Evaluation System of Light Pollution Risk Index Based on Entropy Weight Method

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Abstract. In recent years, the issue of light pollution has garnered widespread attention. To address this concern, the state of California in the United States has developed a grading format to regulate lighting areas for light pollution protection. In order to further study this problem, we have selected six factors related to light pollution, namely population density, per capita gross regional product, total passenger transport, industrial electricity consumption, real estate development investment, and green area of built-up areas in different years in each prefecture-level city in China. Based on the VIKOR model, we have established a light pollution risk assessment system using the obtained compromise value as an assessment index for light pollution levels in different regions. The results have been analyzed using VIIRS satellite remote sensing images, and the average error is 5.24%, indicating good sensitivity to the system. Finally, we have analyzed the assessment results to show that over-development of areas can seriously exacerbate the risk level of light pollution. Therefore, development should be planned rationally to reduce the impact of light pollution.

Keywords: VIKOR, Bartlett's Spherical Test, Principal Component Analysis, KMO.

1. Introduction

In recent years, the widespread use of artificial lighting has resulted in a growing problem of light pollution. According to Environmental Science and Technology on February 25, 2020, global light pollution has become a critical problem that is expected to have immeasurable effects on the environment, ecosystems, and human health. Excessive night-time light can disrupt people's biological clocks, leading to poor quality sleep. Moreover, excessive light can also harm the ecology of plants and animals, upsetting the balance of ecosystems. To effectively assess the risk level of light pollution in different areas, we have adopted the VIKOR model based on the idea of entropy weight method, selected six factors related to the risk level of light pollution, established the light pollution risk index assessment system, and finally calculated the sensitivity of the system by analyzing errors.

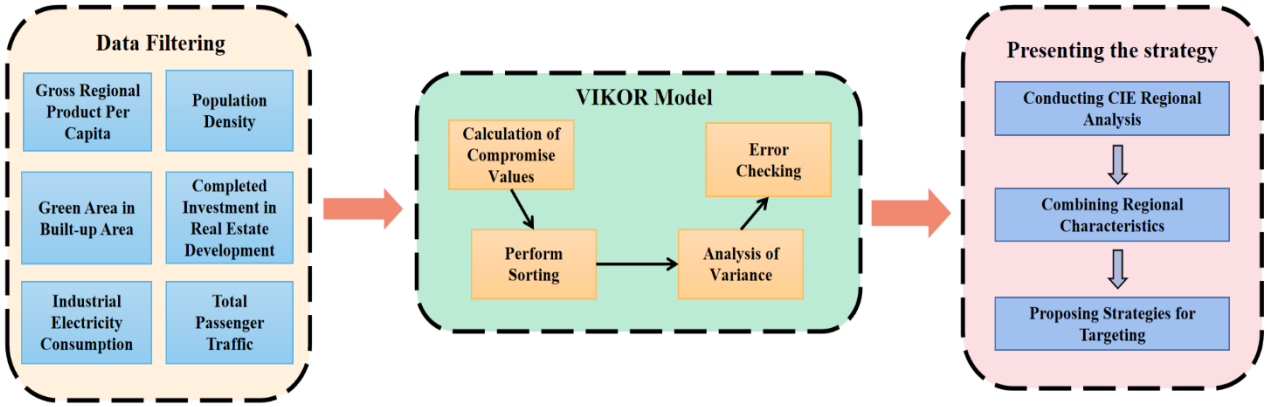


Figure 1. The Overall Framework

2. Related Work

Previous research on light pollution has primarily focused on identifying its causes, quantifying its impact on the environment and human health, and developing strategies to mitigate its effects. In a study conducted by Jiang et al. (2018) [1], the potential use of Luojia 1-01 nighttime light imagery for investigating artificial light pollution was assessed. The researchers compared light pollution

levels, light flux to population size and GDP at the State and County levels in the USA, and at Regional (NUTS2) and Province (NUTS3) levels in Europe, using data from the New World Atlas of Artificial Night Sky Brightness, VIIRS-recorded radiance, and GDP data (Falchi et al., 2019) [2].A database of CEFs could initiate a completely new phase in light-pollution research, with significant economy and advanced accuracy of night-sky brightness predictions. The experiment and its interpretation represent unique progress in the field and contribute to the fundamental understanding of the mechanism by which direct and reflected uplight interact while forming the CEF (Kocifaj et al., 2019) [3]. Isnarti (2020) employed qualitative methods by collecting and categorizing data from library research [4]. Most light pollution research focuses on high-wattage street lamps, but lower-wattage lamps used to illuminate porches, paths, facades, and backyards vastly outnumber street lamps (Justice et al., 2021) [5].Kern-bach et al. (2021) aimed to highlight background and foundational evidence of the effects of light pollution to present context and the basis for early light pollution studies [6]. Other influential work includes Jechow et al. (2020) Light Pollution Risk Assessment Model [7].

3. Proposed Model

To evaluate light pollution, we focus on six indicators such as *population density, gross regional product per capita*, and *industrial electricity consumption*. Then we collect relevant data from 1992 to 2013. We use the multi-criteria compromise solution ranking method based on entropy weight to calculate the index data of each region and obtain the compromise value *Q*, which reflects the level of light pollution in the area. To further rate each region, we rasterize and gray-scale the night brightness images taken by VIIRS remote sensing satellites, and calculate the average gray value *DN* of each region. Next we convert and correct *DN* using the radiation brightness conversion formula to obtain the radiation brightness value L of each area. Finally, we verify the accuracy of the model by comparing the ranking results of the radiance value with the ranking results of the compromise value.

3.1. Data Description

In this model, we choose China's light pollution as the research object. As one of the world's largest economies, China's efforts to mitigate light pollution could have a significant global impact. Therefore, studying light pollution in China can enhance our understanding of the problem and help develop effective strategies to solve the problem of light pollution in China and globally.

3.1.1. Data Source and Analysis

1) Basic Data Collection for Prefecture-level Cities

By retrieving data from the National Bureau of Statistics, the China Statistical Yearbook and the National Center for Earth System Science and Data, three Chinese websites with comprehensive and highly recognized domestic data volumes, we statistically collated the data set of information related to each prefecture-level city in China from 1992 to 2013. We take Guangzhou as an example to show the data in Table 1.

Table 1. Information about Prefecture-level Cities in China by Province from 1992 to 2013 (Partial data)

Administrative district code	*Year*	*Province*	*City*	*GDP*	*Population density*	*Highway passenger volume*	*Urban consumption electricity*
440100	1992	Guangdong	Guangzhou	5107027	824	8061	983053
	1993			7408369	839	9344	983057
	1994			9761829	848	10628	983063
	1995			12430697	870	11911	983078

2) Pixel Brightness Value Data of Remote Sensing Images in Prefecture-level Cities

In this paper, we utilized the nighttime brightness image dataset captured by the VIIRS remote sensing satellite. Based on this dataset, we conducted rasterization and grayscale processing to conduct statistical analysis on the average grayscale value (*DN*) of each region.

From The Night Luminance Map taken by VIIRS Remote Sensing Satellite, we can find that the night sky light pollution varies greatly in various regions of China. Generally speaking, densely populated and urbanized areas have higher levels of light pollution. The worst light pollution is mainly found in the eastern and southeastern coastal regions, as well as major urban centers such as Beijing, Shanghai and Guangzhou. These areas usually have a higher level of ecological civilization development and a higher population density, resulting in a higher demand for artificial lighting. In contrast, less developed and rural areas typically have lower levels of light pollution [8].

In addition, we compared the remote sensing images with the global climate distribution map and found that most of the areas with high light pollution are in the monsoon climate, with mild climate characteristics, supplemented by flat and hot. This is due to light polluting energy consumption that dissipates most of the heat into the air, leading to climate change.

3.1.2. Data Processing

Before data analysis, we must ensure the availability of data. In this regard, the following data processing is made in this paper.

1) Data Screening

We screened the indicators obtained by statistics, and obtained the following six kinds of data closely related to light pollution as key influencing factors for subsequent modeling as follows.

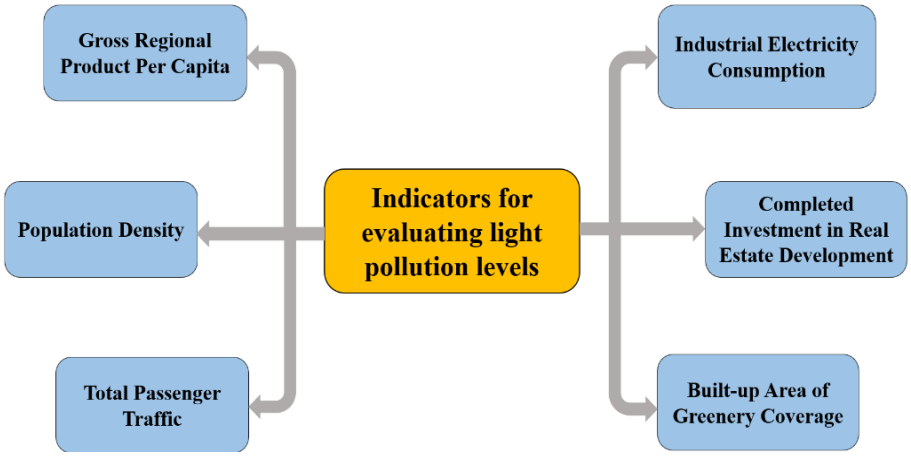


Figure 2. Light pollution level assessment indicator system diagram

2) Missing Value Processing

As population density and per capita gross regional product are not continuous data, we optimized the traditional scheme of filling missing values with the average value. To facilitate subsequent modeling, we processed missing values by imputing them with the corresponding data's average value before and after the same year in prefecture-level cities. This approach improved the accuracy of the data and enabled better modeling results [9].

3) Data Standardization

Since there is a magnitude gap between the selected indicator data in Figure 2, in order to eliminate the influence of the magnitude on the subsequent model analysis, we adopt Z-Score data standardization to process the data.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^2} \tag{1}$$

$$z = \frac{x - \mu}{\sigma} \tag{2}$$

Through all the above steps for data processing, we get the result of the dataset as shown in the Table 2.

Table 2. The Data Set obtained after Data Processing (partial data)

Gross regional product per capita	*Population density*	*Total passenger traffic*	*Industrial electricity consumption*	*Completed investment in real estate development*	*Built-up area of greenery coverage*
-0.844	-0.057	-0.230	-0.553	-0.483	-0.570
-0.798	-0.060	-0.462	-0.551	-0.458	-0.551
-0.755	-0.057	-0.203	-0.548	-0.448	-0.339
-0.712	-0.050	-0.200	-0.544	-0.412	-0.313

3.2. Light Pollution Risk Assessment Model

Due to the different effects of different indicators on light pollution, in order to accurately reflect the influence of different indicators on light pollution, this paper decided to use the entropy weight method to calculate the weight of different indicators. Entropy, as a physical concept in thermodynamics and informatics, is a measure of the disorder of a system. Among them, the larger the entropy is, the more chaotic it is, and the less information it carries. Of various indicators of entropy method to quantify the chaotic degree of the data, said to the quantitative analysis of the influence degree of each indicator light pollution, the specific calculation process is as follows.

Firstly, we calculate the weight of the j^{th} index in the i^{th} sample.

$$y_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{3}$$

Then, we calculate the information entropy of the j^{th} indicator.

$$e_j = -K \sum_{i=1}^{m} y_{ij} \ln y_{ij} \tag{4}$$

Last, we calculate the weight of the j^{th} indicator.

$$\omega_j = \frac{1 - e_j}{\sum_j 1 - e_j} \tag{5}$$

We calculate the normalized data using the entropy weight method and obtain the following results.

Table 3. The Data Set obtained after Data Processing (partial data)

Item	*Weight*
Gross Regional Product Per Capita	0.129
Total Passenger Traffic	0.209
Completed Investment in Real Estate Development	0.362
Industrial Electricity Consumption	0.193
Population Density	0.104
Built-up Area of Greenery Coverage	0.003

It can be seen from the Table 3 that the Completed investment in real estate development has the highest weight, indicating that this indicator contains a huge amount of information, which is of great help to the establishment of the following model.

3.3. Quantify the Level of Light Pollution Risk

In order to further quantify the risk level of light pollution in a certain area, the VIKOR method is used to rank the grade of light pollution in each area (Figure 1).

The VIKOR method, which stands for Multi-Criteria Optimization and Compromise Solution Ranking, was proposed by Opricovic and Tzeng in 1998. This method aims to rank a finite set of decision-making alternatives by maximizing group utility and minimizing individual regret values. The solution obtained by the VIKOR model is a compromise solution that is the feasible solution closest to the optimal solution [10][11]. It is the result of mutual concession between the optimal and worst attributes and addresses the shortcoming of the TOPSIS model in accurately expressing the relative distance between the alternative and ideal solution. The following section outlines the establishment and solution of the VIKOR model [12].

3.3.1. Normalize the Data

For the positive indicator normalization formula.

$$n_{ij} = \frac{o_{ij} - \min(o_j)}{\max(o_j) - \min(o_j)} \tag{6}$$

For the normalization formula of negative indicators.

$$n_{ij} = \frac{\max(o_j) - o_{ij}}{\max(o_j) - \min(o_j)} \tag{7}$$

Where o_{ij} is the element in the data matrix before normalization and n_{ij} is the element in the data matrix after normalization.

If the indicator can aggravate the degree of light pollution, then it is a positive index, else we think it is a negative indicator.

3.3.2. Calculate to Maximize Group Interests and Minimize Individual Regret Values

$$S_i = \sum_{j=1}^{m} \omega_j \left(\frac{Zone_j^+ - n_{ij}}{Zone_j^+ - Zone_j^-} \right) \tag{8}$$

$$R_i = \max_{j=1} \left(\omega_j \left(\frac{Zone_j^+ - n_{ij}}{Zone_j^+ - Zone_j^-} \right) \right) \tag{9}$$

WHERe ω_j is the weight of each indicator obtained by entropy weighting method.

3.3.3. Computational Compromise Solution Q

$$Q_i = (1-k)\left(\frac{S_i - Min(S_i)}{Max(S_i) - Min(S_i)}\right) + k\left(\frac{R_i - Min(R_i)}{Max(R_i) - Min(R_i)}\right) \tag{10}$$

Where k is the decision mechanism coefficient, when k = 0.5, it will balance the group maximum utility and group minimum regret. When k > 0.5, the group's lowest utility is more pursued, when k < 0.5, the group's minimum regret is more pursued.

The following explains the use of the intercept method to take the value of k.

k as a decision mechanism coefficient, which is a range with strong and weak sensitivity.

For each sample data, we process it as follows.

$$a_i = \frac{S_i - Min(S_i)}{Max(S_i) - Min(S_i)} \tag{11}$$

$$b_i = \frac{R_i - Min(R_i)}{Max(R_i) - Min(R_i)} \tag{12}$$

$$Q_i = (1-k)a_i + kb_i \tag{13}$$

And select two adjacent samples *x* and *y* from the sample data.

$$k = \frac{a_x - a_y}{(a_x - a_y + b_y - b_x)} \tag{14}$$

Among all *k*, we choose the best scheme of the minimum calculation result of *Q* as the final result. We take Anhui as an example to show the data of the results in Table 4.

Table 4. The Best Scheme for the Minimum Calculation Result of *Q* (partial data)

Year	*Province*	*Individual regret value (R)*	*Benefit ratio value* (*Q*)
2006	Anhui	0.165	0.894
2007		0.163	0.892
2008		0.163	0.886
2009		0.163	0.887
2010		0.163	0.877
2011		0.162	0.870
2012		0.162	0.866
2013		0.161	0.857

After calculation, we get the *k* value of the combination of different samples, and according to the calculation result of *Q* minimum, we finally select *k* = 0.54 as the decision-making mechanism coefficient of the above calculation results.

3.3.4. Model Checking

For the Model Checking, we collect the image data taken by VIIRS remote sensing satellite from the Internet. And the image data is processed by preliminary median filtering to remove noise, then rasterization and gray processing are carried out, and then the average gray value *DN* of each region

is extracted from the image. Finally, the radiation luminance value is further calculated by using the following formula.

$$L = DN^{3/2} \bullet 10^{-10} \tag{15}$$

Where L is the absolute radiation corrected radiation brightness value in $W/(m^2 \square sr \square \mu m)$, DN is the grayscale value of the image.

Finally, the ranking result $Rank_q$ of the Q value in the data and the ranking result $Rank_l$ of the L value are analyzed by using formula $\delta_i = \frac{\left| Rank_i^q - Rank_i^l \right|}{S}$. Where S is the number of sample data.

We take Anhui as an example to show the error results shown in the Table 5.

Table 5. The Error result(partial data)

Year	*Province*	*Error*
2006	Anhui	0.026
2007		0.063
2008		0.076
2009		0.068
2010		0.034
2011		0.063
2012		0.085
2013		0.096

3.4. Sensitivity Analysis

Through the process of establishing the above model, we select a number of factors closely related to the level of light pollution for analysis and use the VIKOR method to quantitatively rank the risk level of light pollution in each region. We can get the calculation result of the average error $\overline{\delta} = \sum_i \delta_i$ is 0.0524, which shows that the model is accurate.

Finally, by adding noise to change the average value of the normalized factor, we calculate the different compromise value *Q*, and draw the relation curve between the change rate of the compromise value *Q* and the former.

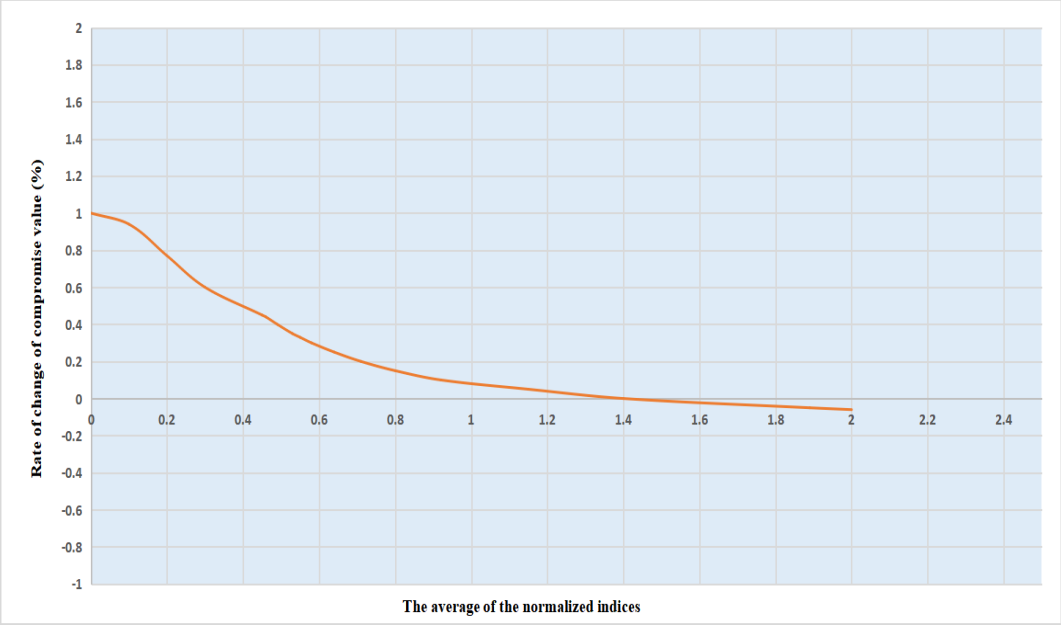


Figure 3. Sensitivity Analysis of Light pollution Assessment Model

From the Figure 3, we can analyze that the model is more stable when the mean value of the normalized factors is around 1.38.

4. Conclusion

According to the results of our light pollution assessment system, we can observe that cities with low per capita GDP and population density, low total passenger traffic, low industrial electricity consumption, and low investment in real estate development exhibit a low light pollution risk level. Conversely, cities with high industrial electricity consumption and investment in real estate development tend to have a high light pollution risk rating. This highlights that excessive development in a region can significantly worsen the degree of light pollution. Therefore, we must adjust our urban planning, adopt appropriate development strategies, protect the ecological environment, and increase measures to mitigate the impact of light pollution.

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