greater the role it can play in the comprehensive evaluation, and the greater its weight. On the contrary, the greater the information entropy of an index, the smaller the variation degree of the index value, the less information it provides, the smaller the role it plays in the comprehensive evaluation, and the smaller its weight.

2.2.3 Subjective and objective combination of empowerment

With l kinds of subjective weighting method [6], the subjective weight set of each indicator determined according to the subjective weighting principle can be obtained:

$$W_s = \{w_{sj} | 1 \leq s \leq J, 1 \leq j \leq m\} \ . \tag{1}$$

with $q-1$ objective weighting method was used to assign weights to evaluation indicators, and an objective weight set was obtained:

$$W_b = \{w_{bj} | l+1 \leq b \leq q, 1 \leq j \leq m\} \tag{2}$$

Suppose that the integrated weight vector of the evaluation index r is:

$$[w_1, w_2, \cdots, w_m] \tag{3}$$

For subjective weight, if the number of decision-makers tends to be large, it can be regarded as extracting samples from the population to estimate the combined weight vector according to the large number theorem of statistics (r)[7].

Suppose l samples and $q-1$ samples are selected respectively from the subjective weight population and the objective weight population. For different evaluation indexes, the relative importance degrees of subjective weight and objective weight is different. If the relative importance coefficients of subjective weight and objective weight are α and β, then the optimization model of integrated combination weight is:

$$minH(w_j) = \alpha \sum_{s=1}^{l} (w_j - w_{bj})^2 + \beta \sum_{s=1}^{l} (w_j - w_{bj})^2 \tag{4}$$

According to the basic idea of moment estimation theory, the important coefficient of the subjective and objective weight of each index can be calculated by combining the expected value with each evaluation index α_j and β_j. According to this idea [7], the multi-index decision matrix can be obtained:

$$\begin{cases} \alpha = \frac{\sum_{j=1}^{m} \alpha_j}{\sum_{j=1}^{m} \alpha_j + \sum_{j=1}^{m} \beta_j} = \frac{\sum_{j=1}^{m} \alpha_j}{m} \\ \beta = \frac{\sum_{j=1}^{m} \beta_j}{\sum_{j=1}^{m} \alpha_j + \sum_{j=1}^{m} \beta_j} = \frac{\sum_{j=1}^{m} \beta_j}{m} \end{cases} \tag{5}$$

For each evaluation index [7], we hope that the smaller the better, so the equivalent completeness linear weighting method is adopted to transform the multi-objective optimization model into a single objective optimization model, namely:

$$\begin{cases} minH = \sum_{j=1}^{m} \alpha \sum_{s=1}^{l} \left(w_j - w_{bj}\right)^2 + \sum_{j=1}^{m} \beta \sum_{s=1}^{l} \left(w_j - w_{bj}\right)^2 \\ s.t. \sum_{j=1}^{m} w_j = 1 \\ 0 \le w_j \le 1, 1 \le j \le m \end{cases} \tag{6}$$

Finally, the optimal combination weight vector based on multiple subjective and objective evaluation indexes is obtained.

2.3. Grey Comprehensive Evaluation Model

The correlation analysis method is the most widely used grey theory, and its correlation coefficient reflects the close degree of each evaluation object to the ideal object. The larger the correlation coefficient is, the better the evaluation index will be. We set i as the ith optical pollution metric index, and take the optimal value of each index as the reference series. According to the correlation coefficient and the optimal combination weight, the correlation degree sequence is obtained, to determine the ranking of the light pollution risk level [8].

3. Results

3.1. Processing of data

Based on the satellite images of global light pollution in 2022 and the measurement criteria of economic factors, government policies, climate factors, and so on, we intuitively selected four provinces in China as the objects of analysis, as shown in Table 2.

Table 2. Area identification and type

location	types of locations
Inner Mongolia	a protected land location
Tibet	a rural community
Guangxi	a suburban community
Shanghai	an urban community

According to China's National Statistical Yearbook, we have identified indicators of development, population, and climate for the above four regions. After the acquisition, we preprocess the data: Normalization and Standardization.

After data preprocessing, we decided to adopt principal component analysis to reduce the dimension of the five indicators of development level, looking for new comprehensive variables that could be represented linearly by the original variables. Table 3 is the cumulative contribution rate of each indicator [9].

Table 3. The cumulative contribution rate of each indicator

number	Characteristic root	Contribution rate	Cumulative contribution rate
1	7.148	79.427	79.427%
2	1.502	16.685	96.111%
3	0.178	1.973	98.084%
4	0.107	1.194	99.278%
5	0.061	0.682	99.960%
6	0.003	0.040	100.00%

Through the principal component analysis, we found that the contribution rate of the first two principal components had reached 96.111%, and the five indicators could be reduced to 2 dimensions to determine the two principal components, as shown in Table 4.

Table 4. Component I or II load coefficient

Name	Component 1 load coefficient	Component 11 load coefficient
GDP	0.922	0.322
Urbanization rate	0.584	-0.022
Electricity consumption	0.162	0.424
Urban built-up area	0.297	0.637
Motor vehicles	0.253	0.528

From the description of the final result factor loading, we find that component 1 mainly depends on GDP and Urbanization rate, component 2 is Urban built-up area, Motor vehicles, and Electricity consumption. Therefore, we named these two main components: economic development level and urbanization construction level. The ultimate dimension reduction is completed.

3.2. Analysis of experimental results

For the subjective weighting of the three direct factors that measure the level of light pollution: artificial light intensity, sky brightness, and spatial extent using AHP, we present a raster map (Figure 2) of three factors for four regions in 2022 [10].

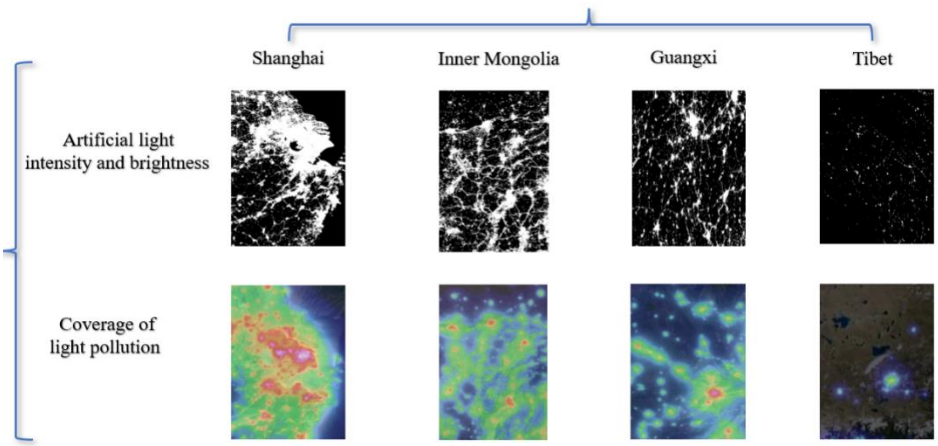

Figure 2. Visual display of light pollution

Based on the above satellite raster map of light pollution and artificial light intensity at night, as well as the literature review, we infer the judgment matrix which is shown in Table 5:

Table 5. The AHP Judgment matrix

Direct factor evaluation	Artificial light intensity	Sky brightness	Spatial extent
Artificial light intensity	1	0.769	0.667
Sky brightness	1.3	1	1.25
Spatial extent	1.5	0.8	1

Then, we determined the respective weights of the three direct factors, which are illustrated in Table 6.

Table 6. The Direct factor’s weight value results

Direct factor	Feature vector	Weight value
Artificial light intensity	0.791	26.371%
Sky brightness	1.160	38.663%
Spatial extent	1.049	34.966%

Using the entropy weight method, we finally get the respective weights of the five indirect factors as Developmental level: 41.43%, Population: 13.04%, Geographic position: 11.85%, Climate: 7.59%, Biodiversity:10.01%.

Finally, the moment estimation method is used to combine the weight results of the AHP and entropy weight method to determine the final weight results, as shown in Table 7.

Table 7. The final weight value results

Factors	Weight value	factors	Weight value
Artificial light intensity	19.394%	Population	4.112%
Sky brightness	28.435%	Geographic position	3.734%
Spatial extent	25.716%	Climate	2.391%
Developmental level	13.058%	Biodiversity	3.156%

According to the weight obtained, we bring the data to calculate the score and ranking (shown in Table 8) of the light pollution risk level in the four regions [11]:

Table 8. Light pollution severity score and ranking

Location	Light pollution risk score	Light pollution severity ranking
Inner Mongolia	83.92	2
Tibet	56.94	4
Guangxi	71.07	3
Shanghai	92.61	1

After that, we drew the four cities’ light pollution risk score distribution map as shown in Figure 3.

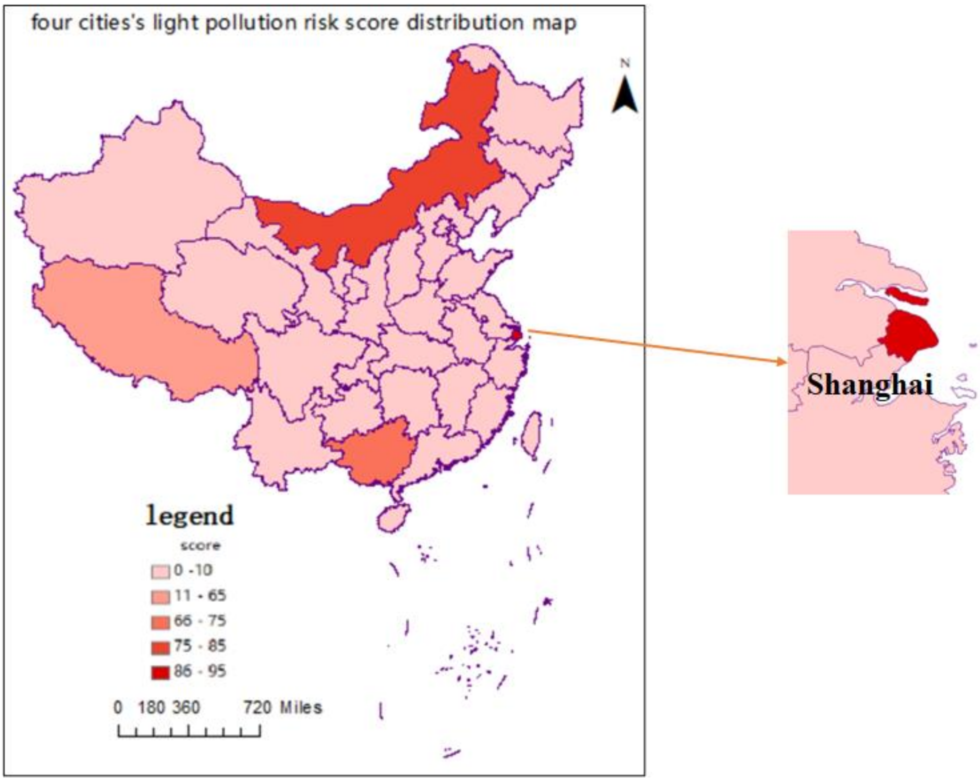

Figure 3. Four cities' light pollution risk score distribution map [12]

4. Conclusions

Due to the high-intensity and extensive development of Shanghai's urban areas, the gross regional product is much higher than that of other cities. In its urban construction high-rise buildings, commercial billboards, vehicle headlights, and other high-intensity light sources have also intensified. Shanghai has a suitable climate, high population density, generally high per capita disposable income, and a very large per capita urban share, indicating that the pursuit of material life of the public is higher, entertainment activities in the lighting and publicity links increase the light pollution of the city. Therefore, Shanghai light pollution is the most serious.

In recent years, as a nature reserve in China, Inner Mongolia's forest ecosystem has been effectively improved, but due to insufficient government measures to prevent light pollution, excessive artificial light sources, and the use of a large number of light pollution. But its population density is low, so the light pollution level is slightly lower than in Shanghai.

Guangxi region is located in a remote area in the south, and economic development is relatively slow. Far from large cities and industrial areas, the natural environment is relatively good, and the source and density of light pollution are relatively low. Therefore, the degree of light pollution is light, but because of the large number of motor vehicles owned by the residents of Guangxi province, so its light pollution problem should not be underestimated.

Tibet is located in a high altitude, low oxygen plateau area, with good atmospheric stability, away from cities and industrial areas, the source and density of light pollution are relatively low. With low population density and relatively low urbanization, lighting demand is relatively low, so light pollution is relatively light. Low electricity consumption, low emissions, and sparse population density and the national protection policy for Tibetan ecological reserves make it the lowest level of light pollution.

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