Research on Light Pollution Risk Level in Different Regions--Hangzhou As An Example

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Abstract. When human beings enjoy the prosperity of the city, it is difficult to escape the ubiquitous light pollution. In order to develop a widely applicable metric to determine the level of light pollution risk, the article establishes a light pollution risk level identification model. The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is adopted for comprehensive evaluation of 4 types of light pollution. In order to improve the weight assignment process of TOPSIS, the entropy weight method (EWM) is used. Finally, the article conducts K-Means clustering algorithm to grade the risk level of different locations. The proportion of regions of high risk, medium risk and low risk are 28.57%, 42.86% and 28.57% respectively.

Keywords: CBE, EWM, TOPSIS, K-Means clustering algorithm.

1. Introduction

With the acceleration of urbanization and the influx of more and more people into cities, the demand for nighttime lighting increases. The excessive use of artificial light sources makes the scope of light pollution continue to expand. Light pollution can blur the starry sky, reducing the visibility and observation quality at night. It can also destroy the ecological environment and disrupt the biological clock of animals. The radiant energy emitted by lighting fixtures has an impact on animal life and growth. In addition, light pollution has negative effects on human health, such as eye damage, cancer induction, and physiological discomfort [1-2].

Correctly assessing the level of light pollution risk and proposing reasonable strategies for preventing and controlling light pollution are now at top of the agenda. It is a social system project that requires all-round participation and joint efforts from the government, manufacturers, and individuals.

Su used the light environment simulation software to establish typical models of three types of light pollution in residential areas. Through calculation, the quantitative relationship between various light pollution levels in residential areas at night and their environment was obtained [3]. Hajra Nisar et al. synthesized and tracked Spatio-temporal changes in light pollution. VIIRS-DNB is used to provide the night sky measuring information about artificial light pollution, called SQM-L. Analysis of the nighttime satellite data in Lahore showed that light pollution had increased significantly over the past 7 years [4].

The article builds a light pollution risk level identification model to systematically evaluate the level of light pollution risk. Light pollution is divided into four forms. Various types are analyzed separately. Then the article adopts TOPSIS for comprehensive evaluation. The EWM is used to improve it. Finally, K-Means clustering algorithm is conducted to cluster the results. The framework is shown in Figure 1.

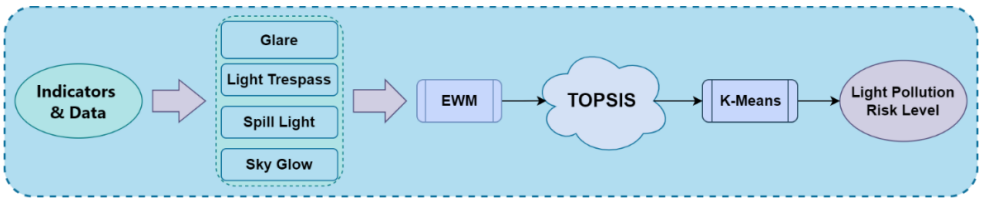


Figure 1. Framework of identification model

2. Light pollution risk level identification model

2.1. Evaluation of different forms of light pollution risk

2.1.1 Classification of light pollution forms and selection of indicators

The main performance of light pollution can be summarized as: glare, light trespass, spill light, reflected light and sky glow [5-7], as shown in Figure 2.

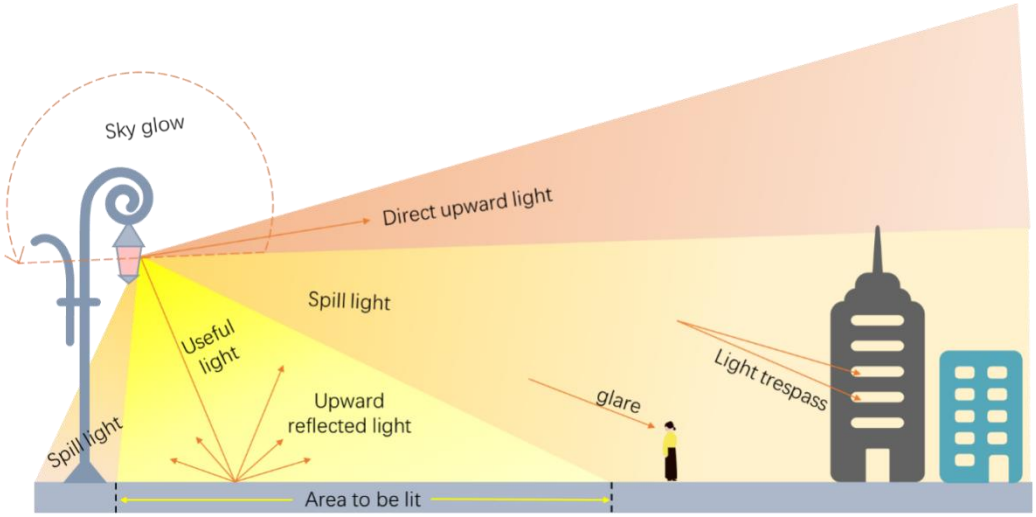


Figure 2. Useful light and various types of light pollution

After correlation analysis, it's found that the correlation coefficient between glare and reflected light is over 80%[8], so the reflected light indicator is discarded. Finally, four forms of light pollution risk level measurement indicators are determined: glare, light trespass, spill light, and sky glow. On this basis, the indicators are further subdivided, comprehensively considering the number of skyscrapers, ground brightness, population density, greening rate, and other influencing factors. The specific identification system is shown in Figure 3.

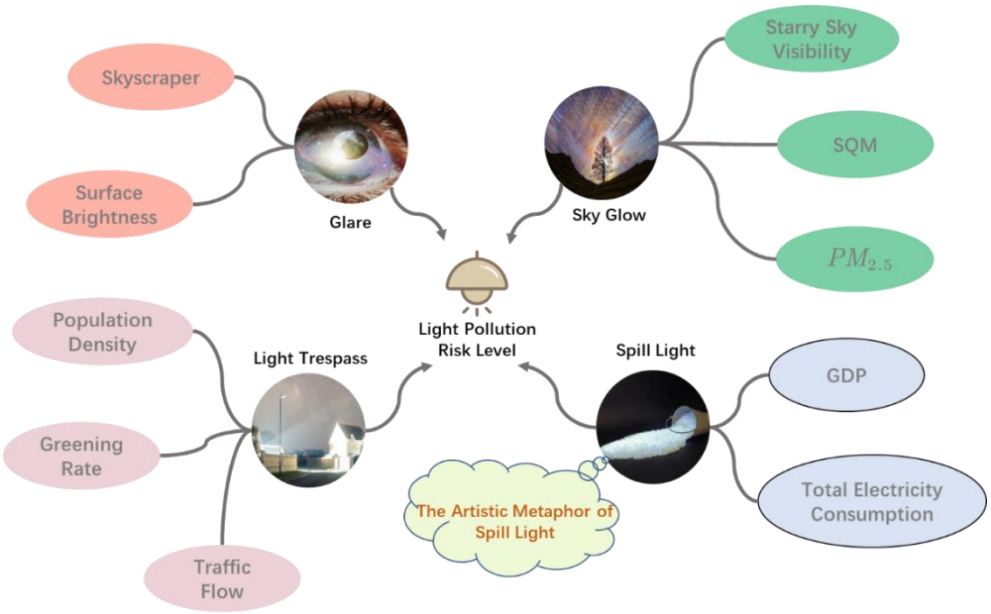


Figure 3. Indicators of light pollution risk level identification

2.1.2 Evaluation of glare pollution risk

- **Skyscraper**

Through the comprehensive brightness glare evaluation method Cumulative Brightness Evaluation (CBE)[9], proposed by Bennett, the glare brightness calculation formula is as follows.

$$CBE_{Tol} = \frac{67.1}{L_b^{0.5}} \sum_n \left(\frac{L_i^{1.67} \times \omega_i}{8.8 \times 10^{-3} \times \theta_i^2 + 1.35} \right) \tag{1}$$

CBE_{Tol} represents the comprehensive brightness glare constant, ω_i refers to the solid angle of the ith light source, θ_i stands for the glare angle generated by the ith light source, L_i represents the brightness of the ith light source, L_b is the background brightness of the glare environment, n means the number of glare light sources.

Based on the reliability of the data, the article improves and simplifies the calculation formula of comprehensive brightness glare as follows.

$$CBE_{Tol} = \sum_i^n \left[\int_0^{+\infty} \frac{1}{\tan^{-1}(h_i/x_i)} dx_i \right] \tag{2}$$

n represents the number of skyscrapers in the area, h_i represents the height of the ith skyscraper, and x_i refers to the distance between the evaluation site and the ith skyscraper.

- **Surface brightness**

Su carried out the Spearman test on the ground brightness and glare degree. The result shows that the correlation coefficient was 0.717[3]. Therefore, ground brightness and glare degree have a very large positive correlation.

To sum up, the correlation coefficient weighting method is used to obtain the calculation formula of glare pollution risk level, as shown below.

$$R_g = CBE_{Tol} + 0.717 \times G_a \tag{3}$$

R_g means glare pollution risk level and G_a means the average brightness of the ground.

2.1.3 Assessment of light trespass pollution risk

- **Selection of data**

The article selects population density, greening rate, and traffic flow as the indicators. Among them, population density and traffic flow are positive indicators, and greening rate is a negative indicator. The data of each district in Hangzhou are obtained from the Hangzhou Data Open Platform and the Hangzhou City Brain Data Platform, as shown in Table 1.

Table 1. Data of indicators for light trespass pollution assessment

Region	Density of population	Greening rate	Traffic flow
Yuhang	1302.200637	25.3	171997
Shangcheng	10848.09016	29.9	211968
Binjiang	6978.65651	38.5	208621
Xiaoshan	2160.79377	24.6	202470
Gongshu	9420.042017	36.6	261254
Xihu	3486.313734	45.2	272568
Qiantang	1446.586421	33.8	316584
Linping	4111.332168	42.1	217697
Fuyang	456.9011532	23.7	90058
Lin’an	202.9407062	17.5	95114
Jiande City	190.740629	19.9	130408
Tonglu County	248.2772603	17.4	110346
Chun’an County	74.3069799	56.71	96853
West Lake Scenic Area	402.4898374	61.2	60043

- **The entropy weight method (EWM)**

The EWM is one of the weighting methods that measures the dispersion level of different information sources in decision making. It determines the weight of each criterion by calculating the degree of their influence on the decision-making result [10].

Suppose given i index $X_1, X_2, X_3, \ldots, X_i$. and $X_s = \{X_1, X_2, \ldots, X_i\}$. The normalized results are $X_1', X_2', X_3', \ldots, X_i'$, as shown below.

$$X_i' = \frac{X_i - \min(X_s)}{\max(X_s) - \min(X_s)} \tag{4}$$

The formula of information entropy is calculated as follows.

$$e_j = -\ln(n)^{-1} \sum_{i=1}^{n} p_{ij} \ln p_{ij} \tag{5}$$

P_{ij} represents the index ratio of the jth scheme in the ith index.

By normalizing the information utility value, the entropy of each index is as follows.

$$w_j = \frac{1 - E_j}{k - \Sigma E_j} (\mathrm{j} = 1, 2, ..., m) \tag{6}$$

The data is preprocessed with regularization and normalization, and then use the entropy weight method to assign weights to the preprocessed indicators. The weight calculation results are as shown in Table 2.

Table 2. Results of entropy weight method for light trespass pollution assessment

Index	e	d	Weight (%)
Density of population	0.739	0.261	62.148
Greening rate	0.903	0.097	23.11
Traffic flow	0.938	0.062	14.742

In Table 2, e represents information entropy value and d means information utility value.

The results in Table 2 show that the maximum value of index weight is population density (62.148%), and the minimum value is greening rate (14.742%).

The light trespass contamination risk level is as below.

$$R_t = 62.148\% \times P + 23.11\% \times C - 14.742\% \times G \tag{7}$$

R_t represents the risk level of light trespass light pollution, P stands for population density, C means traffic flow, and G refers to for greening rate.

2.1.4 Evaluation of spill light pollution risk

Spill light is the light scattered from the lighting device and irradiated beyond the lighting range. The article selects gross domestic product (GDP) and regional total effective electricity consumption (EEC) as two indicators [11].

Define X and Y as two sets of data, and their Spearman correlation coefficient follows formula below [12].

$$SP_c = 1 - \frac{6 \sum_{i=1}^{n} d_i^2}{n(n^2 - 1)} \tag{8}$$

SP_c represents Spearman correlation coefficient, and di refers to the grade difference between X_i and Y_i.

By analyzing the spearman correlation coefficient between regional GDP and EEC, the result is shown in Figure 4.

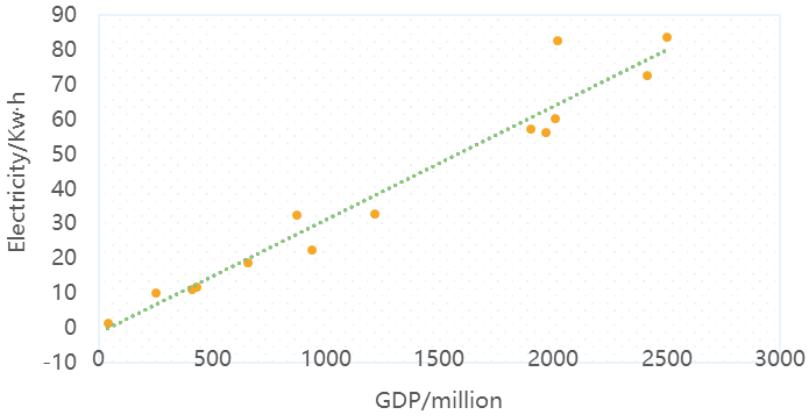


Figure 4. Relationship diagram of GDP and EEC

It can be seen from the figure that there is obvious positive correlation between GDP and EEC. Therefore, the relative ratio method is used to quantify the risk level of spill light pollution [13].

$$R_s = 1 - \frac{GDP}{EEC} \tag{9}$$

R_s indicates the risk level of spill light pollution, and EEC represents the total electricity consumption of the location.

2.1.5 Assessment of sky glow pollution risk

A certain relationship exists between PM2.5 concentration and light pollution. PM2.5 absorbs and scatters light, which affects the transmission and reflection of light in the atmosphere. This leads to an increase in the risk level of light pollution [14].

SQM and PM2.5 concentration are chosen as indicators. SQM refers to the sky quality index [15]. The higher the value, the lower the light pollution.

The data is from darkmap.cn, as shown in Table 3.

Table 3. Data of indicators for sky glow pollution assessment

Region	SQM	$PM_{2.5}(ug/m^3)$
Yuhang	19.2	30.4
Shangcheng	18.6	28.5
Binjiang	18.5	30.8
Xiaoshan	19.1	32.6
Gongshu	18.5	31.7
Xihu	18.9	28.1
Qiantang	19.3	30.7
Linping	18.6	30.2
Fuyang	19.4	30.5
Lin'an	20.3	30.3
Jiande City	20.3	22.9
Tonglu County	20.1	26.5
Chun'an County	20.4	18.6
West Lake Scenic Area	19.5	26.4

The article regularizes and normalizes the data, and then uses the EWM to assign weights to the preprocessed indicators. The weight calculation results are as shown in Table 4.

Table 4. Results of entropy weight method for sky glow pollution assessment

Index	e	d	Weight (%)
$PM_{2.5}(ug/m^3)$	0.96	0.04	29.271
SQM	0.902	0.098	70.729

The results in Table 4 show that the maximum value of index weight is SQM (70.729%), and the minimum value is $PM_{2.5}(ug/m^3)$ (29.271%).

The sky glow pollution risk level is as below.

$$R_s = 29.271\% \times PM_{2.5} - 70.729\% \times SQM \tag{10}$$

2.2. Light pollution risk evaluation based on TOPSIS

The weight of each index is calculated by entropy weight method to reduce the influence of subjective factors. The weight calculation results of entropy weight method are as shown in Table 5.

Table 5. Results of weight calculation for light pollution evaluation

Index	e	d	Weight (%)
R_g	0.915	0.085	28.655
R_t	0.894	0.039	35.963
R_s	0.961	0.065	13.228
R_{sg}	0.935	0.065	22.153

TOPSIS is adopted to comprehensively rank different regions. The parameters follow principles as follows [16].

Calculate the Euclidean distance between the index selected or constructed. The optimal vector is as below.

$$D^+ = \sqrt{\sum_{j=1}^{n} (Z_{ij} - Z_j^+)^2} \tag{11}$$

The worst vector is as follows.

$$D^- = \sqrt{\sum_{j=1}^{n} (Z_y - Z_j^-)^2} \tag{12}$$

The relative proximity to the optimal value is denoted as the comprehensive score of a location's light pollution risk level.

$$W_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{13}$$

It is considered that the higher the score, the heavier the light pollution. Through TOPSIS, the article obtains the comprehensive scores of 14 districts and then ranks them, as shown in Table 6-7

Table 6. Score and rank after TOPSIS for 14 districts

Region	D_+	D_-	Score	Rank
Binjiang	0.266	0.777	0.745	1
Gongshu	0.373	0.782	0.677	2
Xihu	0.384	0.73	0.655	3
Shangcheng	0.438	0.788	0.643	4
Yuhang	0.433	0.702	0.619	5
Xiaoshan	0.439	0.634	0.59	6

Table 7. Score and rank after TOPSIS for 14 districts (continued)

Region	D_+	D_-	Score	Rank
Qiantang	0.43	0.61	0.587	7
Linping	0.491	0.593	0.547	8
Lin'an	0.619	0.493	0.443	9
Fuyang	0.62	0.474	0.433	10
Chun'an County	0.772	0.448	0.367	11
Tonglu County	0.763	0.393	0.34	12
Jiande City	0.752	0.381	0.336	13
West Lake Scenic Area	0.918	0.344	0.272	14

2.3. Risk level classification based on K-means clustering algorithm

K-Means clustering algorithm is used to cluster the results [17]. The algorithm is an unsupervised learning one used to divide a data set into K different clusters or groups. It iteratively divides the sample points in the data set into K clusters, making the distance between each sample point and the center point of the corresponding cluster it the smallest.

According to the clustering coefficient from Spss, the elbow figure is shown in Figure 5.

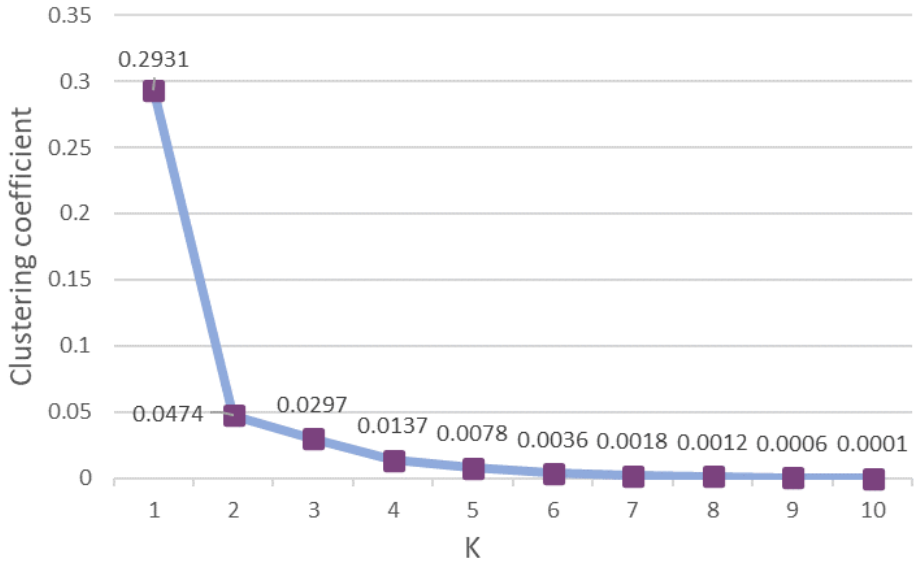


Figure 5. Line chart of aggregation coefficient

It can be seen from the figure that when the value of K is from 1 to 3, the degree of distortion changes the most. With K exceeding 3, the degree of distortion is significantly reduced, so we set k as 3 [18]. The result is shown in Table 8.

Table 8. Results of clustering

Classification	Frequency	Percent (%)
Low	4	28.571
Medium	6	42.857
High	4	28.571

3. Result Analysis

After evaluating and analyzing the risk level of light pollution in various districts of Hangzhou, the results can be concluded in Figure 6.

Region	District	Light Pollution Risk Level	Clustering result
Binjiang	Urban community	0.74500956	High risk
Gongshu		0.67712027	
Xihu		0.65503189	
Shangcheng		0.64285902	
Yuhang	Rural community	0.61878982	Medium risk
Xiaoshan		0.59086439	
Qiantang		0.58659046	
Linping		0.54724959	
Lin'an		0.4433179	
Fuyang		0.43311127	
Chun'an County	Rural community	0.36698018	Low risk
Tonglu County		0.33968195	
Jiande City		0.33589835	
West Lake Scenic Area	Protected land location	0.27243889	

Figure 6. Classification results of light pollution risk level

In general, the light pollution in the urban center is the most serious, while the light pollution in the suburbs, rural areas and protected areas is relatively low. However, with the process of urbanization and the development of modernization, the degree of light pollution in some suburban and rural areas has also increased, and it is necessary to further strengthen the supervision and governance of light pollution.

4. Conclusions

With the intensification of urbanization and the development of industrialization, demand for light at night is increasing. Light pollution is becoming more and more serious. Excessive use of artificial light sources not only wastes energy, but also has a serious impact on the living environment of wild animals and plants. In addition, light pollution can also have a negative impact on human physical and mental health, such as sleep disorders, vision problems, and emotional disorders. In order to evaluate the light pollution risk level of different regions, a light pollution risk level identification model is established [1-2].

Light Pollution is divided into 4 types: glare, light trespass, spill light, and sky glow. In order to evaluating the glare pollution risk, CBE and correlation coefficient weighting method is used. For light trespass, the EWM is adopted to weight population density, greening rate, and traffic flow. For spill light, the risk level is assessed based on relative ratio method (GDP divided by total electricity consumption). For sky glow, the EWM is adopted to weight PM2.5 and SQM. TOPSIS, improved by the EWM, is used for comprehensive evaluation of light pollution. Finally, K-Means clustering

algorithm is conducted to grade the risk level of different locations. The proportion of locations of high risk, medium risk and low risk are 28.57%, 28.57% and 42.86% respectively.

The study of light pollution risk level still has more and broader content that needs to be discussed. The article envisages that future research on regional light pollution risk level can be carried out in the following directions:

- The impact of light interference on people is intangible, cumulative, and uncertain, so it is difficult to quantify. The impact on people's mental health needs further qualitative and quantitative research.
- Glare, encroachment light, and overflow light produced by different light sources are not the same, leading to different light pollution. The distinguishment remains to be done.

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