A Light Pollution Comprehensive Index Model Based on EWM

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Abstract: Light pollution is a major problem in modern society. In this paper, a Light Pollution Comprehensive Index (LPCI) model is established with three dimensions: environment, society and climate, and the weight of each index is calculated by the entropy weight method. The result shows that social factors account for the largest proportion of weight. The model is also used to evaluate China's light pollution index. The result shows that Shanghai had the highest light pollution index, while Gansu had the lowest.

1. Introduction

With economic and technological advances, the number of lighting installations has proliferated, and the reflective surfaces of buildings in cities have increased, exposing more and more areas of the world to above-natural light levels. The rapid development of industry and economy brings about an inevitable problem -- light pollution. In order to study the light pollution problem, we establish the Light Pollution Comprehensive Index Model (LPCI) to evaluate the risk of light pollution in China.

2. Selection of indicators

A wide range of factors affect the level of light pollution risk, from the economic and society factors that cause light pollution to the impact that light pollution will have. To evaluate the level of light pollution accurately and scientifically, we select the 12 most influential indicators and divide them into three dimensions, Society, Environment and Climate.

2.1 Society

• Economy Growth (*EG*)

In modern society, artificial light generated by colonies is a source of light pollution. An important indicator to measure the development of a colony is the economy. Undoubtedly, economic prosperity will cause a colony to produce more artificial light, which will increase light pollution.

• Population Density (PD)

Population density is the number of people per unit area, which can evaluate the population concentration more effectively. The growth of the population living in the area will increase the amount of night light needed for production and living. This factor is also considered in the model of

R.H. Garstang [1].

• Urbanization Rate (UR)

When the majority of people live in cities, the light pollution generated by cities will increase. We select the indicator of urbanization rate for this consideration.

$$UR = \frac{Population in Urban Areas}{Overall Population}$$
(1)

• Urban Area (UA)

An area consists of urban and non-urban areas. Light pollution mainly occurs in urban areas where population is concentrated. The size of urban area will directly affect the range of light. In order to eliminate the dimensional problem caused by the area difference of each region, we choose the ratio of urban area and regional area to measure this index.

$$UA = \frac{Actual \, Urban \, Area}{Region \, Area} \tag{2}$$

• Road Lighting (*RL*)

As one of the artificial light sources, road lighting lamp is an indispensable index to evaluate light pollution. In order to eliminate the area dimensional differences between regions, we also use the unified index of the ratio of the number of road lighting lamps to the area to measure.

$$RL = \frac{Actual \, Urban \, Area}{Region \, Area} \tag{3}$$

• Crime Rate (CR)

There is a certain relationship between light and crime rate, that is, too little light leads to the rise of crime rate [2]. Considering this factor, the moderate amount of light is necessary. This positive effect of artificial light reduces the risk level of light pollution, so it is important to note that this is a negative indicator.

• Car Parc (CP)

We choose this indicator because the artificial light sources used by cars driving at night will exacerbate light pollution. At the same time, the increase of the number of cars increases the probability of traffic accidents caused by glare. In order to eliminate the dimensional influence of population number in each region, this paper chooses the per capita vehicle number in each region.

2.2 Environment

• Forest Coverage (FC)

While reflecting artificial light from urban surface space, plants can also shield light and reduce the propagation of light to the sky [3]. Therefore, regional forest coverage is an important index to evaluate the level of light pollution. It is important to note that this indicator mainly improves light pollution levels in non-urban areas due to the geographical distance between cities and forests.

• Green Area Rate (GAR)

To improve the level of light pollution in urban areas, we select green area rate to evaluate. Urban greening, distributed in urban parks, neighborhoods, streets and other places, can directly reduce light pollution levels.

• Plain Area Ratio (PA)

Plain areas are potentially associated with light pollution. On the one hand, plain areas are often

suitable locations for settlements to be established, which brings artificial light; On the other hand, light in plain cities is more efficient when it is not blocked by terrain than in mountains and hills. We use the ratio of plain area to district area as a relative index.

$$PA = \frac{Plain Area Ratio}{Region Area} \tag{4}$$

• Biomass (*BIO*)

Biomass refers to the total number or dry weight of all species in a community. Light pollution at night interferes with circadian rhythms and may result in reduced biomass. Thus, biomass can be used to assess the risk of light pollution at night. In order to facilitate calculation, we use *ArcGIS* raster data to estimate the biomass of each province.

• Nature Reserves Ratio (NRR)

Similar to the function of forest coverage rate and green area rate, nature reserves use their own vegetation to absorb and cover light to prevent further spread of light pollution.

2.3 Climate

• Cloud Optical Thickness (COT)

Because clouds are very reflective, effectively increasing the chance of light being reflect back to the ground, they will be a factor to consider for nighttime light pollution. Night sky brightness will increase with the increase of cloud thickness [4], that is, cloud thickness has a positive promoting relationship with light pollution. We use regional mean cloud thickness to measure the influence of cloud on nighttime light pollution.

• PM Emission (PME)

Aerosol is a kind of solid or liquid particle that has a great influence on air visibility. It scatters light and blocks artificial light propagation at night [5]. Particulate matter emissions, a major component of aerosols, are select to represent this factor.

• Relative Humidity (*RH*)

Light pollution is affected by atmospheric transmittance, and humidity is a major factor affecting atmospheric transmittance [6]. Therefore, relative humidity is considered when evaluating the risk of light pollution.

• Number of Snow days (NSD)

Snow on the ground will enhance the reflection of artificial light on the ground and increase light pollution at night. Therefore, this paper chooses the number of annual snow days to consider this factor.

• Number of Fog days (NFD)

Foggy weather will reduce the visibility of the atmosphere, thereby increasing the attenuation coefficient of light and shortening the distance of daylight. In foggy weather, the visible distance in daylight is only 0.5m [3]. We chose the annual number of foggy days to represent the foggy weather conditions in the region.

3. Data source and preprocessing

Due to China's vast territory and great regional differences, we choose 31 provinces in China as samples. Data is from NOOA [7], National Bureau of Statistics [8], China Statistical Yearbook [9], NASA [10].

In the missing value processing and duplicate value checking, we use Python to clear the data and eliminate unrepresentative factors and indicators containing many missing values. Secondly, the selection results are cleared twice. Interpolation method is used to fit the missing data and deviation data. Finally, we standardize data as follows.

$$Z_{ij} = \begin{cases} \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}}, x_{ij} \text{ is the positive index} \\ \frac{\max x_{ij} - \min x_{ij}}{\max x_{ij} - x_{ij}}, x_{ij} \text{ is the negative index} \\ \frac{\max x_{ij} - x_{ij}}{\max x_{ij} - \min x_{ij}}, x_{ij} \text{ is the negative index} \end{cases}$$
(5)

 x_{ij} represents the original data of the *i* indicator of the *j* sample, Z_{ij} represents the standard value of the *i* indicator of the *j* sample, $i = 1,2,3 \dots m, j = 1,2,3 \dots m$ is the indicator number, *n* is the sample number, $0 \le Z_{ij} \le 1$.

3.1 Weight calculation based on EWM

In this paper, EWM is used to calculate the weight of each index. The entropy weight method adopts the objective weighting method and calculates the objective weight according to the index variability and the discreteness of the data itself. The specific calculation process is as follows:

Calculate the information entropy of each evaluation index E_i :

$$E_{i} = -\frac{1}{\ln n} \sum_{j=1}^{n} \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}} \ln \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}}$$
(6)

According to the information entropy of each index, calculate the weight of each index ω_i :

$$\omega_i = \frac{1 - E_i}{n - \sum_{i=1}^n E_i} \tag{7}$$

The calculation results are as follows:

Table 1	Weights of indicators

Dimension	Indicator	Attribute	Weight (%)	
	Economy Growth	+	7.564	
	Population Density	+	6.045	
Society	Urbanization Rate	+	1.893	
	Urban Area	+	12.651	
44.61%	Road Lighting	+	7.024	
	Crime Rate	-	1.718	
	Car Parc	+	7.716	
	Forest Coverage	-	5.158	
Environment	Plain Area Ratio	-	5.581	
	Green Area Rate	-	11.890	
29.79%	Biomass	-	4.509	
	Nature Reserves Ratio	-	2.655	
	Cloud Optical Thickness		3.692	
Climate	PM Emission	-	11.749	
	Relative Humidity		2.486	
25.60%	Number of Snow days		5.076	
	Number of Fog Days		2.593	

The results show that in the society dimension, urban area accounts for the largest weight, reaching 12.651%. In the environment dimension, the weight of green area ratio is the largest, reaching 11.890%. In terms of climate, the largest proportion of particulate matter emissions is 11.749 percent. Among the three dimensions, the society dimension accounts for the largest proportion, indicating

that the society dimension is the one that needs to be considered and paid attention to the most when evaluating the risk level of light pollution.

3.2 Establishment of LPCI Model

Next, we build LPCI model as follows. LPCI is a weighted combination of society, environment, and climate dimensions, where γ_i denotes the corresponding weights in Table 1.

$$LPCI = \gamma_1 Society + \gamma_2 Environment + \gamma_3 Climate$$
(8)

4. Analysis of LPCI model results

Based on LPCI model established above, we further calculate the light pollution risk level scores of 31 provinces in China. The result shows that the risk of light pollution is the highest in Shanghai, reaching 0.731, followed by Beijing. The lowest risk of light pollution is in Gansu.

The high-risk areas of light pollution are concentrated in the eastern part of China, followed by the central part, while the risk of light pollution is generally low in the western part of China, as shown in Figure 1.

						Hig	gh
Ningxia	Jiangxi	Henan	Fujian	Beijing			
0.233	0.303	0.366	0.52	0.707			
Qinghai	Guangxi	Liao ning	Hebei	Jiangsu			ndex
0.215	0.286	$0.3\check{6}1$	0.508	0.674			ve I
Nei Mongol	Shanxi	Hainan	Hubei	Guang dong			rehensi
0.215	0.267	0.36	0.507	0.647			duid
Xin Jiang	Shaanxi	Jilin	Anhui	Tian jing			tion Co
0.207	0.248	0.352	0.49	0.599			ollu
Tibet	Gui zhou	Sichuan	Heilong jiang	Zhe jiang			Light P
0.149	0.242	0.346	0.423	0.592			
Gansu	Yunnan	Chong qing	Hunan	Shan dong	Shang hai		
0.138	0.241	0.328	0.371	0.572	0.731	Low	

Figure 1 Light pollution level score

5. Conclusions

We are looking at the problem of light pollution and we establish a LPCI model to evaluate the regional light pollution risk and evaluate the light pollution degree in province in China. We take a risk assessment of light pollution need from the society, environment, climate three dimensions to consider multiple factors. Society factors account for the largest proportion. When apply the LPCI model to China, the result shows that the risk of light pollution is the highest in Shanghai, reaching 0.731, followed by Beijing. The lowest risk of light pollution is in Gansu.

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