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Research on Light Pollution Risk Level Assessment System Based on FCM-PSO

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Abstract: Light pollution has profound implications on human physiological rhythms, ecological balances in wildlife, and traffic safety, with its adverse effects becoming increasingly pronounced in the context of escalating urban lighting. In order to conduct a thorough analysis and assessment of the risks associated with light pollution, this study establishes a Light Pollution Risk Level Evaluation System. Grounded in the current light pollution scenario in the United States, we precisely define 20 fundamental indicators for light pollution risk levels. Through Principal Component Analysis, we identify ten major indicators, subsequently utilizing the FCM-PSO algorithm to cluster these indicators into five core parameters: Nocturnal radiation intensity, Population density, GDP, Built-up area, and Light intensity. Furthermore, employing the entropy weight method combined with the TOPSISfusion model, we conduct weighted calculations on these five core indicators to enhance the applicability of the evaluation system. According to the evaluation criteria, the computed weights for each indicator in the light pollution index are as follows: Radiation intensity 0.31, Light intensity 0.289, GDP 0.232, Population density 0.093, Built-up area 8%. This model not only provides a comprehensive assessment of light pollution risks but also serves as a valuable methodological reference for similar studies in the future.

Keywords: Light Pollution Risk Level Evaluation System; PCA; FCM-PSO; Entropy Weight Method—TOPSIS

Introduction

The global surge in artificial lighting, driven by a growing population, has led to widespread light pollution. Defined as excessive use of artificial lighting, it erases starlight and moonlight, altering natural nocturnal luminosity [1-4]. There's a pressing need to investigate its nuanced effects, providing empirical data for strategic mitigation. Addressing light pollution not only enhances human life but also preserves the environment, emphasizing the scholarly value in its study. Existing research delves into determinants and impacts, with Czarnecka et al. highlighting urban concentration due to abundant artificial lighting, intensifying reflections and refractions, impacting urban quality of life [5]. Sparse regions show lower pollution . Posudin et al.'s study identifies light pollution in specific street lamp configurations causing incidents, potentially inducing temporary blindness in drivers or pedestrians [6].

While existing research explores factors and consequences, a gap exists in assessing regional light pollution hazard levels. This paper proposes a robust Light Pollution Risk Level Evaluation System, using data from NASA's VIIRS, the 2015 World Atlas, aurora predictions, observatories, and national economic data. This initiative aims to explore factors contributing to light pollution, enhancing understanding of its multifaceted implications.

1. Basic Principles

1.1 Principal Component Analysis (PCA)

Characterizing light pollution involves 20 initial indicators for PCA. The dataset, spanning 2015 to 2019, for each country, was obtained from myskynight and UNESCO. Assuming m evaluation objects with n indicators (Xij), the original data is structured into a matrix.

$$X = \left\{ \begin{matrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \cdots & \cdots & \cdots & \cdots \\ x_{n1} & x_{n2} & \cdots & x_{np} \end{matrix} \right. \tag{1}$$

Consequently,

$$z_{ij}=\frac{x_{ij}-\overline{x_j}}{S_j^2}(i=1,2,\dots,\ \ m;\ \ j=1,2,\dots,n) \tag{2}$$

The method to calculate the correlation matrix is as follows:

$$r_{ij}=\frac{\sum_{k=1}^{n} z_{kj}gz_{ki}}{n-1}(i=1,2\dots,m;j=1,2\dots n) \tag{3}$$

If a matrix undergoes only scaling transformations on a vector or some vectors without rotation effects, these vectors are termed eigenvectors, with their scaling values being the eigenvalues.

Principal component loadings reflect the mutual correlation between principal components and original variables. The loadings of original variables on principal components are measured by calculating variance contribution rates $w_i=\frac{\lambda_j}{\sum_{j=1}^{n}\lambda_j}$ and cumulative contribution rates $y_i=\frac{\sum_{j=1}^{p}\lambda_j}{\sum_{j=1}^{n}\lambda_j}$.

1.2 FCM-PSO Algorithm

The FCM-PSO algorithm integrates Particle Swarm Optimization (PSO) with the traditional FCM algorithm to overcome sensitivity to initial cluster centers. The algorithm can be summarized in the following steps:

- ***Initialization:***Set initial cluster centers and membership degrees, specify parameters (e.g., particles, velocity range).
- ***Compute Fitness:***Calculate fitness based on current centers and memberships, record optimal solution.
- ***Update Velocity:***Update particle velocities based on the current particle position and the global optimum.
- ***Update Position:***Update particle positions based on velocities. Recalculate fitness.
- ***Stopping Criterion:***Criterion: Terminate when a specified iteration limit is reached or if fitness improvement is insignificant.
- ***Output Results:*** Output final cluster centers and memberships, effectively partitioning the dataset.

1.3 Entropy Weight-TOPSIS Model

For weight assignment, traditional methods rely on data patterns or use objective methods. This study introduces an innovative approach: the Entropy Weight-TOPSIS evaluation model.

Normalize indicators with different magnitudes to a common range. Given n evaluation indicators, construct the initial data matrix $X=(x_{ij})_{mxn}$, resulting in a standardized data matrix denoted by $X=(x_{ij})_{mxn}$.

$$X'_{ij}=\frac{X_{ij}}{\sqrt{\sum_{i=1}^{m}x_{ij}{}^2}} \tag{4}$$

Assign weights to the obtained indicators. Let the weights be denoted by w_j, resulting in a weighted data matrix r_i:

$$r_{ij}=w_i x_{ij}{}' \tag{5}$$

Construct a data matrix after processing $R=(r_{ij})_{mxn}$, defining the maximum value for each indicator (each column) as r_j^+ and the minimum value as r_j^-.

Calculate the weights of the transformed indicators w_j:

$$Score=\frac{d_i{}^-}{d_i{}^+ + d_i{}^-} \tag{6}$$

2. Empirical Analysis

2.1 Selection of Indicators

From literature, Elsahragty noted dispersed illumination elevates light pollution [7]. Liu et al. identified urban light pollution assessment indicators like environmental brightness zoning, lights-out time, light color control, spacing control, uplight ratio, and brightness balance [8]. We've consolidated these factors into fundamental assessment indicators.

In the U.S., cities like Boston, New York, Philadelphia, and Washington show increased light pollution due to factors like population, economic growth, and diverse architecture. This suggests a correlation between light pollution and population, economic development, and urban area size.

Based on the preceding literature review on light pollution and the analysis of the Light Pollution Map, partularly focusing on the United States, we propose the establishment of the following 20 light pollution assessment indicators, as outlined below.

Table 1 Summary of Evaluation Indicators

Evaluation Indicators	Evaluation Indicators	Evaluation Indicators
1 Nocturnal radiation intensity	8 Brightness balance	15 Ambient brightness
2 Population	9 Exterior Lighting	16 Up-lighting ratio
3 GDP	10 Light color	17 Area spacing
4 Built-up area	11 Indoor strength	18 Lights out time
5 Light intensity	12 Installation of lighting equipment	19 Lighting standards for residential areas
6 Sky brightness distribution	13 Shade form	20 Exposure ratio
7 Glare level	14 Control level	

2.2 Clustering Experimental Results

Through principal component analysis and FCM-PSO algorithm analysis, using Python, after normalizing various data, correlation coefficients are then calculated, as shown in Figure 2.

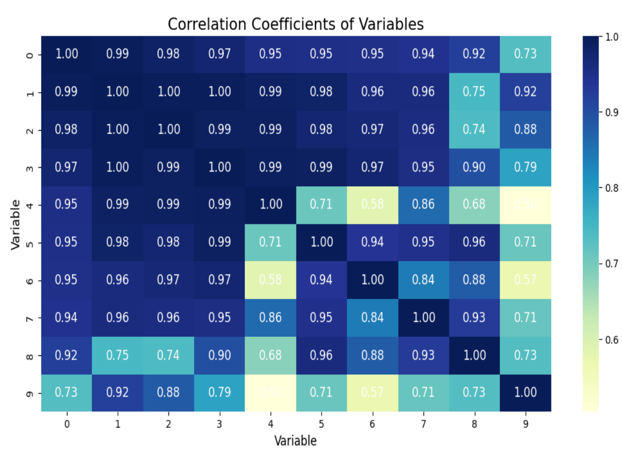

Figure 1 Correlation Coefficient Matrix Chart

Correlation matrix plot indicates strong correlations, often exceeding 0.7, particularly Nocturnal Radiation Intensity and GDP with light pollution (coefficients up to 0.996). This suggests PCA suitability for data analysis, designating these as primary indicators.

Eigenvalues and eigenvectors were computed, and results are in Table 3. Eigenvalues less than 1 suggest inferior explanatory power compared to the mean value of original variables. Focusing on eigenvalues greater than 1, two were calculated, λ_1=2.841, λ_2=1.092.

Table 2 Variable Analysis Table

Ingredient	Initial Eigenvalue			Extraction of squares and loading		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	2.6353	20.2676	90.1984	2.6353	22.2676	90.1984
2	2.5341	20.4680	91.4674	2.5341	21.4680	91.4674
3	2.3842	17.8678	94.6724	2.3842	19.8678	94.6724
4	2.2372	16.3535	97.7963	2.2372	18.3535	97.7963
5	2.1331	14.3821	98.7883	2.1331	17.3821	98.7883

After calculating the eigenvalues, the eigenvectors were obtained by computing the principal component loading values. The calculation results are shown in the t able below.

Table 3 Principal Component Factor Loading Matrix

	Ingredients	
	1	2
Nocturnal radiation intensity	0.998	0.014
Population	0.997	-0.057
GDP	0.994	0.079
Build-up area	0.986	-0.097
Light intensity	0.986	-0.118

After principal component analysis, the PSO-FCM algorithm clustered the top ten factors in Python. Clusters varied from 2 to 8, and mean silhouette coefficients were calculated. The plot revealed the highest coefficient at 5 clusters.

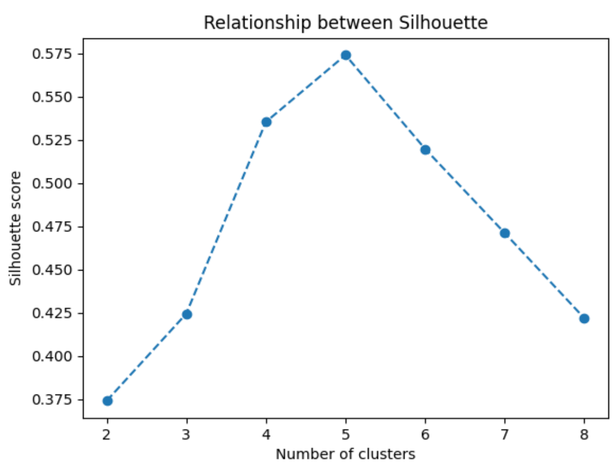

Figure 2 Silhouette Coefficient and Relationship between Cluster Numbers

In the optimal clustering scenario, the dataset can be partitioned into five distinct classes: {1,9}, {2}, {3}, {4,10}, and {5,6,7,8}. These classes are characterized by Nocturnal Radiation Intensity, Population, GDP, Build-up Area, and Light Intensity, respectively.

2.3 Hierarchy Division

Weighted Overlay Analysis categorizes indicators by overlaying levels determined by four primary evaluation indicators. Emphasis is on influential impact and weight coefficients for assessing light pollution. A hierarchical indicator weight system is established, with quantified indicators in the table below:

Table 4 Quantitative Indicators

Nocturnal radiation intensity(A1)	$1.3*10^{-9}Wcm^{2}*sr$	0
	$1.3*10^{-9}Wcm^{2}*sr\leq$	10
Population(A2)	100thousand people	1
	100thousand people≤,500thousand people	5
	500thousand people≤	7
GDP(A3)	1 billion dollars	0
	1 billion dollars≤,3billion dollars	3
	3 billion dollars≤	6
Build-up area(A4)	$50km^{2}$	1
	$50km^{2}\leq,100km^{2}$	5
	$100km^{2}\leq$	7
Light intensity(A5)	6.34lux	1
	6.34lux≤,11.35lux	4
	11.35lux≤	7

Based on the scoring of each indicator, we propose a light pollution classification standard, dividing the range into five intervals, as illustrated in Table 6.

Table 5 Standards for Light Pollution Levels in Four Geographic Locations

Level	Light pollution level	Light Pollution Assessment
Level 0	No light pollution	<3.0
Level 1	Mild light pollution	[3.0,5.25)
Level 2	Moderate variable light pollution	[5.25,6.0)
Level 3	Heavy light pollution	[6.0,7.0]
Level 4	Severe light pollution	>7.0

According to the evaluation criteria, the weighted contributions of each indicator to the light pollution index are calculated as follows: Radiation Intensity 0.31, Light Intensity 0.289, GDP 0.232, Population 0.093, and Built-up Area Impact Factor 8%.

3. Conclusion

Studying light pollution's impact and implementing preventive measures is crucial for improving lives and protecting the environment. Understanding influencing factors helps adopt intervention strategies. Methods like PCA, optimized FCM clustering, Entropy Weight-TOPSIS can enhance the light pollution risk assessment system. This enables a more precise hazard evaluation and formulation of preventive measures.

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