

Light Pollution Evaluation System Establishment And Solution Strategy Determination

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Abstract. Based on the empirical analysis, this paper first analyzed the current situation of light pollution control, established a model measuring the regional light pollution levels by the combination weighting approach, and used cluster analysis (CA) to classify all samples into two different categories: light pollution and heavy pollution. The results of the cluster analysis showed that urban and suburban communities tend to be in the category of heavy light pollution, while rural and protected communities are in the category of light light pollution. Secondly, targeted intervention strategies were proposed for three different dimensions and proved to be effective through gray prediction. Eventually, through the implementation of the above measures, light pollution can be effectively controlled and the level of environmental protection can be improved.

Keywords: Light Pollution Evaluation System; Two-way fixed effects model; Combination weighing approach; Cluster analysis; Gray prediction model

1 Introduction

Longcore, T., et al. & Kloog, I., et al. (2013) revealed that light pollution affects ecosystems, hurts wildlife, and endangers human health, making prevention efforts imperative^{[1][2]}. This study addresses light pollution measurement research and current improvements.

Many researchers have conducted studies related to light pollution. Mendez et al. (2021) revealed that LEDs' blue-rich spectra might generate light pollution in varied metropolitan environments, underlining the necessity for responsible LED technology use and regulation^[3]. Yamada et al. (2022) used satellite data to find large temporal fluctuations in night sky brightness and underlined how natural cycles and human activities can affect light pollution levels, which can help policymakers and focused initiatives minimize light pollution^[4]. High-tech is considered. Barentin and Regimbart (2022) say spectroradiometers, high-resolution cameras, and satellite data can measure urban light pollution. Researchers can accurately educate policy-making and urban planning and identify light pollution reduction priority zones using these methods^[5]. Communities' light pollution vulnerability requires socioeconomic and ecological factors (Pérez et al., 2023). Researchers and policymakers should include social, economic, and environmental concerns when studying and controlling light pollution^[6]. Nobody can ignore individual power. Alvarado et al. (2023) demonstrated how grassroots efforts can collect data and raise light pollution awareness. Citizen science projects improve policy implementation by engaging citizens in local and global light pollution issues^[7].

These studies highlight the complexity of light pollution assessment and policymaking, yet no thorough evaluation method exists. The combined weight method (CWM), a combination of the entropy weight method (EWM) and the Delphi method (DM), is used to develop a light pollution risk evaluation model to develop an intervention policy for lighting control tasks to reduce light pollution. Before that, a two-way fixed effects model (TFEM) is created to understand indicator positive and negative correlations. Additionally, this article uses cluster analysis (CA) to classify all samples into two categories: light pollution and heavy pollution. Therefore, it also proposes targeted intervention policies based on the different levels of pollution. The gray prediction model (GPM) predicts risk levels in 6 years and compares them to intervention techniques to prove strategy efficiency.

A novel contribution of this study is as follows. First, this report includes environmental aspects in light pollution observations, making them more thorough. Second, the two-way fixed effects model (TFEM) improves light pollution evaluation. Third, this article provides forecasts of the proposed intervention policies to ensure that the policies are effective. The rest of this paper follows this structure. This paper's model, methodology, and data processing are described in Section 2. Section 3 describes policy making and forecasts. Section 4 concludes, explains the results and suggests future research.

2 Methodology

2.1 Light Pollution Risk Level Evaluation Model

Data Resource. Light pollution affects regional development, population, wildlife, etc. These factors inversely affect light pollution and its risk level. According to the literature review above, this paper divided various secondary indicators in each dimension, light intensity, environmental circumstances, and artificial light, and added tertiary indicators for refining. Data for measurement are collected from each country's EPA website, World Bank database, and other sources, totally 16 localities from developed and developing countries, including the US, Mexico, China, and Germany, were given 14 tertiary indicators for 2017-2021.

Indicator Definition. The secondary indications of our model need to be taken into account. The population and the level of regional development are selected as two supplementary indicators at the level of light intensity. We choose the three secondary indicators, biodiversity, geographic resources, and climate at the level of environmental condition. Then we build up three supplementary indicators of glare, light trespass, and over-illumination at the artificial light level. The description of each secondary and tertiary indication is shown below.

Light Intensity. Level of Development (DL). Development disparities within an area can lead to the emergence of diverse sectors, which can alter the utilization of light sources and artificial light intensity and density. This level quantifies with five primary metrics., Gross Household Product (GHP), Level of Modernization (LM), Patent Applications for Green Invention (PAGI), Marketability Level (ML), Proportion of Secondary and Tertiary Industries (PSTI).

Population (POP). Population also affects artificial light use. The higher the population, the more artificial light is needed to maintain evening life and for amusement. We counted permanent residents in 16 locations for analysis.

Environment Condition. Biodiversity(Bio). Light pollution harms biodiversity because artificial light reduces species' luminous characteristics and causes habitat loss at night. At this level, we measure Green Area (GA) since organisms gather there and its magnitude symbolizes their abundance. The 16 communities' NEPA websites provided the data.

Geography Resources(GR). Abundant geographic resources affect artificial light consumption. PRE measures renewable energy at this level. PRE is the community's renewable energy share. Compared to traditional energy, it can generate electricity and reduce light pollution.

Climate(CLI). Artificial light frequency affects climate and night sky clarity. We measure this level using three tertiary markers, Haze Condition(HC), Carbon Emission(CE), Pollute Index(PI).

Artificial Light. Glare(GLA). GLA refers to visual conditions that cause visual discomfort and reduce the visibility of objects due to inappropriate luminance distribution or the presence of extreme luminance contrasts in space or time. We use the Glare Index to quantify glare.

Light Trespass(LT). LT refers to the damage caused to the human body when light enters unintended places. For the measurement of this indicator we choose Light Environment Management Zone(LEMZ) as a tertiary indicator. This facet of ordinance mainly address light pollution in the form of light trespass into different areas at night.

Over-illumination(OI). Overuse of lighting equipment contributes to light pollution. We used the World Bank Database's Overall Illumination Rate (OIR) for each town to show this issue.

Two-way Fixed Effects Model. The final indicators of light pollution danger are identified. To identify the possible effect of them, we initially collected DMSP/LOS evening light remote sensing data for these 16 communities as the dependent variable. Since the data we collected were panel data and were qualified by Hausman's test, this paper decided to use a fixed effects model. Table 1 reports the regression results for the two-way fixed effects model using Stata completed for the (1) mixed regression model (OLS), (2) fixed effects model (FE_robust), and (3) two-way fixed effects model (FE_TW_DED).

Table 1. Panel Data Regression Results

| Dimension | Index(II) | Index(III) | (1)OLS | (2)FE robust | (3)FE TW DED | |
|-----------------------|----------------------|--------------|----------|--------------|--------------|-----------|
| Light intention | Level of development | GHP | 0.362** | 0.282** | 0.213** | |
| | | LM | 0.198 | 0.182* | 0.099** | |
| | | PAGI | -0.241* | -0.126* | -0.131*** | |
| | | ML | 0.217** | 0.213* | 0.013** | |
| | | PSTI | 0.012* | 0.121** | 0.172*** | |
| Environment condition | Population | RP | 0.028* | 0.183* | 0.025* | |
| | | Biodiversity | GA | -0.028*** | -0.183** | -0.094*** |
| | Geography resources | PRE | -0.118** | -0.120** | -0.166** | |
| | | Climate | HC | 0.191 | 0.162* | 0.181*** |
| | | | CE | 0.017** | 0.012** | 0.015** |
| Artificial light | Glare | PI | 0.021 | 0.031 | 0.014 | |
| | | GI | 0.213** | 0.124*** | 0.114*** | |
| | Light trespass | LEMZ | 0.043** | 0.031** | 0.092** | |
| | Over- | OIR | 0.031* | 0.012** | 0.037** | |

illumination

Notes: This table presents the estimate of different light pollution indicators. *, **, and *** refer to the p value being less than the 10%, 5%, and 1% significance levels, respectively. t values are in parentheses.

Among the independent variables, PAGI,GA and PRE have negative coefficients, indicating that they produce a negative effect on the dependent variable, while the rest of the indicators are positive indicators. In addition GHP has the largest coefficient, which means that it has the greatest influence on the level of light pollution risk.

Weight Calculation Based on Combination Weighting Approach. Entropy weighting method (EWM) is a common objective weighting method for measuring value dispersion in decision making^[8]. It assumes that the greater the dispersion, the higher the differentiation, the more information can be obtained, and the indicator should be given a higher weight. Data normalization converts all data to 0–1 to unify it. Seeing each dimension, for the country i and index j, the weight of it is named f_{ij} , calculated as the following:

$$f_{ij} = \frac{r_{ij}}{\sum_{i=1}^m r_{ij}} \quad (1)$$

Where m represents the amount of the country we selected for calculation.

Meanwhile, the function of information entropy, e_j is calculated as the following:

$$e_j = -\ln\left(\frac{1}{n}\right) \sum_{i=1}^m \ln(f_{ij}) \quad (2)$$

On the basis of the content above, we finally attain the weight of index j in each dimension, W_{E_j} calculated as the following:

$$W_{E_j} = \frac{1 - e_j}{m - \sum_{j=1}^n e_j} \quad (3)$$

We get the final weight by EWM of the three dimensions are shown as the following.

$$\alpha_1 = W_{E_1} = (0.023, 0.091, 0.061, 0.065, 0.059, 0.187)^T \quad (4)$$

$$\alpha_2 = W_{E_2} = (0.040, 0.021, 0.055, 0.116, 0.112)^T \quad (5)$$

$$\alpha_3 = W_{E_3} = (0.083, 0.052, 0.035)^T \quad (6)$$

The Delphi Method is a structured method that invites a number of experts or experienced administrators in a particular field to make predictions and ultimately reach a consensus on an issue. We sent the identified indicators in the form of a questionnaire to professors of relevant disciplines in key universities and combined their scores to obtain subjective weights.

The Delphi method has greater advantages than the entropy weighting method in determining the weights according to the decision maker's intention, but is relatively less objective and more subjective; while using the objective weighting method has objective advantages, but does not reflect the degree of importance attached to different indicators by the participating decision makers, and will have certain weights and degrees opposite to the actual indicators^[9].

Therefore, in view of the shortage of the present objective and subjective weighting methods, a new combination weighting approach is put forward.

Subject-objective combination weights W_j is:

$$W_j = \frac{\sqrt{\alpha_j \beta_j}}{\sum_{j=1}^n \sqrt{\alpha_j \beta_j}} \quad (7)$$

α_j denotes the weights obtained by the entropy weighting method, while β_j denotes the result obtained by the Delphi method. Table 2 shows the final results.

Table 2. The Final Result Of The combination weighting approach

| Indicators(I) | Weight | Indicators(II) | Weight | Indicator(III) | α_j | β_j | W_j | | |
|-----------------------|--------|----------------------|--------|-------------------|------------|-----------|-------|-------|-------|
| Light intention | 0.486 | Level of development | 0.299 | GHP | 0.023 | 0.034 | 0.029 | | |
| | | | | LM | 0.091 | 0.087 | 0.093 | | |
| | | | | PAGI | 0.061 | 0.070 | 0.069 | | |
| | | | | ML | 0.065 | 0.034 | 0.049 | | |
| | | | | PSTI | 0.059 | 0.096 | 0.079 | | |
| Environment condition | 0.344 | Population | 0.187 | POP | 0.187 | 0.112 | 0.152 | | |
| | | | | Biodiversity | 0.040 | GA | 0.040 | 0.025 | 0.033 |
| | | Geography resources | 0.021 | PRE | 0.021 | 0.034 | 0.028 | | |
| | | | | Climate | 0.283 | HC | 0.055 | 0.021 | 0.036 |
| Artificial light | 0.17 | Glare | 0.083 | CE | 0.116 | 0.027 | 0.059 | | |
| | | | | Light trespass | 0.052 | PI | 0.112 | 0.128 | 0.126 |
| | | | | | | GI | 0.083 | 0.113 | 0.102 |
| | | | | Over-illumination | 0.035 | LT | 0.052 | 0.121 | 0.083 |
| OIR | 0.035 | 0.098 | 0.061 | | | | | | |

Evaluation Results of Light Pollution Risk Level. After obtaining the weights of each indicator using the combination weighting approach, we applied it to four communities, a protected land location, a rural community, a suburban community, and an urban community. To better observe the results of our model, the average of the indicators for the four communities in each type of community constituency is used as the data for our application of the model. The result are shown in Table 3.

Table 3. Application Results

| Community | Protected land | Rural community | Suburban community | Urban community |
|------------|----------------|-----------------|--------------------|-----------------|
| Risk Level | 11.27 | 19.28 | 32.83 | 68.82 |


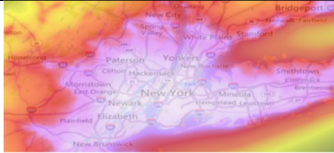
We can easily see that urban community has an obvious higher level of light pollution. According to the analysis above, GHP has the greatest impact on the degree of light pollution. So although urban communities may possess more patent applications for green invention, there is still a more serious light pollution problem. Meanwhile, the glare index and overall illumination rate are above standard in some communities, which needs to be attached importance to. Compared rural communities with suburban communities, the difference is not quite large. Since they have similar values of several indicators, the problem of light pollution is not that serious. In terms of protected land location, the condition is quite optimistic. Since

the development of it is based on the preservation of the original landscape, there is no excessive modification of artificial light technology. As a result, preserving the present situation may work well.

2.2 Clustering Analysis of Light Pollution Risk Levels by Location

By using K-means cluster analysis, we classified the selected 80 community samples according to the severity of light pollution without prior criteria. The results show the categories to which the sample observations belong and the distances to the centers of the classes to which they belong. The clustering model divides the 80 samples we selected into two categories, in which the first category has 55 samples selected, mainly including rural and protected communities, partly suburban communities, and few urban communities; the second category has a total of 25 samples selected, mainly including urban communities, some suburban and rural communities, and a small number of protected land location. From Table 4, it can be found that communities fall into two types. Based on the central values of the indicators grouped in the index system, we call the first category "communities with low light pollution" and the second "communities with high light pollution".

Table 4. Cluster Comparison

| Feature Elements | Typical Community Representative | |
|------------------------------------|---|--|
| Category | 1:Communities with low levels of light pollution | 2:Communities with high levels of light pollution |
| Community Light Pollution Portrait |  |  |
| Quantity of this types | 55/80(68.75%) | 25/80(31.25%) |

3 Strategies Making for Light Pollution Control

3.1 Three Intervention Strategies for Light Pollution

Specific Strategies. Initially, critically examine the street lighting design of roads and the outer material of buildings for improvement. Make it in strict accordance with the requirements of the road lighting code, the choice of lamp type, the inequality of light distribution, installation height and spacing, etc. In the regular lighting of the highway must be used cut-off type, semi-cut-off type street lights. Further, encourage the manufacture of green inventions and patents for local residents. The local government can provide an incentive mechanism for green inventions and patent manufacturing applications, offering material rewards and social recognition for each green invention or patent application. Finally, continuously increase the green area by covering a lot of greenery in the feasible area. Add wall-mounted vertical greening, plant climbing plants on the building's exterior walls, and

choose appropriate plants based on the building's appearance, topography, and texture, such as ivy, vines, and passion flower.

Impact of Intervention Strategies. We utilize a grey prediction model to anticipate light pollution risk levels in mild and heavy light pollution locations in the next years. We then compare results to light pollution in regions without initiatives so that the influence of our suggested intervention policy can be seen more clearly. We average all the indicators collected for the areas of heavy light pollution to obtain a set of data that can reflect the areas of heavy light pollution in a comprehensive manner, bringing into our model to find out the light pollution risk level of the heavy light pollution area in 2017-2021 respectively. Next, we utilize a gray prediction model to anticipate the trend of light pollution risk levels in significantly light polluted locations from 2022-2027 without intervention efforts. Based on the strategy's substance and expert literature, we predict Strategy 1 will cut the rate of rise of the GI indicator by 0.6% and the OIR indicator by 0.2%. Strategy 2 will boost PAGI indicator growth by 1%. Strategy 3 will raise GA growth by 2.8% and reduce CE growth by 0.1%. Finally, we make Figure 1 to show the gray correlation forecast of light pollution in heavy polluted regions and the comparison plots following the intervention strategy.

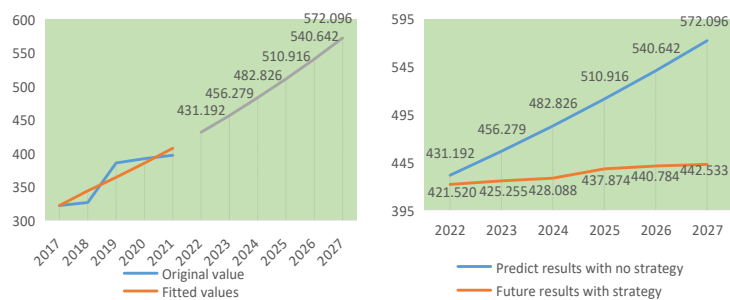


Fig. 1. Grey Prediction Results and Results of Comparison

Consistent with the approach above, we average the indicators collected for the light pollution areas to obtain a set of data that can reflect the light pollution areas in a comprehensive manner, and bring them into our model to find the light pollution risk levels of the light pollution areas from 2017 to 2021, respectively. The following step matches contaminated regions' analysis. Figure 2 shows the results.

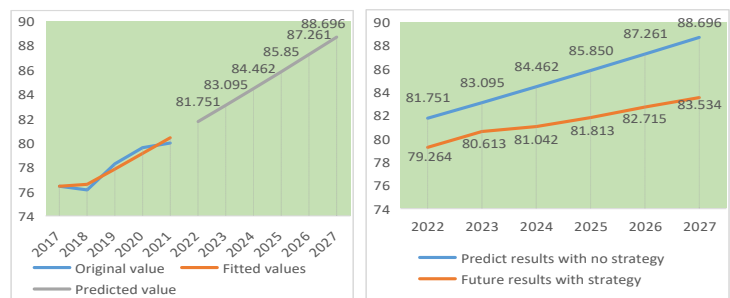


Fig. 2. Grey Prediction Results and Results of Comparison

4 Conclusions

This paper establishes a measurement model of regional light pollution level through the combined weighting method, and obtains the light pollution level indices of four kinds of communities as follows: 11.27 in protected land location, 19.28 in rural community, 32.83 in suburban community, and 68.82 in urban community, respectively. It is found that the urban and suburban communities tend to fall into the category of heavy light pollution through the clustering analysis, and the rural and protected communities fall into the category of mild light pollution. targeted intervention strategies are proposed for each of the three classes in the light pollution evaluation model, and the effectiveness of the intervention strategies is demonstrated through gray prediction, which suggests that the governmental departments should strictly review the design of roadway streetlights and building façade materials, encourage green inventions and patented manufacturing by local residents, and continually increase the area of green areas, covering green belts in large quantities where feasible. This analysis also shows that all indicators need to work together to control light pollution, thus demonstrating the superiority of our proposed intervention strategy.

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