Light Pollution Risk Assessment and Intervention Strategies: A Comprehensive Approach

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ABSTRACT

This study presents a comprehensive approach to assess light pollution risk levels and develop targeted intervention strategies to mitigate its impact on urban development. We collect and preprocess data to establish indicators influencing light pollution risk levels, applying an improved evaluation model combining the entropy weight method and gray correlation analysis, with principal component analysis for verification. Our research investigates the effects of location on light pollution risk levels and explores intervention strategies addressing highly weighted factors, such as the quantity and type of artificial light, geographical location, and natural light. We conduct site-specific correlation analyses for Beijing, China, and Sydney, Australia, to determine the most effective intervention strategy for each location and its impact on risk levels. The study concludes with a sensitivity analysis confirming the stability and validity of the proposed model, demonstrating its applicability for urban planning and policy development.

Keywords: Light pollution, Entropy weight method,Grey correlation analysis, Sensitivity analysis

1. INTRODUCTION

In response to the growing need for light pollution control, some cities have implemented management measures or established environmental standards. However, these methods and standards lack uniformity, have limited applicability, and are typically only effective within a specific region. Currently, there is no dedicated light pollution legislation at the national level, leaving environmental protection departments and judicial bodies without a legal framework to guide and support administrative law enforcement in light pollution infringement cases. Compared to water, air, and soil pollution control, addressing light pollution presents unique challenges due to the absence of specific legal regulations and the limited, scattered, and principle-oriented nature of existing norms related to light pollution.

Environmental standards serve as the primary foundation for environmental law enforcement and constitute a significant aspect of environmental justice. The identification of pollution sources and affected areas, assessment of pollution intensity, and determination of pollution monitoring methods and control measures all rely on environmental standards as a basis. At present, national light environment standards are not well-developed, and cities lack unified planning, standards, monitoring, and prevention measures for light environments. The establishment of environmental standards in local light pollution control practices is inconsistent, with differing indicators and values.

In this paper, we developed a universal indicator to determine the risk level of light pollution at a given site, with which we evaluated and discusses light pollution risk levels in four distinct types of locations: protected land, rural communities, suburban communities, and urban communities. Three potential intervention strategies are studied to mitigate light pollution, outlining specific actions for each strategy and their expected impact on the overall light pollution levels. The effectiveness of the indicator is examined by selecting two study locations and applying the developed indicator to identify the most effective intervention strategy for each site.

2. THE DESCRIPTION OF THE PROBLEM

2.1 Develop a widely applicable indicator to identify the light pollution risk level of the location

First, data is collected and preprocessed. Next, the factors influencing light pollution risk levels at a location are established, divided into two tiers. The primary index includes factors such as the quantity and type of artificial light, the direction, and intensity of light emission, geographical location, and the amount and type of natural light. The secondary

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index mainly considers 13 aspects, including urban lighting conditions. An improved evaluation model, combining the entropy weight method and gray correlation analysis, is then applied to determine the light pollution risk level at a location using relevant data. Finally, principal component analysis is utilized for verification purposes..

2.2 Apply indicators and explain results in four different types of locations

Variations in the locations of protected land, rural communities, suburban communities, and urban communities influence the changes in indicator data related to factors affecting light pollution risk levels, as addressed in Task 1. By analyzing the four types of locations, relevant index values are altered, and a sensitivity analysis is conducted to determine the differences in index data, which subsequently result in distinct light pollution risk levels at a given location.

2.3 The three potential intervention strategies to address light pollution involve targeted changes to the influencing factors affecting light pollution risk levels at a location

In Task 1's entropy weight method solution, the quantity and type of artificial light, the geographical location of the area under consideration, and the number and type of natural light are assigned high weight. Consequently, these factors are specifically adjusted, and the potential impact of these strategies on overall light pollution is explained.

2.4 Apply indicators and explain their results in different types of locations

Two sites, Beijing, China, and Sydney, Australia, are selected for correlation analysis between their respective intervention strategies and the influencing factors that affected light pollution risk levels. This analysis aimed to determine the most effective intervention strategy for each location and discuss the impact of the chosen strategy on the site's risk level.

3. ASSUMPTIONS AND SYMBOLS

In this section, we make several assumptions as the preliminary for the following study. The symbols used in this paper are also defined in this section.

3.1 Theoretical assumptions

Figure.1. shows the response function of the light pollution effect, and (1) shows the specific form of the response function.

$$Z = f_c\left(E\right) \tag{1}$$

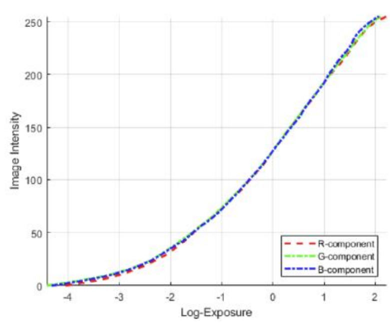

Figure 1. Light pollution response function.

3.2 Basic Assumptions

We make the following basic assumptions to make it clear for further analysis.

It is assumed that the infrastructure of the location selected in this article meets the requirements required for the topic.

Suppose only the data on light pollution given in the topic are considered.

Suppose that the factor of sudden burst is not considered.

Suppose that the official data published by different regions and websites is consistent.

It is assumed that factors other than those given by the question are not taken into account.

3.3 Symbols

Table1. Symbols definition.

Symbol	Significance
t	Evaluation indicators
i	i samples
j	j item indicator
p_{ij}	The first sample value under the indicator is the weight of the indicator j i
e_j	The entropy value of the first indicator j
$I_{(c)}$	The size of the impact

4. DEVELOP A WIDELY APPLICABLE INDICATOR TO IDENTIFY THE LIGHT POLLUTION RISK LEVEL OF THE LOCATION

4.1 Normalization

The normalized linear transformation method is adopted to standardize raw data, addressing the comparability issue between data indicators. By standardizing the original data of various influencing factors, the indicators are brought to the same order of magnitude, facilitating comprehensive comparative evaluation. Normalization allows for the distribution of values between 1 and 100, and their significance can be determined by weighting and summing them to obtain their total score.

$$S = \frac{R_t - R_{\min}}{R_{\max} - R_{\min}} \times T \tag{2}$$

4.2 Indicators for evaluating the risk level of light pollution at one location

Table II shows the light pollution risk level evaluation indicators and indicator descriptions for a site.

As depicted in Figure.3., the evaluation indicator system framework in this paper is structured into two "goal-criterion" levels to enable a clearer understanding of the interrelationships between indicators. The lower-level indicator group represents the status of the preceding level of indicators.

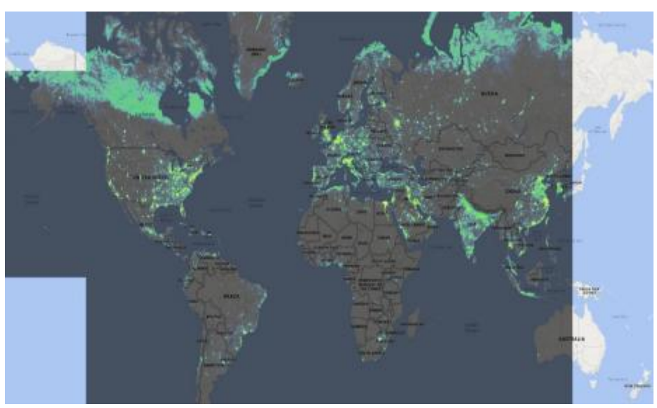

Figure 2. Global light pollution distribution map in 2022.

4.3 Hierarchical Model

Construct a pairwise comparison matrix

We normalize the data to ensure values range between 1 and 100 and then employ the analytic hierarchy process to verify the concept of the consistency matrix. A pairwise comparison matrix is constructed by taking the sum of two factors at a time and using a positive number to represent the ratio of their combined importance. This process results in the formation of the pairwise comparison matrix :$X_iX_ja_{ij}X_iX_j$.

$$a_{ij} = \frac{1}{a_{ji}} \ , \ a_{ij} > 0 \ , \quad i, j = 1,2,3 \tag{3}$$

Table 2. Evaluation Indicators of Light Pollution Risk Level at OneLocation.

	Level 1 Indicators	Secondary Indicators
The risk level of light pollution at a location	The amount and type of artificial light	Urban lighting conditions
		Number of cars
		Whether direct lighting is available
		Glow color
		Urban lighting conditions
	The direction and intensity of light emission	Launch direction
		Emission intensity
	Consider the geographic location of the region	Regional GDP
		population
		Biodiversity
		Regional latitude and longitude
	Amount and type of natural light	Regional elevation
		Regional climate
		Regional sky brightness

X_i compare X_j	a_{ij}
Same Importance	1
Slightly More Important	3
Significant	5
Very Important	7
Absolutely Important	9

There is an intermediate state between each of the two levels, which can be taken 2,4, 8.And the constructed pairwise comparison matrix is A.

$$A = \begin{pmatrix} 1 & \frac{4}{3} & \frac{4}{3} \\ \frac{3}{4} & 1 & 1 \\ \frac{3}{4} & 1 & 1 \end{pmatrix} \tag{4}$$

Given the complexity of hypothetical factors and the logical rationality of the evaluation standard system, it is essential to test the logical relative rationality of the pairwise comparison matrix to avoid excessive subjectivity and one-sidedness, ensuring a more accurate evaluation system for the 402 influencing factors. In other words, we need to verify:

$$a_{ij} \cdot a_{jk} = a_{ik} \ , \ i, j, k = 1, \cdots, 3 \tag{5}$$

Employing matrix theory, it can be demonstrated that an orderly pairwise comparison matrix is a uniform matrix if and only if it has the maximum eigenvalues. In other words, if the inconsistency is not severe, it can still be considered acceptable. Consequently, the calculated maximum eigenvalue can be used to determine whether the matrix is consistent. $\mathrm{nAA}\lambda\max(\mathrm{A}) = (\mathrm{n})\mathrm{AA}$

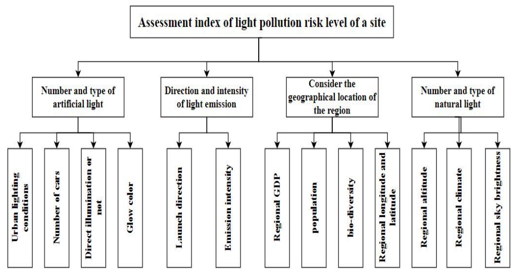

Figure 3. Indicator system for evaluating the risk level of light pollution at a site.

Consistency Test

There are three steps to measuring acceptable metrics and ways to seek them:i) Calculate the degree of inconsistency measured by the consistency index CI and calculate it using as:

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{6}$$

ii) Find the corresponding mean random consistency indicator RI (random index). For fixed, the mechanism results in a comparison matrix. Take a sufficiently large subsample from it and define it as:

$$RI = \frac{\lambda'_{\max} - n}{n-1} \tag{7}$$

For the n taking value from $\{1, 2, 3, 4, 5, 6, 7, 8, 9\}$, the RI is $\{0, 0, 0.58, 0.90, 1.12, 1.24, 1.32, 1.41, 1.45\}$, respectively. iii) Calculate consistency ratio CR (consistency ratio) as:

$$CR = \frac{CI}{RI} \tag{8}$$

The maximum eigenvalue obtained is:

$$\begin{gathered} \mathrm{A}\lambda = 3.000, \\ \mathrm{CI} = -6.6613\mathrm{e} - 16, \\ \mathrm{RI} = 1.12, \\ \mathrm{CR} = -1.2810\mathrm{e} - 15 < 0.1, \end{gathered} \tag{9}$$

The proof successfully passes the consistency test, indicating that our hypothesis regarding weight importance is feasible. As a result, we employ a feasible weight comparison among the three factors of risk loss, supply credit, and supply quantity, using the strongly correlated risk loss as the primary ranking evaluation index.

4.4 Topsismodel–entropy weight method

Data analysis is conducted using SPSS software, which first calculates and creates the variable 'data1' in MATLAB to transform the processed data into a matrix form. This is achieved by applying:

$$\max - x \tag{10}$$

In order to eliminate the influence of different indicator dimensions, we standardize the forward matrix, and the forward matrix is as follows:

$$X=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{13} \\ x_{21} & x_{22} & \cdots & x_{23} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{n3} \end{bmatrix} \tag{11}$$

For a standardized matrix denoted Z, each element in Z:

$$z_{ij} = x_{ij} / \sqrt{\sum_{i=1}^{n} x_{ij}^2} \tag{12}$$

Then a standardized matrix for 3 evaluation indicators can be obtained as:

$$Z=\begin{bmatrix} z_{11} & z_{12} & \cdots & z_{13} \\ z_{21} & z_{22} & \cdots & z_{23} \\ \vdots & \vdots & \ddots & \vdots \\ z_{n1} & z_{n2} & \cdots & z_{n3} \end{bmatrix} \tag{13}$$

The maximum and minimum values are defined as:

$$\begin{gathered} Z^{+}=(\mathrm{Z}_1^{+}, Z_2^{+}, \ldots, Z_m^{+}) = (\max\{Z_{11}, Z_{21}, ..., Z_{n1}\}, \\ \max\{Z_{12}, Z_{22}, ..., Z_{n2}\}, ..., \max\{Z_{1m}, Z_{2m}, ..., Z_{nm}\}) \\ Z^{-} = (Z_1^{-}, Z_2^{-}, ..., Z_m^{-}) = (\min\{Z_{11}, Z_{21}, ..., Z_{n1}\}, \\ \min\{Z_{12}, Z_{22}, ..., Z_{n2}\}, ..., \min\{Z_{1m}, Z_{2m}, ..., Z_{nm}\}) \end{gathered} \tag{14}$$

The distances of the first evaluation object from the maximum value and minimum values are defined as:

$$\begin{gathered} D_i^{+} = \sqrt{\sum_{j=1}^{m} \left(Z_j^{+} - z_{ij}\right)^2} \;\; i(i=1,2,\cdots,402) \\ D_i^{-} = \sqrt{\sum_{j=1}^{m} \left(Z_j^{-} - z_{ij}\right)^2} \;\; i(i=1,2,\cdots,402) \end{gathered} \tag{15}$$

respectively.

Then, the first unnormalized score for the subject can be calculated as:

$$S_i = \frac{D_i^{-}}{D_i^{+} + D_i^{-}} \tag{16}$$

The closer is S_i to 1, the higher the score.

4.5 Comprehensive comparisons draw conclusions

Given the considerable statutory constituents of the analytic hierarchy in this evaluation system, our evaluation indicators are relatively few, and subjective factors constitute a significant portion. The Topsis entropy weight method leverages the extensive grassland attachment data in this study, accurately reflecting the disparities among various evaluation schemes, and enabling a more comprehensive determination of the most important influencing factors based on the three indicators.

For the quantity and type of artificial light, the direction and intensity of light emission, the geographical location of the area under consideration, and the amount and type of natural light, the optimal solution is:

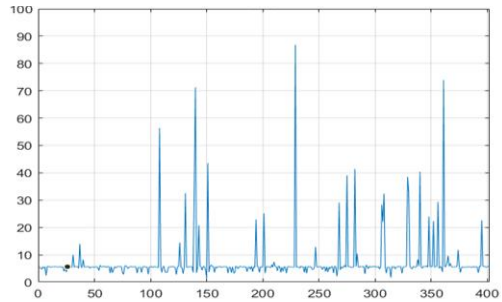

Figure 4. Indicator system for evaluating the risk level of light pollution at a site.

$$S^*(H)=0.1176, S^*(M)=0.0588, S^*(L)=0.0392, S^*(N)=0.0294 \tag{17}$$

4.6 Model validation

Factor analysis models

Set p variables $X_i(i=1,2,\cdots,p)$, if represented as

$$X_i=u_i+a_{i1}F_1+\cdots+a_{im}F_m+\varepsilon_i,(m\le p) \tag{18}$$

Or

$$\begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_\mathrm{p} \end{bmatrix}=\begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_\mathrm{p} \end{bmatrix}+\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & & \vdots \\ a_{p1} & a_{p2} & \cdots & a_{pm} \end{bmatrix}\begin{bmatrix} F_1 \\ F_2 \\ \vdots \\ F_\mathrm{m} \end{bmatrix}+\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_\mathrm{p} \end{bmatrix} \tag{19}$$

Or

$$X-u=AF+\varepsilon \tag{20}$$

Thereinto

$$X=\begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_\mathrm{p} \end{bmatrix}, u=\begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_\mathrm{p} \end{bmatrix}, A=\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{12} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & & \vdots \\ a_{p1} & a_{p1} & \cdots & a_{pm} \end{bmatrix}, \varepsilon=\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_\mathrm{p} \end{bmatrix} \tag{21}$$

where $F_1,F_2,\cdots,F_p$, there are common factors, which are inestimable, and the loading factors are their expression coefficients. ε_i is a special factor, which cannot be included in the previous m common factor, and satisfies:

$$E(F)=0, E(\varepsilon)=0, Cov(F)=I_m,$$

$$D(\varepsilon)=Cov(\varepsilon)=diag(\sigma_1^2,\sigma_2^2,\cdots,\sigma_m^2), Cov(F,\varepsilon)=0。 \tag{22}$$

The nature of the factor analysis model includes:

Decomposition matrix of covariance of the X original variable The correlation coefficient between the first variable and the first common factor is the factor load, which reflects the j important correlation between the first a_{ij} j common factor and the first i variable. A larger absolute value represents a higher degree of correlation.

The statistical significance of the commonality of variables, The sum of squares of the elements in the row of the factor loading matrix is called the X_i commonality of the variables, which can be calculated as:

$$h_i^2 = \sum_{j=1}^{m} a_{ij}^2 \tag{23}$$

Finding the variance on both sides of equation (4.1) yields:

$$Var\ (X_i) = a_{i1}^2 Var\ (F_1) + \cdots + a_{im}^2 Var\ (F_m) + Var\ (\varepsilon_i)$$

$$1 = \sum_{j=1}^{m} a_{ij}^2 + \sigma_i^2 \tag{24}$$

From (21), it can be concluded that the X_i yield of all special and common factor pairs is 1. If σ_i^2 is very small and $\sum_{j=1}^{m} a_{ij}^2$ close to 1, it indicates that the factor analysis results are good.

The sum of squares of the elements of each column in the subload matrix and X_i the variance contribution to all is called $S_j = \sum_{j=1}^{p} a_{ij}^2$. This is the statistically significant variance of the common factor and F_j is important relativity for measurement.

Since the sum of squares of the common factor coefficients of other special factors is equal to the corresponding eigenvalue root, that is, the variance of the common factor. We have:

$$S_j = \sum_{j=1}^{p} a_{ij}^2 = \lambda_j . \tag{25}$$

The mathematical model of principal component analysis can be put as:

$$\begin{cases} F_1 = a_{11}X_1 + a_{21}X_2 + \cdots + a_{p1}X_p \\ F_2 = a_{12}X_1 + a_{22}X_2 + \cdots + a_{p1}X_p \\ \cdots\cdots\cdots \\ F_k = a_{1k}X_1 + a_{2k}X_1 + \cdots + a_{pk}X_p \end{cases} \tag{26}$$

where

$$a_{jl} = \sqrt{\frac{u_{jl}}{\lambda_l}} (j = 1, 2, \cdots, p, l = 1, 2, \cdots, k) \tag{27}$$

with u_{jl} denoting the initial load of the first j index against the first principal component, λ_l representing the corresponding principal component feature value, and the comprehensive expression model can be obtained by referring to the above expression, as

$$Y = b_1 X_1 + b_2 X_2 + \cdots + b_p X_p \tag{28}$$

where

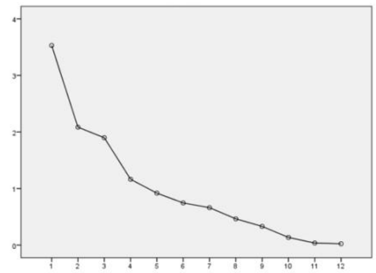

Figure 5. gravel diagram.

$$b_j = \frac{a_{jl} \times \theta_l}{\sum_{l=1}^{k} \theta_l} \tag{29}$$

The calculation steps for principal component analysis can be summarized as follows.

First, collect standardized original data p dimensional random vectors, $X = (x_1, x_2, \cdots, u_p)^T$ n samples, $x_i = (x_{i1}, x_{i2}, \cdots, d_{ip})^T, i = 1,2,\cdots,n, n > p$ form matrices, and transform the standard matrix is given as

$$Z_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j}, i = 1,2,\cdots,n; j = 1,2,\cdots,p \tag{30}$$

Where

$$\bar{x}_j = \frac{\sum_{i=1}^{n} x_{ij}}{n}, s_j^2 = \frac{\sum_{i=1}^{n} \left(x_{ij} - \bar{x}_j\right)^2}{n-1} \tag{31}$$

Then, find the correlation coefficient matrix Z for the standardized matrix

$$R = \left[r_{ij}\right]_p xp = \frac{Z^T Z}{n-1} \tag{32}$$

where $r_{ij} = \dfrac{\sum z_{kj} \cdot z_{kj}}{n-1}, i, j = 1,2,\cdots,p$.

The third step is to solve the characteristic equation of the R sample correlation matrix to $\left|R - \lambda I_p\right| = 0$ obtainafeature root, determine the principal component according to the determined $\dfrac{\sum_{j=1}^{m} \lambda_j}{\sum_{j=1}^{p} \lambda_j} \geq 0.85$ value, so that the utilization rate of the information reaches more than m 85%,for each , $j_0 b, j = 1,2,\cdots,m$ solve the system of equations $R_i b = j_0 b$ to obtain the unit eigenvector b_j^o .

Thereafter, use accurate variable indicators to convert principal components as

$$U_{ij} = z_i^T b_j^o, j = 1,2,\cdots,m \tag{33}$$

The main components m after comprehensive evaluation can be obtained. The gravel diagram is shown in Figure. 4.

5. APPLY INDICATORS AND EXPLAIN RESULTS IN FOUR DIFFERENT TYPES OF LOCATIONS

5.1 Protected Land

For the protected land, the optimal solutions for factors including the quantity and type of artificial light, the direction and intensity of light emission, the geographical location of the area under consideration, and the quantity and type of natural light are as follows:

$$
\begin{gathered}
S^*(H) = 0.1245, S^*(M) = 0.0612, \\
S^*(L) = 0.0412, S^*(N) = 0.0301; \\
S^*(H) = 0.1301, S^*(M) = 0.0623, \\
S^*(L) = 0.0422, S^*(N) = 0.0389; \\
S^*(H) = 0.1243, S^*(M) = 0.0631, \\
S^*(L) = 0.0422, S^*(N) = 0.0323; \\
S^*(H) = 0.1302, S^*(M) = 0.0665, \\
S^*(L) = 0.0403, S^*(N) = 0.0333;
\end{gathered} \tag{34}
$$

5.2. Rural Community

For the rural community, the optimal solutions for factors including the quantity and type of artificial light, the direction and intensity of light emission, the geographical location of the area under consideration, and the quantity and type of natural light are as follows：

$$
\begin{gathered}
S^*(H) = 0.1302, S^*(M) = 0.0621, \\
S^*(L) = 0.0434, S^*(N) = 0.0296; \\
S^*(H) = 0.1311, S^*(M) = 0.0685, \\
S^*(L) = 0.0403, S^*(N) = 0.0416; \\
S^*(H) = 0.1341, S^*(M) = 0.0578, \\
S^*(L) = 0.0397, S^*(N) = 0.0408; \\
S^*(H) = 0.1297, S^*(M) = 0.0633, \\
S^*(L) = 0.0399, S^*(N) = 0.0376;
\end{gathered} \tag{35}
$$

5.3 Suburban Community

For the suburban community, the optimal solutions for factors including the quantity and type of artificial light, the direction and intensity of light emission, the geographical location of the area under consideration, and the quantity and type of natural light are as follows：

$$
\begin{gathered}
S^*(H) = 0.1325, S^*(M) = 0.0622, \\
S^*(L) = 0.0408, S^*(N) = 0.0311; \\
S^*(H) = 0.1266, S^*(M) = 0.0599, \\
S^*(L) = 0.0364, S^*(N) = 0.0413; \\
S^*(H) = 0.1333, S^*(M) = 0.0567, \\
S^*(L) = 0.0358, S^*(N) = 0.0407; \\
S^*(H) = 0.1266, S^*(M) = 0.0702, \\
S^*(L) = 0.0436, S^*(N) = 0.0299;
\end{gathered} \tag{36}
$$

5.4 Urban Community

For theurban community, the optimal solutions for factors including the quantity and type of artificial light, the direction and intensity of light emission, the geographical location of the area under consideration, and the quantity and type of natural light are as follows：

$$\begin{aligned}
&S^*(H) = 0.1331, S^*(M) = 0.0682,\\
&S^*(L) = 0.0407, S^*(N) = 0.0337;\\
&S^*(H) = 0.1268, S^*(M) = 0.0567,\\
&S^*(L) = 0.0409, S^*(N) = 0.0408;\\
&S^*(H) = 0.1269, S^*(M) = 0.0633,\\
&S^*(L) = 0.0475, S^*(N) = 0.0403;\\
&S^*(H) = 0.1322, S^*(M) = 0.0569,\\
&S^*(L) = 0.0412, S^*(N) = 0.0366;
\end{aligned} \tag{37}$$

6. THE THREE POTENTIAL INTERVENTION STRATEGIES TO ADDRESS LIGHT POLLUTION INVOLVE TARGETED CHANGES TO THE INFLUENCING FACTORS AFFECTING LIGHT POLLUTION RISK LEVELS AT A LOCATION

6.1 Correlation Analysis

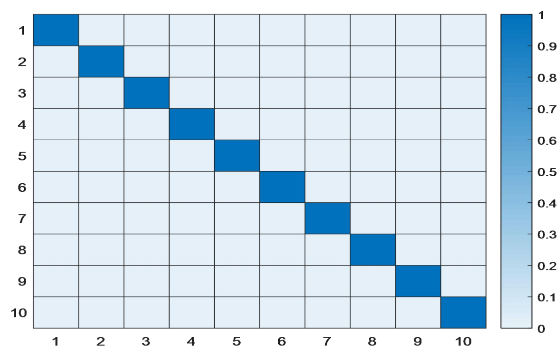

Figure 6. Correlation between dimensions.

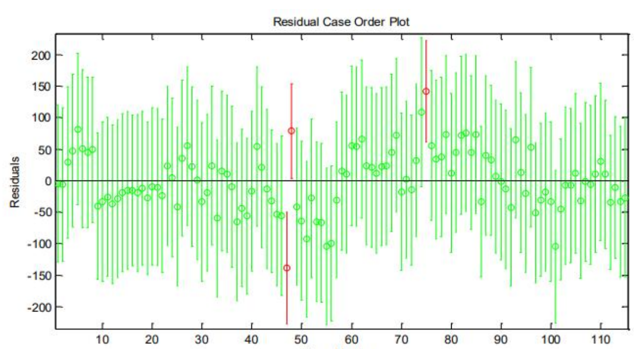

Figure 7. Residual plot.

In model establishment, verifying the model's fit involves a significance test of the regression equation. This test evaluates whether the linear relationship of the variables in the sample regression equation is significant, that is, whether at least one of the multiple regression coefficients in the overall regression equation can be inferred from the sample to be different from zero. This primarily demonstrates the significance of the sample regression equation. The test method is the analysis of variance, where the population variation of the dependent variable is decomposed into the sum of regression squares and the sum of error squares, expressed as:

$$L_{yy} = Q + U \tag{38}$$

Thereinto

$$L_{yy} = Q + U \tag{39}$$

$$Q = \sum_{i=1}^{N} \left(y_i - \hat{y} \right)^2 \tag{40}$$

$$U = \sum_{i=1}^{N} (\hat{y}_i - \overline{y})^2 \tag{41}$$

Moreover, the significance of the overall regression can be tested, specifically, whether a significant linear relationship exists with the k independent variables under consideration. This can be expressed as:

$$F = \frac{U / k}{Q / (n-k-1)} \tag{42}$$

The test is compared to different critical values respectively. If $F \geq F_{0.01}\left(k, n-k-1\right)$, the regression is considered to be highly significant or significant at the 0.01 level; if $F_{0.05}\left(k, n-k-1\right) \leq F \leq F_{0.01}\left(k, n-k-1\right)$, the regression is considered significant at the 0.05 level; if $F_{0.1}\left(k, n-k-1\right) \leq F \leq F_{0.05}\left(k, n-k-1\right)$, the regression is considered significant at the level of 0.01; finally, if $F < F_{0.1}\left(k, n-k-1\right)$, the regression is not significant, and the linear relationship with this independent variable is not exact. The correlation between dimensions is shown in Figure. 5., and the residual plot is shown in Figure. 6.

The analysis is presented in Table.3.

Table 3. Model summary.

model	R	R-Square	Adjusted R side	Error in standard estimates	Durbin Watson
1	0.575	0.119	0.082	0.433	1.910

The R-squared value in the table is 0.575, which exceeds 50%. This suggests that the model's predictions are accurate and that the research model holds substantive significance.

Table. IV. assesses the meaningfulness of the regression equation. Given that the significance level is 0.005, which is less than 0.05, it can be concluded that the equation is indeed meaningful.

Table 4. ANOVAa.

model		Sum of Squares	Degree of Freedom	Mean Square	F	Salience
1	Regression	3.648	6	0.608	3.236	0.005
	Residuals	27.054	144	0.188		
	Total	30.702	150			

Table 5. VIF diagnostics.

parameter	estimate	standard error	95% confidence interval lower limit	95% confidence interval upper limit	95% range after clipping lower limit	95% range after clipping upper limit
1	-60.167	.000	-60.167	-60.167	-60.167	-60.167
2	-1.065	.000	-1.065	-1.065	-1.065	-1.065
3	-25.936	.000	-25.936	-25.936	-25.936	-25.936
4	-23.591	.000	-23.591	-23.591	-23.591	-23.591
5	-33.704	.000	-33.704	-33.704	-33.704	-33.704

The regression equation for the independent and dependent variables is:

$$x = 1.496y_1^2 - 12.833y_2^2 - 1.017y_3^2 + 27.320y_4^2 + 1.753y_5^2 \tag{43}$$

7. APPLY INDICATORS AND EXPLAIN THEIR RESULTS IN DIFFERENT TYPES OF LOCATIONS

Upon observation, it is evident that the extent of M/H-ER/HO ST level light pollution in Beijing and surrounding areas is steadily expanding (as depicted in Figure. 2.), while the L level is consistently shrinking. This indicates a rise in the overall level of light pollution in Beijing. We analyzed the proportional changes of the four light pollution levels (represented in screen pixels) using the R method, which validated our observations: the H-ER level (increasing from 9.6% to 12.7%) and H-ST level (increasing from 1.4% to 2.3%) experienced a gradual rise, while the M level had a significant increase (from 29.3% to 44.3%). Meanwhile, the L level continued to decrease (from 56.4% to 34.6%), indicating a shift in overall dominance from the L level to the M level, as shown in Figure. 8.

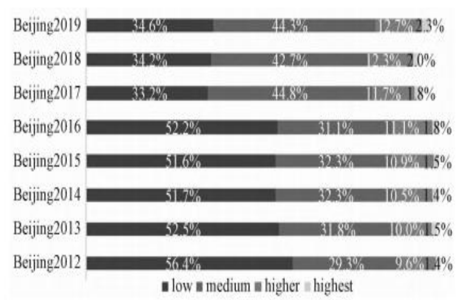

Figure 8. Statistics on changes in four light pollution levels in Beijing.

The above observations are analyzed by LTA, and the results are consistent (as shown in Figure.9.), which verified the above analysis.

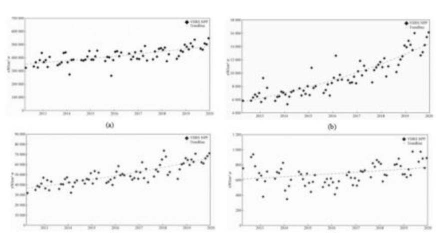

Figure 9. LTA analysis of light pollution (a) in Beijing, (b) surrounding area of Beijing, (c) the City of Sydney, (d) surrounding area of Sydney.

In summary, the transformation of light pollution in Beijing displays the following characteristics: there has been a substantial increase in light pollution along the routes between Beijing and its surrounding cities (or urban areas), primarily in the M and H-ER levels. The shifts in M and H-ER levels are the most conspicuous, indicating an outward diffusion in urban areas. The H-ST level typically clusters in the core business districts, office spaces, and transportation hubs; its coverage has expanded to some extent but then stabilized. The airport zone has consistently remained at the H-ST level for several consecutive years. The onset of new large-scale construction, particularly apparent at night, can lead to a significant exacerbation of light pollution.

8. SENSITIVITY ANALYSIS

In this section, we conduct a sensitivity analysis of the proposed model and method. First, we set several different parameters for the score and observe the impact on preventing light pollution.The sensitivity index of light pollution probability in considering the geographical location of the area and the quantity and type of natural light are 0.25, indicating that the two had the same degree of response to the change of light pollution probability.

9. DISCUSSION AND CONCLUSION

In this section, we evaluate the advantages and drawbacks of the proposed method and finally reach a conclusion.

9.1 Discussion

In our methodology, correlation analysis, grey correlation, and mixed regression models are employed to investigate the relationship between grassland data and chemical constituents. The results obtained were highly satisfactory, demonstrating the efficacy of these models.

Further, we proposed a hybrid clustering algorithm founded on density and hierarchical clustering, which consists of two distinct stages: density clustering and cohesive hierarchical clustering. This innovative approach contributes to the robustness of our results.

However, this study also has its limitations. The data source employed in this research is narrow, and the volume of data available for analysis was not as extensive as desired. This limitation could potentially affect the generalizability of our findings and would be an area for improvement in future studies.

9.2 Conclusion

Most cities strategically position their industrial zones on the periphery, far from densely populated areas. These zones, due to their relatively singular function, facilitate easier light pollution control. It is crucial, while ensuring normal production requirements, to regulate the quantity, density, brightness, and color of lighting and indicator lights to minimize light scatter and avoid unnecessary energy waste.

Furthermore, when considering light environment standards for road traffic, we must balance the needs for traffic surveillance and driving safety. Centralized regulation is needed for the flashing lights of traffic electronic monitoring equipment. While these installations are beneficial for traffic oversight and maintaining urban order, caution is required in their deployment to avoid the misconception that more equipment equates to better results.

For necessary electronic monitoring equipment, stringent environmental standards should be implemented, including considerations such as installation location, light brightness, beam angle, flash frequency, and fill light intensity. This will help prevent light pollution caused by equipment strobing and flashing, thus reducing interference for motor vehicle drivers.

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