 https://doi.org/10.1051/e3sconf/202337503015

A light pollution risk model based on improved assessment and prediction methods

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Abstract: As light pollution becomes increasingly severe, its impact is becoming more widespread for instance affecting human health, social stability, and the ecological environment to varying degrees. In order to measure the risk level of light pollution and develop related measures, we propose the Light Pollution Risk Index (LPRI) and create various assessment, intervention and prediction models around it. It include three models: The LPRI Scoring System, The Light Pollution Risk Classification Model and the HSE Intervention Strategy & Potential Impact Prediction Model. Firstly, we use the improved EMW-AMP to determine the weights and elicicit the concepts for next models. We select 6 representative areas in different kinds of locations, combine the integrated weights with the Topsis method to score and rank. Followed by invoking K-Means cluster analysis, we reselect 108 areas and the consequence classifies the light pollution risk level into three levels: level A significant risk, indicator range from 0 to 4.23, level B average risk, indicator range from 4.23 to 7.64, and level C low risk, indicator range from 7.64 to 10. Then, followed by prediction of LPRI with a Grey linear regression combination prediction model. The predicted results can accurately and clearly reflect that the application of HEIS in Wuhan and HSIS in Los Angeles, which is the most effective. At the same time, we find that intervening in one or two of H, S, and E must have a non-positive effect on the risk indicator of the other side. Finally, we briefly discuss how the intervention strategies in Wuhan and Los Angeles affect the individual indicators and thus the level of risk.

Keywords: Light pollution; LPRI; improved EMW-AHP; Topsis; Grey linear regression combination prediction model

1. Introduction

Light pollution refers to the phenomenon of excessive light sources generated in human activities. It interferes with natural night environments and even damages biological clocks. According to the research, more than 90% of light pollution harms human life, destroys ecological environment, and causes social impact[1].

Worse still, a study published recently in the academic journal Science Advances reveals that more than 80% of the global population currently resides under the debilitating impact of light pollution, with one-third can no longer able to see the Milky Way. If the problem of light pollution continues to worsen, the entire population of the Earth may be deprived of the awe-inspiring sight of the starry sky one day.

Therefore, we urgently need a pinpoint model to appraise and forecast light pollution conditions in the present and the future. At the same time, reasonable intervention strategies are proposed to alleviate the crisis of light pollution and improve people's awareness of the impact of its impact.

2. Light Pollution Risk Indicator

2.1 Indicator selection

By referring to the papers and data, as well as experts' comments, we finally establish a model to measure the risk level of light pollution, and select 10 indicators from three aspects: human, ecological and social[2]. They are the impacts on physiology, psychology, GDP, energy, traffic, astronomical observation, animals, plants, climate, night sky.

2.2 Improve EWM-AHP

Because of the shortcomings of using entropy or hierarchical analysis alone, based on these two methods, we propose an improved entropy-based Analytic Hierarchy Process (AHP) method. It combines the subjective weights θ_i obtained through the AHP method with the objective weights β_i obtained through the entropy weighting method. In this way, the comprehensive weights ω_S can be obtained. Through several operations such as weighting and normalization, we can get the weights of each indicator as shown in Table 1.

Table 1: Indicators and their final synthetical weights

Upper-level		Sub-level		Normalized composite weights	Improved synthetical weight
Indicator	**Weight**	**Indicator**	**Synthetical weight**		
Human	0.169	Physiology	0.067	0.551	0.093
		Psychology	0.054	0.449	0.076
Ecology	0.443	Animals	0.162	0.323	0.143
		Plants	0.143	0.286	0.127
		Climate	0.082	0.163	0.072
		Night sky	0.113	0.227	0.101
Society	0.388	Traffic	0.102	0.269	0.104
		Energy	0.088	0.232	0.090
		GDP	0.078	0.205	0.080
		Astronomical observations	0.111	0.293	0.114

3. LPRI Scoring System Based on Topsis

In this section, we intend to combine the combined weights obtained above and evaluate three aspects of human risk index, ecological risk index, and social risk index based on the Topsis method to facilitate subsequent cluster analysis, and finally combine the weights of the criterion layer to obtain the light pollution risk index LPRI.
First of all, we take 24 regions and collected their indicators, positive and orthogonalize each indicator to eliminate the influence of dimension. Then, calculate the distance between the evaluation objects and the best value and the worst value. Ultimately, we can get their results: a score for each area in three aspects.
Combining the individual weights of HSE obtained by hierarchical analysis, the light pollution risky index calculation formula can be constructed as follows:

$$LPRI=\omega_{A1}HRI+\omega_{A2}SRI+\omega_{A3}ERI \quad (1)$$

where HRI is the human risk index, SRI is the social risk index, and ERI is the ecological risk index.

4. Light Pollution Risk Classification

In this chapter , we improved the traditional clustering method and created a 3D clustering model for forecasting the degree of light pollution. We mainly use k-means clustering analysis method to classify the light pollution risk level. Data sets of three dimensions include ***HRI***, ***SRI*** and ***ERI***, and the levels are classified into significant risk ***A***, general risk ***B*** and low risk ***C***.
We select **108 regions** for clustering, and the clustering results are shown below, with the three clusters having the centers of mass (3.6,2.7,3),（6,5.5,6.5）,（8.7,8.7,9.5）.

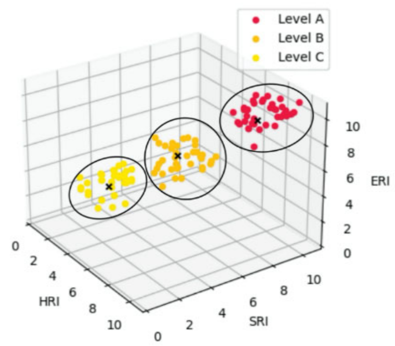

Figure1: The clustering results

We then invoke the light pollution risk index formula to calculate LPRI and quantitatively classify the risk level, and the classification results are as follows:

Table 3: Classification results

Level A	Level B	Level C
0~4.23	4.23~7.64	7.64~10

With the classification range, we can roughly divide the risk levels of the four areas. It is not difficult to see that the risk of protected land areas belongs to grade C, the risk of suburban and rural communities except Lusaka belongs to grade B, and the risk of urban areas belongs to grade A. This further proves the accuracy and feasibility of the evaluation model.

5. HSE Intervention Strategy & Potential Impact Prediction

5.1 HSE Intervention Strategy

According to the requirements of the title, three specific and stable intervention measures are proposed in this section for ***HRI***, ***SRI*** and ***ERI*** in ***LPRI*** to reduce the harm and influence caused by light pollution, namely ***HSIS***, ***HEIS*** and ***SEIS***.
The three intervention strategies are as follows:

1. Human health
(1) Reduce the irrational use of light.

2. Ecological sustainable development
(1) Strictly limit the use of glass curtain walls.
(2) Setting up protection areas for organisms sensitive to light environment.

3. Social stability
(1) Make relevant regulations on electricity consumption.
(2) Strengthen publicity about light pollution.
(3) Allocate light sources wisely.

5.2 The Principle of Gray Linear Regression Combination Forecasting Model

The gray linear regression combined forecasting model is an implicit gray combined model, which can improve the lack of exponential growth trend in linear regression and make up for the lack of linear growth in the gray forecasting model, which can improve the stability and accuracy of model forecasting. The combined forecasting model can be expressed by the formula.[6]

$$\hat{x}^{(1)}(k) = c_1 e^{vk} + c_2 k + c_3 \tag{2}$$

where v, c_1, c_2, c_3 are coefficients to be determined.

The derivation leads to a proposed estimate of the parameter v

$$\hat{v} = \frac{\sum_{m=1}^{n-3}\sum_{t=1}^{n-2-m} v_m(t)}{\frac{(n-2)(n-3)}{2}} \tag{3}$$

The estimation of parameters c_1, c_2, and c_3 can be estimated using the least squares method, and the derivation process is as follows. We let

$$\boldsymbol{c} = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix} = \left(\boldsymbol{A}^T \boldsymbol{A}\right)^{-1} \boldsymbol{A}^T \boldsymbol{X}^{(1)}$$

where:

$$\boldsymbol{A} = \begin{pmatrix} e^{\hat{v}} & 1 & 1 \\ e^{2\hat{v}} & 2 & 1 \\ \vdots & \vdots & \vdots \\ e^{n\hat{v}} & n & 1 \end{pmatrix} \qquad \boldsymbol{X} = \begin{pmatrix} X^{(1)}(1) \\ X^{(1)}(2) \\ \vdots \\ X^{(1)}(n) \end{pmatrix}$$

Thus, the predicted values of the generated sequence are:

$$\hat{x}^{(1)}(k) = c_1 e^{vk} + c_2 k + c_3 \tag{4}$$

From one single cumulative reduction of the equation above, we can get the predicted value of the original series $\widehat{X}^{(0)}(k)$:

$$\widehat{X}^{(0)}(k+1) = \widehat{X}^{(1)}(k+1) - \widehat{X}^{(1)}(k) \tag{5}$$

Figure 2. Reduce the irrational use of light

5.3 Model testing

The combined model can be evaluated for good or bad prediction results by using a posteriori difference test, calculated as follows:

First calculate the mean of the original series as well as the standard deviation:

$$\overline{x}^{(0)} = \frac{1}{n}\sum_{k=1}^{n} x^{(0)}(k) \tag{6}$$

$$S_1 = \sqrt{\frac{\sum[x^{(0)}(k) - \overline{x}^{(0)}]^2}{n-1}} \tag{7}$$

And calculate the mean value of the residual series:

$$\Delta^{(0)} = \frac{1}{n}\sum_{k=1}^{n}\left[x^{(0)}(k) - \hat{x}^{(0)}(k)\right] \tag{8}$$

Then calculate the standard deviation of the absolute error series:

$$S_2 = \sqrt{\frac{\sum[\Delta^{(0)}(k) - \Delta^{(0)}]^2}{n-1}} \tag{9}$$

After that, calculate the value of the check ratio:

$$C = \frac{S_2}{S_1} \tag{10}$$

The small error probability is:

$$P = p\{|\Delta^{(0)}(k) - \Delta^{(0)}| < 0.6745 S_1\} \tag{11}$$

where the magnitude of C and P can classify the prediction accuracy of the model into the following classes, as shown in the following figure 2.

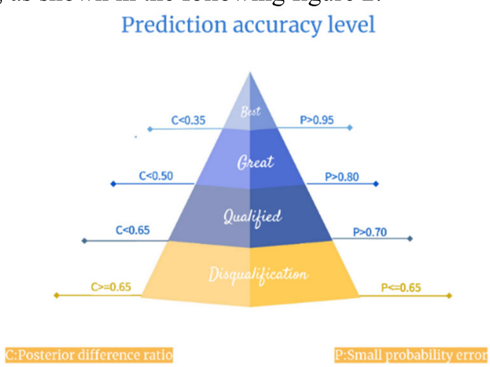

Figure 2: The prediction accuracy level

After validation and calculation, the posterior differences C and the probability of small errors P of the prediction results for the two regions are shown in the following table 4:

Table 4: The prediction results for the two regions

Area	Post-test difference ratio C	Small error probability P	Prediction accuracy level
Los Angeles	0.389	0.814	Great
Wuhan	0.576	0.725	Qualified

6. Conclusion

For the **Topsis** model based on the **improved EMW-AHP**: It integrates the weights from subjective and objective perspectives, which can effectively avoid large differences in weights owing to specific subjective factors or objective factors. Compared with the simple **EMW-AHP**, the improved version can integrate the subjective and objective weights more reasonably What's more, it can solve the problem that Indicator weights do not conform to reality.
For the **k-**means **three-dimensional cluster analysis model**: It has the advantages of combining information from multiple variables to classify samples, and the analysis results are simple and intuitive, which is mainly utilized in this paper for light pollution classification.
For the **Grey** linear **regression combination forecasting model**: The combination is suitable for both series with exponential growth trend and series with linear trend. It exploits the useful information of both single models to improve the accuracy of the model predictions by overcoming the shortcomings of each.
To sum up, light pollution is a global problem and has different degrees of harm to human, ecology and society. Aiming to solve this problem, we proposed the concept of Light Pollution Risk Index ***(LPRI)***, which contains three major aspects: Human Health Risk Index ***HRI***, Social Risk Index ***SRI***, and Ecological Risk Index ***ERI***.
Firstly, we build an ***improved EMW-AHP*** model. Through carefully screening the parameters of the model and determining the weights of the 10 selected indicators, the model was made as close to reality as possible. Secondly, we make full use of the Topsis model to score and rank the 24 cities under 4 different locations, and accurately derived the scores and rankings. Next, we select 108 cities randomly as the training set to classify them into three classes A, B and C with the **K-means 3D clustering model**. Finally, we test the 24 cities mentioned in the previous paper as the validation set. As a result, it shows that the K-means 3D clustering model is established scientifically and reasonably.
With the goal of reducing a city's future Light Pollution Risk Index (LPRI) and mitigating the effects of light pollution on various aspects, We propose a Grey linear regression combination forecasting model and three intervention strategies: ***HSIS***, ***HEIS***, and ***SEIS***. According to the question, we select two cities, Los Angeles and Wuhan to conduct the experiment. The results indicate that for Wuhan, the HEIS intervention strategy is optimal, however, for Los Angeles, the HSIS intervention strategy is optimal.
LPRI's research shows that the harm caused by light pollution should not be underestimated. We have to pay great attention to this problem and adopt practical solutions to combat it. In general, we should do our best to establish an eco-friendly and sustainable world for all mankind.

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