A Light Pollution Risk Assessment Model Based on TOPSIS and EWM-AHP Methods

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Abstract. With the development of industrialization and urbanization, light pollution has become increasingly serious in various countries. Assessing the risk level of light pollution (LPRL) is the foundation and the most important step to study the light pollution problem. In this paper, five primary indicators and 13 secondary indicators are selected, and the indicator weights are determined by EMW and AHP. The light pollution risk levels of different regions are calculated by the Topsis method. The output results show that the LPRL is highest in urban areas, followed by suburban and rural areas, and the LPRL in protected land is lowest, and the model results are consistent with the actual situation. Finally, this paper analyzes the weights of different indicators in the LRPL model, and proposes corresponding intervention policies for the three factors with the highest weights.

Keywords: Light Pollution Risk Level, EWH, AHP, TOPSIS.

1. Introduction

A modification in the natural night-light of the outside surroundings because of artificial light compromising human health and ecological balance is termed light pollution. It includes glare, light trespass, over-illumination and light clutter. Excessive and misdirected light from streetlights, homes, and towns not only interferes with wildlife, stargazing, sleep habits, and professional astronomy, but it also wastes a vast amount of energy. [1-2] The global light pollution situation is shown in Figure 1.

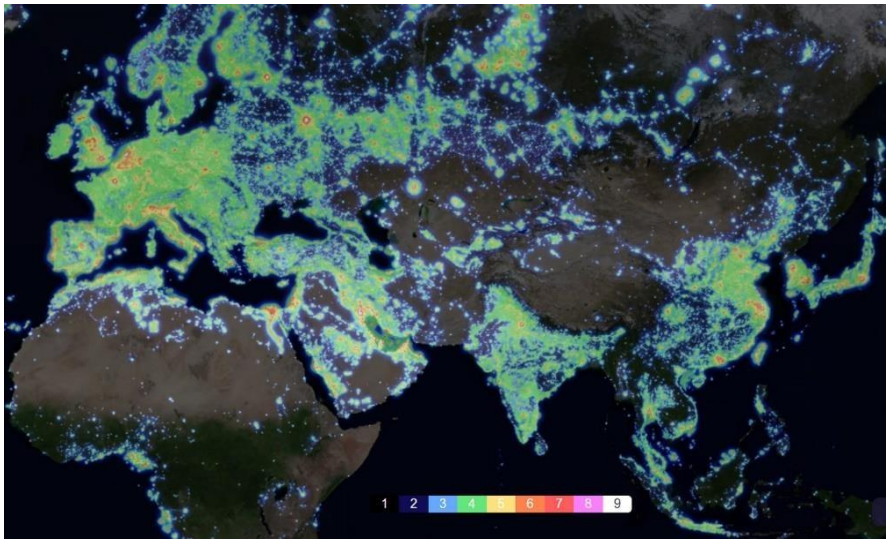


Figure 1. Global light pollution map

Current studies on light pollution risk levels are as follows.Qiming Zheng et al. used multispectral nighttime images acquired by JL1-3B satellite and machine learning algorithms to assess light pollution risk levels in different regions [3].Zihao Zheng et al. used multisensor NTL data to assess light pollution in protected areas in Africa [4]. Some researchers measured light pollution by sky mass meter and all-sky digital camera measurements [5]. In summary, current studies on light pollution risk levels are based on data collected by sensors, satellites, or specific instruments, and this research method is demanding on research equipment. In contrast, the assessment method proposed in this paper is based on statistical data and comprehensive weighting of the topsis evaluation method, which is simple and fast.

2. Establishment and verification of light pollution risk level assessment model

2.1. Light Pollution Risk Level Assessment Model

The risk level of light pollution refers to the potential of a city to produce serious light pollution, and the comprehensive level of harm to society after generating light pollution.

In this section, this paper build an index named the Light Pollution Risk Level (LPRL) Index, which is used to measure the light pollution risk level of a city. To get this index, it is first necessary to collect indicators related to urban light pollution. Then, the corresponding weights of each index are calculated by two objective and subjective weighting methods, entropy weight method and analytic hierarchy method. Once the weight of each indicator is known, the light pollution risk level index can be calculated by weighted summation.

2.1.1 Indicators selection

The risk level of light pollution is mainly reflected in five aspects: population, development level, natural environment, transportation, and night lighting. Based on relevant research, this paper selects several important indicators to assess the risk level of light pollution in a country, as shown in Figure 2.

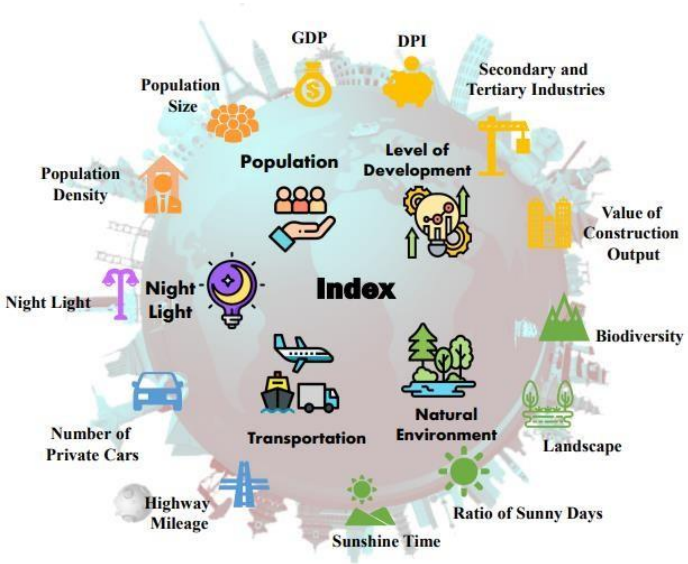


Figure 2. The indicators of LPRL index

(1) Demographic indicators

In terms of population, cities with different populations have different potential to produce light pollution, and cities with large populations have a correspondingly increased demand for artificial lighting, so the risk of light pollution in cities with large populations is relatively high.

At the same time, population density can also reflect the risk of light pollution, and Skyglow is often prone to occur over densely populated communities. Sky glow refers to the "glow" effect that can be seen over populated areas.

(2) Level of development indicators

GDP and disposable income per capita can reflect the economic level of a region. Areas with developed economic levels have high demand for nighttime lighting and more serious light pollution.

Areas with a high percentage of secondary and tertiary industries require a large amount of lighting to support mineral development and commercial activities. Therefore communities with a high share of secondary and tertiary industry structure are also prone to light pollution.

The gross value of the construction industry represents the gross value of the construction industry in a community in a year. A high gross building output indicates a large building cluster in the area. Light pollution can be caused by reflected light from large buildings[6]. The effect of buildings on light pollution is shown in Figure 3 below

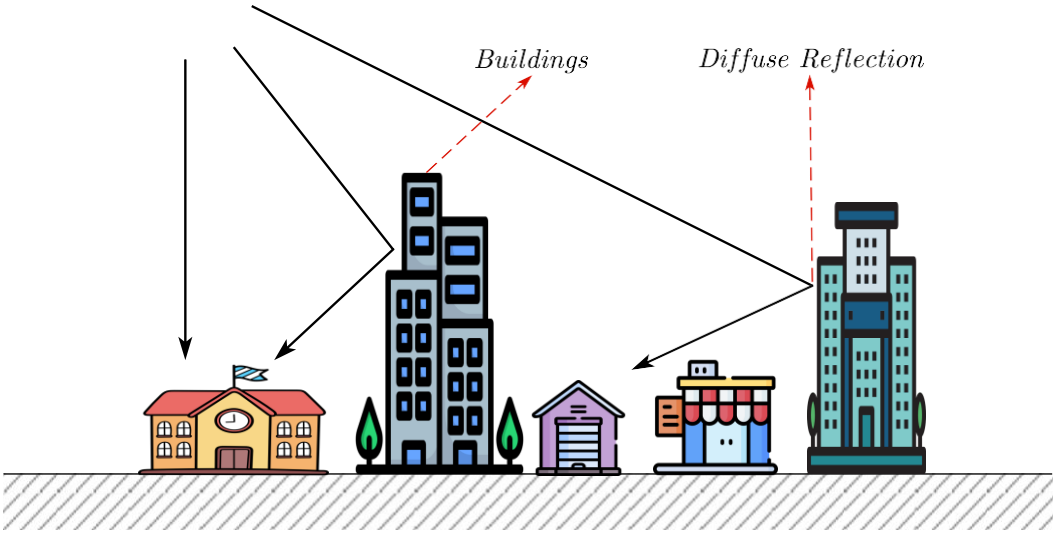


Figure 3. The reflection of sunlight by buildings

(3) Natural indicators

Regarding the climatic aspects, the effect of natural light near illuminated places expands to other unilluminated areas, especially during low clouds [7]. Since the cloud cover area is dynamic and difficult to measure, and according to geographic science, the cloud thickness is thinner on clear days, this paper uses the number of times from clear days to characterize the cloud cover area of an area.

In addition, geographic topography will also have some impact on light pollution. Due to the natural geomorphological features such as hills, mountains and depressions, vertical shadows can cause discrete dark areas can slow down the development trend of light pollution. In order to simplify the model, this paper only considers the three landforms of mountains, hills and plains.

Annual sunshine hours, sunshine hours refer to the length of time the sun shines during the year from sunrise to sunset. Intense daylight causes buildings to reflect light, promoting light pollution.

Light pollution can disrupt animal behavior, alter competitive interactions and predatory relationships, and affect animal physiology[8]. Also nighttime light pollution affects species diversity. Therefore, we introduce a certain regional species as an evaluation index, and when the regional biological species are small, the harm caused by light pollution is greater.

(4) Traffic indicators

When light pollution is high, it can endanger the visual function of pedestrians and drivers, and even cause traffic accidents. Therefore, we use the number of road miles in a community to measure the traffic development of an area. The higher the number of road miles, the more vulnerable it is to light pollution.

Private car ownership indicates the total number of private cars of a community's residents. The lights from cars driving at night are also a source of light pollution.

(5) City lig hts at night

Urban lighting at night is one of the direct sources of light pollution. Nighttime shopping areas, commercial streets, residential areas, and roads all require the use of a large number of lighting devices. Therefore, urban nighttime lighting index is also an important indicator of light pollution risk.

2.1.2 Indicators processing

After completing the collection of indicators, the 12 indicators need to be normalized, and here the indicators need to be divided into two categories, namely benefit-based indicators and cost-based indicators.

The standardized formula for benefit-based indicators is as follows:

$$\widehat{x_{ij}} = \frac{x_{ij} - \max(x_i)}{\max(x_i) - \min(x_i)} \tag{1}$$

The cost-type normalization formula is as follows:

$$\widehat{x_{ij}} = \frac{\max(x_i) - x_{ij}}{\max(x_i) - \min(x_i)} \quad (2)$$

Where x_{ij}denotes the value of the ith indicator in the jth region, max(x_i)denotes the maximum value of the ith indicator, and $\min(x_i)$ denotes the minimum value of the ith indicator.

Specific indicators are classified as shown in Figure 4

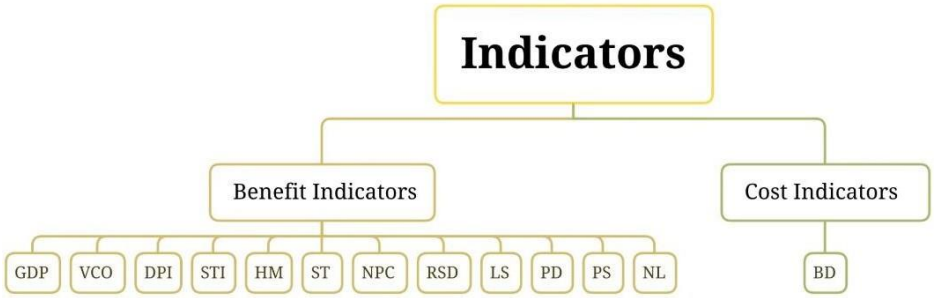


Figure 4. Benefit indicators and cost indicators.

2.1.3 Weight calculation

There are two types of methods for determining indicator weights: subjective weighting methods and objective weighting methods, and using one of these weighting methods singularly will inevitably lead to overly subjective or objective weighting. Therefore this time, both AHP and EWM are used to determine the weights of indicators.

(1) The Entropy Weight Method

The entropy weight method (EWM) is an important information weight model that has been extensively studied and practiced. The method is not only easy to calculate, but also takes into account the correlation among indicators, which can weaken the influence of outliers[9].

First, calculate the entropy value of the ith indicator, and the calculation formula is as follows:

$$E_i = -\frac{\sum_{j=1}^{n} P_{ij} * lnP_{ij}}{\ln n} \quad (3)$$

Where E_iÎ[0,1], the larger the value of E_i, the higher the degree of differentiation of index i, and the more information it contains.

The weights of different indicators are defined as follows:

$$\omega_{ij} = \frac{1 - E_i}{\sum_{i=1}^{m}(1 - E_i)} \quad (4)$$

Where ωijE represents the weight of the jth index in the ith level index of the entropy weight method.

(2) The Analytic Hierarchy Programming

AHP can be described as a method of assessment and decision making that provides a percentage distribution of choice points based on the factors that influence the decision[10]. Starting from the second layer of the indicator structure, two pairs of comparison matrices on a scale of 1-9 are constructed for the factors of each layer.

After calculation, we obtain the weight ωi = [0.2, 0.37, 0.12, 0.06, 0.25] of the first-level indicator, in addition, after obtaining the weight, we also need to test the consistency test formula as follows:

$$I = \frac{\lambda_{max} - n}{n - 1} \quad (5)$$

$$CR = \frac{CI}{RI} \quad (6)$$

After testing, the CR=0.0241<0.1 of the first-level index judgment matrix is considered to pass the consistency test. Repeat the above process for the secondary indicators thereafter to obtain the weights corresponding to each secondary indicator.

(3) Comprehensive weight

In order to avoid being too subjective or objective in our determined weights, we introduce the weight preference mathematical formula, corresponding to the comprehensive weight:

$$\widehat{\omega_{ij}} = \theta_1 * \omega_{ijE} + \theta_2 * \omega_{ijA} \tag{7}$$

where $\theta 1 = \theta 2 = 0.5$, $\widehat{\omega_{ij}}$,ω_{ijE},ω_{ijA}represents the comprehensive weight, the weight obtained by the EWM, and the weight obtained by the AHP respectively.

The results of the calculation of the weights of each index are shown in Figure 5 below

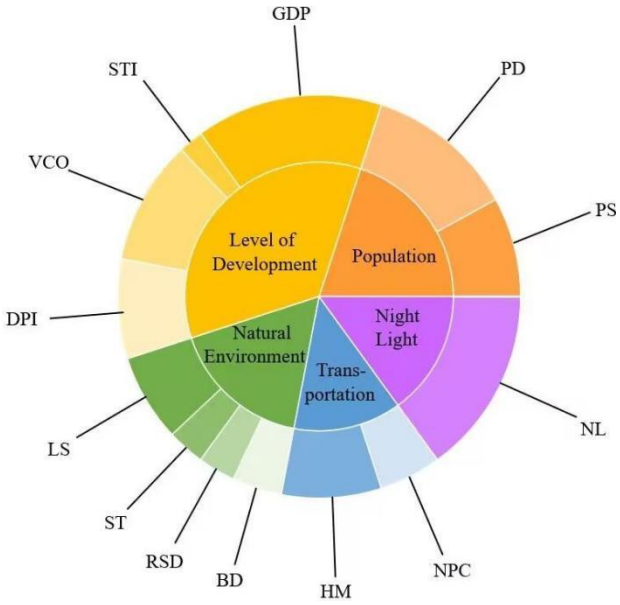


Figure 5. Weights for each indicator

The results of the study showed that Night Light is the most influential factor (15%), since excessive night light is the apparent cause for light pollution. Along with it is GDP (15%) in Level of Development (37%), which makes sense as a more developed place comes with higher GDP and more severe pollution. Apart from Night Light and GDP, Population density ranks third (12%). If population is large, more pollution will be produced, and meanwhile more people get influenced.

(4) The TOPSIS method

The TOPSIS method is a commonly used comprehensive within-group evaluation method that makes full use of information from raw data and the results accurately reflect gaps between evaluation programs. By calculating the distance between each evaluation object and the optimal solution and the worst solution, the relative proximity of each evaluation object to the optimal solution is obtained as a basis for evaluating the advantages and disadvantages.

In this paper, the weighted TOPSIS comprehensive evaluation method is adopted, and the weights are the comprehensive weights obtained above, and the distance between the positive ideal solution and the negative ideal solution is obtained.

$$D_i^+ = \sqrt{\sum_{j=1}^{m} \widehat{\omega_{ij}} * \left(X_i^+ - x_{ij}\right)^2} \quad D_i^- = \sqrt{\sum_{j=1}^{m} \widehat{\omega_{ij}} * \left(X_i^- - x_{ij}\right)^2} \tag{8}$$

Where D_i^+ and D_i^- represent the distance from the ith community to positive and negative ideal solutions.

Therefore, the risk of light pollution in each region can be defined as:

$$C_i = \frac{D_i^-}{D_i^- + D_i^+} \tag{9}$$

The positive ideal solution distance of each community is
$D^+ = \{0.113,0.328,0.291,0.295, \ldots ,0.904,0.866\}$
and the negative one is
$D^- = \{0.687,0.324,0.291,0.347, \ldots ,0.039,0.022\}$

2.2. Model Validation

Now we have the model to measure the risk level of light pollution in communities. So firstly in this paper we need to classify the selected 21 communities into urban, suburban, rural areas and conservation sites by population and then calculate their corresponding light pollution risk levels.

According to the concept of community division, the protected areas are: Daxing'anling area, Xishuangbanna area, suburbs: Baotou, Guyuan, Sanming, Xining, Kaifeng, Kunming, Tangshan, rural areas: Leshan, Benxi, Guiyang, Yinchuan, Lishui, urban areas: Hangzhou, Beijing, Wuhan, Xi'an, Chengdu, Harbin, Shantou.

Taking the indicators collected by the above 21 cities into the light pollution risk level assessment model, we can know the light pollution risk level of 21 cities, as shown in the figure 6:

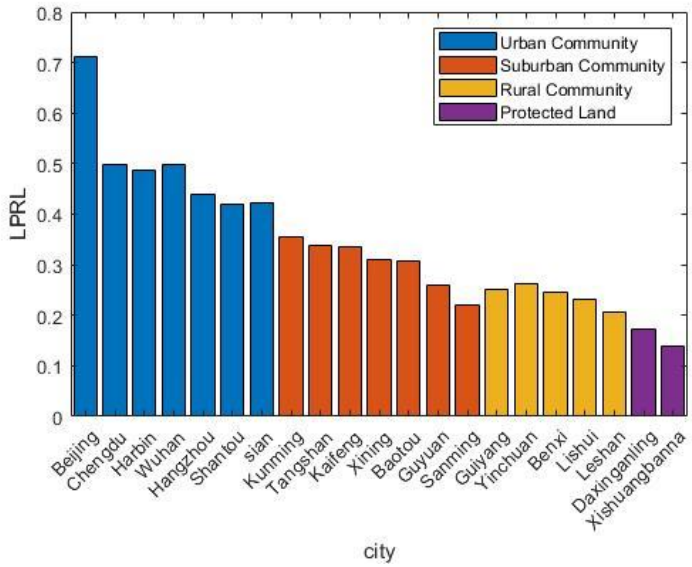


Figure 6. Ranking of light pollution risk levels in 21 cities

Calculating the LPRL of 21 cities and plotting it into a histogram shows that as the level of urbanization in the region increases, the risk of light pollution also shows an upward trend. The light pollution risk level of urban communities is generally high, with 7 cities having a light pollution risk level above 0.4, while the land protected area has the lowest light pollution risk level, and the light pollution risk level is below 0.2.

To further verify the validity of the model,after calculating the corresponding light pollution risk levels of 21 communities, four areas of Beijing, Kaifeng, Leshan and Daxing'anling were selected to obtain the Portel light damage index of the corresponding cities by visiting the luminous rocker satellite, and the light pollution risk level was compared with the Portel light damage index. The test results are shown in Figure 7.

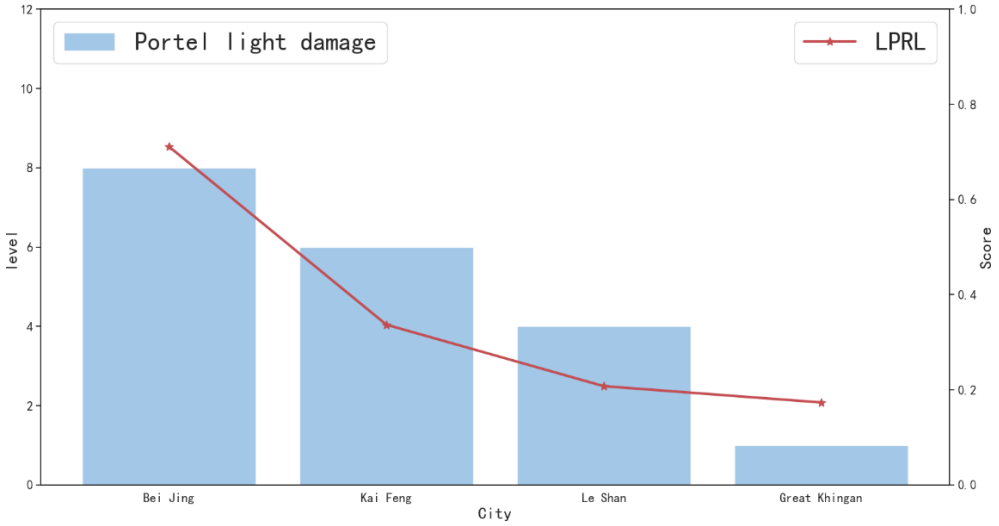


Figure 7. LPRL and its Portle light pollution levels in 4 representative cities.

In,Figure7 it is clear that the Portel light damage index corresponding to Beijing as an urban community is higher at 8, Kaifeng as a representative city in the suburbs has a Portel light damage level of 6, Leshan Portel light damage level is 4, the lowest Porter light damage level in the Daxing'anling area is 1 their size is consistent with our estimated light risk level.Therefore, the effectiveness of our model is verified.

3. Propose intervention policies

Now that our model can calculate the risk of light pollution in different communities, it is clear that different interventions proposed by the government will have different effects on some of these factors, thereby changing the level of light pollution risk in the community.

In this section, the paper proposes relevant intervention policies based on the three indicators (population, nighttime lights, and traffic)with the highest weights.

3.1. Migration policy

Population is one of the main factors affecting the risk level of light pollution, and most urban communities have high population density. Therefore, moving part of the population to surrounding cities can effectively alleviate the high risk of light pollution. This intervention requires state governments to develop corresponding migration rates and implement the policy for five consecutive years of their term of office to guide urban dwellers to migrate to surrounding cities.

3.2. Curfew and lighting improvement policy

Night light is one of the important sources of light pollution, we can control the amount of urban night lights by implementing curfew policy and limiting the time of light on or forcing part of the lights to turn off, while using asymmetric LAMP devices, compared with conventional LAMP devices, can reduce light pollution by 10% ~ 50% . In adopting this policy, governments should set a light intensity index that needs to be reduced every year, by stipulating the use time of night lights in shopping malls, and urging the construction industry to agree to adopt or replace LAMP devices for lighting, and adopt smart street lighting equipment.

3.3. Promote public transport

A large number of vehicle lights at night is also one of the sources of urban light pollution. If the government through the promotion of community public transportation, the issuance of a certain number of public transport coupons, and the license plate number tail number single and even number restriction policy, can effectively reduce the use and even ownership of community residents' private cars.

4. Conclusion

In this paper, a light pollution risk assessment model was developed using AHP, EWM and TOPSIS methods. The different places are then classified into urban, suburban, rural communities and protected areas based on population density. Applying the established model, it can be seen that the LPRL is generally higher in urban areas, followed by suburban and rural areas, while the light pollution level is lowest in protected areas. The results of the study are consistent with reality. Finally, the weights of the different indicators in the model were analyzed. Policies such as curfew and lighting improvement, public transport promotion and migration are proposed for the three factors with the highest weights: night lighting (12%), private car ownership (8%) and population (15%).

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