Advances in Computer, Signals and Systems (2023)
Clausius Scientific Press, Canada

DOI: 10.23977/acss.2023.071107
ISSN 2371-8838 Vol. 7 Num. 11

Light pollution evaluation system based on combination weighting method

Zhengqi Xin[1,*], Man Yuan[1], Lei Yang[2], Dianwei Li[3], Jiahui Huang[4]

[1]*School of Mechanical and Power Engineering, Harbin University of Science and Technology, Harbin, 150080, China*
[2]*School of Economics and Management, Harbin University of Science and Technology, Harbin, 150080, China*
[3]*School of Electrical and Electronic Engineering, Wuhan Polytechnic University, Wuhan, 430023, China*
[4]*School of Management, Wuhan University of Science and Technology, Wuhan, 430065, China*
[*]*Corresponding author: xin_9_23@163.com*

Keywords: Light pollution, Combination weighting method, Metabolic GM (1,1)

Abstract: Light pollution is often overlooked, but according to statistics, it has increased by at least 49% globally in the past 25 years. In this paper, the Combination weighting method, metabolic GM (1,1) model, and other methods are used to study the light pollution problem. A light pollution risk level evaluation system is established by using the combination weighting method and several indicators related to light pollution. Based on the analysis of samples from China and the United States, a range of light pollution control strategies is proposed encompassing three key aspects: electricity accessibility, population density, and biodiversity coverage. The light pollution situation of the two locations in the upcoming year is predicted and compared using a combined approach of the metabolic GM (1,1) model, considering various strategies as well as no strategy implementation. Ultimately, it can be seen that the strategy of electricity accessibility is more effective. The establishment of a light pollution evaluation model enables the measurement of the effectiveness of prevention and control strategies, thereby enhancing the ability to effectively manage light pollution.

1. Introduction

Light pollution is the deterioration of darkness caused by artificial light at night, both inside and outside human infrastructures [1]. Although light sources at night provide convenience for human work, the resulting light pollution may have a certain impact on the environment, as well as human health. For example, changes in color and intensity of light pollution have a complex effect on animal vision [2], light pollution has an impact on spring development of urban trees and shrubs [3], light pollution disrupts circadian rhythms, significantly affecting cell division and cancer development [4], ALAN impacts nocturnal and diurnal insects through effects on movement, foraging, reproduction, predation risk, and development [5]. Individual local government units and local groups are also beginning to work on strategies to intervene in light pollution.

Unfortunately, there is still less research on the effects of light pollution and how to mitigate them [6]. Josiane Meier et al. provided an analytical framework that facilitates the systematic description and comparative analysis of the diverse array of contemporary conflicts regarding outdoor lighting [7]. Gokhale et al. proposed a variety of ways to reduce light pollution: using Unihedron SQMs to quantify light pollution, increasing awareness about the nuisance and dangers of light pollution, working with city and school authorities to transition to outdoor lights with color temperatures less than 3000 K, installing light shields and light friendly fixtures to reduce light pollution [8]. John C. Barentine et al. described the challenge of quantifying light pollution threats to ecologically sensitive sites in the context of efforts to conserve natural nighttime darkness, and assess the current state of the art in detection and imaging technology as applied to this realm [9]. Franz Hölker et al. believed that the formulation of light pollution policies should consider not only energy efficiency, but also human well-being, the structure and function of ecosystems, and the interconnected socioeconomic consequences [10].

In this paper, the Combined Weighting Method (CWM) is employed to establish an evaluation method for assessing the risk level of light pollution, which effectively integrates both humanistic influence and natural influence. Simultaneously, this methodology is applied in discussions aimed at formulating strategies to mitigate the risk level of light pollution. By taking China and the United States as case studies, this evaluation system enables a comparative analysis of the light pollution risk level index between implemented and non-implemented strategies in these two countries, thereby facilitating the identification of optimal approaches for reducing light pollution.

2. Models

2.1 Combined Weighting Method

The weights of each index are calculated by using three methods, namely the analytic hierarchy process (AHP), which is representative of the subjective weighting method, the criteria importance through intercriteria correlation (CRITIC), and the entropy weight method (EWM), which are commonly used in the objective weighting method [11]. Then, the weight calculated by the three methods is synthesized by multiplication to obtain the combination weight, namely the combination weighting method (CWM). The combined weighting method has better accuracy than the single method.

AHP is used for subjective weighting, and the judgment matrix of the index is

$$G=\begin{vmatrix} u_{11} & \cdots & u_{1j} \\ \vdots & \vdots & \vdots \\ u_{i1} & \cdots & u_{ij} \end{vmatrix},\ u_{ij}\cdot u_{ji}=1, \tag{1}$$

where u_{ij} denotes the importance of the i-th element to the j-th element. The weight vector is calculated by geometric average method as

$$\omega_{1i}=\frac{\left(\prod_{j=1}^{n}u_{ij}\right)^{\frac{1}{n}}}{\sum_{k=1}^{n}\left(\prod_{j=1}^{n}u_{kj}\right)^{\frac{1}{n}}},(i=1,2,....n). \tag{2}$$

EWM is used for objective weighting. The index variability is calculated by formula (3).

$$p_{ij}=\frac{x_{ij}}{\sum_{i=1}^{n}x_{ij}}, \tag{3}$$

Using the index variability, the information entropy is calculated as

$$e_i=-k\sum_{i=1}^{n}(p_{ij}\cdot\ln p_{ij}),\quad k=\frac{1}{\ln n}, \tag{4}$$

and the information entropy redundancy is calculated as $g_i=1-e_i$. Finally, the weight of each index can be obtained by formula (5).

$$\omega_{2i}=\frac{g_i}{\sum_{i=1}^{n}g_i} \tag{5}$$

The CRITIC is used for objective weighting. The dispersion degree refers to the difference between the values of a criterion in each evaluation scheme. It is expressed in the form of standard deviation, as shown in formula (6).

$$S_j=\sqrt{\frac{\sum_{i=1}^{n}\left(x_{ij}-\overline{x}_j\right)^2}{n-1}} \tag{6}$$

The conflict degree reflects the amount of similar information between different criteria. The conflict degree is calculated by

$$R_j=\sum_{i=1}^{p}(1-r_{ij}), \tag{7}$$

where r_{ij} represents the correlation coefficient between the evaluation index. It can be obtained that the weight of each index calculated by formula (8).

$$\omega_{3i}=\frac{S_j\times R_j}{\sum_{j=1}^{p}(S_j\times R_j)} \tag{8}$$

Calculate the combination weight: The multiplicative synthesis is to multiply the weight of an index obtained by various weighting methods, and then normalize to get the combination weight [12]. The resulting combination weight is calculated by formula (9).

$$\omega_i=\frac{\prod_{k=1}^{3}\omega_{ki}}{\sum_{i=1}^{n}\prod_{k=1}^{3}\omega_{ki}} \tag{9}$$

2.2 Metabolic GM (1,1) Model

The GM(1,1) model is used to make predictions by using the time series of the prediction object itself. It is based on random time series, and a new time series is formed by summing up time, and the law of sequence is approximated by the solution of first-order linear differential equation. It is characterized by fewer samples required and higher model accuracy, which has a good effect on prediction. Metabolism GM (1,1) overcomes the shortcomings of conventional GM (1,1), takes into account the influence of the disturbance factors that enter the system over time, and removes old information while constantly adding new information, making the whole system constantly updated and more in line with reality.

The grey differential equations for GM (1,1) are equation (10) [13],

$$\begin{cases} x^{(0)}(k)+az^{(1)}(k)=b \\ x^{(0)}=\{x^{(0)}(1),x^{(0)}(2),\ldots,x^{(0)}(n)\} \\ x^{(1)}(k)=\sum_{i=0}^{k}x^{(0)}(i)=x^{(1)}(k-1)+x^{(0)}(k)\ , \\ z^{(1)}(k)=\dfrac{x^{(1)}(k)+z^{(1)}(k-1)}{2} \end{cases} \tag{10}$$

where, $x^{(0)}$ is the initial non-negative data column, $x^{(1)}$ is the generated data obtained by summation once, $z^{(1)}$ is the adjacent generated sequence of $x^{(1)}$, b represents the grey action, and $-a$ represents the development coefficient. The matrix form is

$$u=(a,b)^{T},Y=\begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \cdots \\ x^{(0)}(n) \end{bmatrix},B=\begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \cdots & \cdots \\ x^{(0)}(n) & 1 \end{bmatrix}. \tag{11}$$

The estimated value of the parameters a and b is obtained by the ordinary least squares, as shown in equation (12).

$$\hat{u}=\left(\hat{a}\ \hat{b}\right)^{T}=(B^{T}\ \ B)^{-1}B^{T}Y \tag{12}$$

The bleaching equation of GM (1,1) is

$$\frac{dx^{(1)}(t)}{dt}=-\hat{a}x^{(1)}(t)+\hat{b}. \tag{13}$$

Taking the initial value $\hat{x}^{(1)}(t)|_{t=1}=x^{(0)}(1)$ gives the solution to equation (14).

$$x^{(1)}(t)=\left[x^{(0)}(1)-\frac{\hat{b}}{\hat{a}}\right]c^{-\hat{a}(t-1)}+\frac{\hat{b}}{\hat{a}} \tag{14}$$

Add the nearest information data $x^{(0)}(m+1)$ to the original data sequence, and correct the new sequence as equation (15).

$$x^{(0)}=\{x^{(0)}(2),x^{(0)}(3),\ldots x^{(0)}(m+1)\} \tag{15}$$

3. Results

Three-level indicators are constructed to measure the light pollution risk level, and they are shown in 0. The risk level of light pollution in the figure is primarily determined by two factors: humanistic influence and natural influence. Given that natural influences are beyond human control, greater emphasis is placed on humanistic influences as the foundation for devising strategies to mitigate light pollution. The weight calculation results are shown in 0.The weight value of 0 shows the influence of each factor on light pollution. It can be seen from the table that the most serious influence on light pollution is the mean sunshine duration, and the least influence on light pollution is the average working hour.

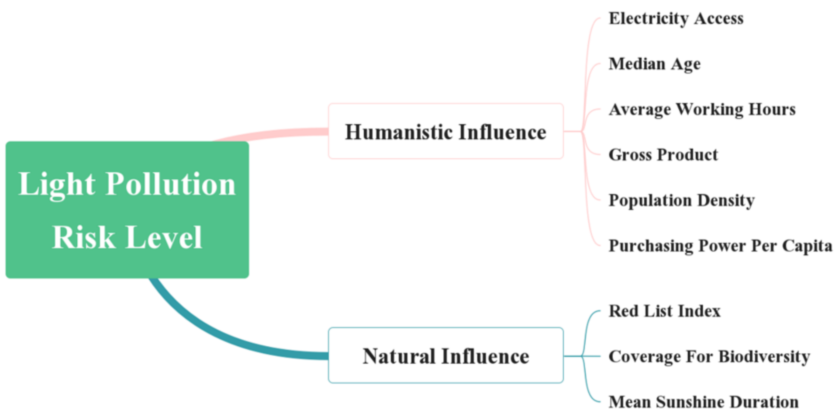


Figure 1: Three-level indicator of light pollution risk level

Table 1: The weight results of each method

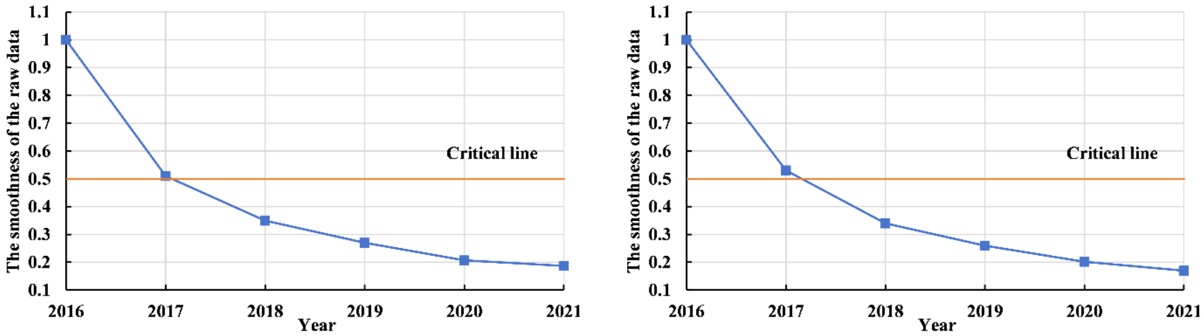
Index	AHP	EWM	CRITIC	CWM
Electricity Access	0.39	0.06	0.15	0.15
Median Age	0.07	0.19	0.14	0.08
Average Working Hours	0.05	0.03	0.23	0.02
Gross Product	0.22	0.15	0.12	0.17
Population Density	0.16	0.22	0.18	0.28
Purchasing Power Per Capita	0.12	0.34	0.17	0.30
Red List Index	0.30	0.35	0.33	0.26
Coverage For Biodiversity	0.16	0.20	0.31	0.08
Mean Sunshine Duration	0.54	0.45	0.36	0.66

According to the impact of light pollution, three different light pollution treatment strategies are proposed:

Strategy One: Develop intervention strategies from electricity access to reduce light pollution risk levels. Implementation case: the night lighting equipment such as street lamps could be changed from a timing switch to a photosensitive switch, to avoid opening at bright times due to climate, season, and other reasons; limit the use of some decorative lights; encourage the public to form the habit of turning off lights; reduce the ratio of spill lights [14].

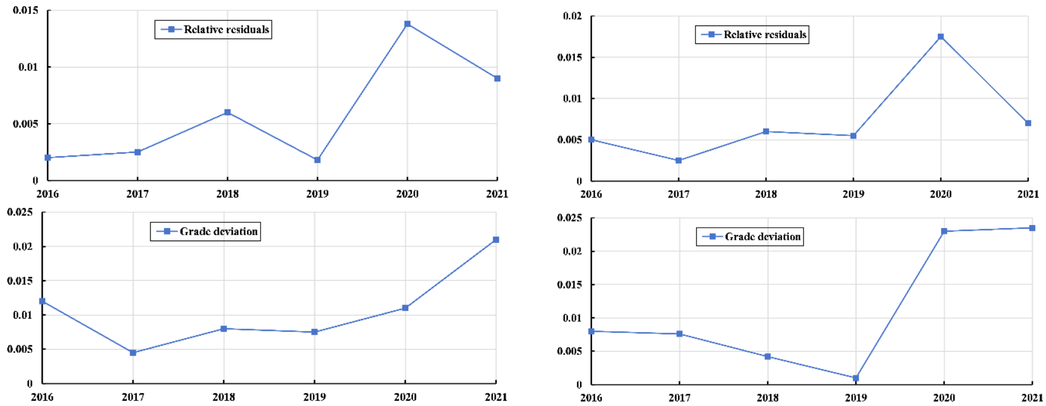
Strategy Two: Develop strategies to reduce light pollution risk levels in terms of population density. Implementation case: develop land around to reduce population density; relax administrative controls on urban land use and density [15]; offer plenty of job opportunities, a pleasant climate, and an attractive lifestyle elsewhere; provide good population policies [16]; reduce the construction of tall buildings; improve the transportation lines, convenient travel; distribute social resources equally.

Strategy Three: Develop strategies to reduce light pollution risk levels in terms of coverage for biodiversity. Implementation case: optimize light color to enrich biodiversity [17]; reduce the use of artificial lights in vegetation [18]; improve green coverage; comply with the Bonn Convention [19]; create environmental protection areas and reduce the use of artificial light sources.



(a) Test results of data from China (b) Test results of data from the United States

Figure 2: Test result of quasi-exponential law test



(a) Test results of data from China (b) Test results of data from the United States

Figure 3: Residual test and Pole ratio residual test results

The collected data from China and the United States are tested using a quasi-exponential law, and the test results are shown in 0. Except for the first two periods, the smoothness ratio of the later periods greater than 90% is lower than 0.5, indicating that the two groups of data have been tested by the quasi-exponential law.

Residual test and calculation results are shown in 0. The average relative residuals are 0.55% and 0.73% respectively. The average grade ratio deviations are 0.010567 and 0.011137 respectively. The results show that the model fits the original data very well.

Data from 2015 to 2021 are used to project the levels of light pollution risk in 2022 and 2023, and as a case where no strategy is implemented in both places. Three strategies are implemented for the two places respectively, and the key factors are revised down or up by 3% from the forecast year 2022 according to the focus of the strategies. At the same time, the levels of light pollution risk are increased or decreased according to the correlation coefficient of potential influencing factors and major factors. Finally, the adjusted values are used as the values for implementing each strategy in 2023. The results of the two places under four different schemes are shown in 0.

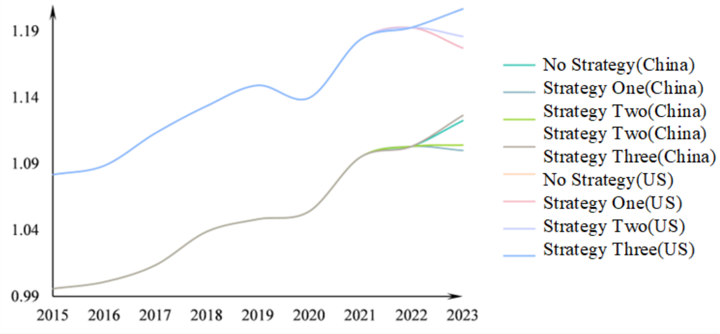


Figure 4: The comparison of the four cases

According to the results shown in 0, strategy one reduces the risk level of light pollution to a greater extent than the other two strategies in China and the United States, that is, strategy one can sacrifice a smaller cost in exchange for a smaller risk level of light pollution. At the same time, if the light pollution is not controlled, according to the predicted results, the light pollution will be further aggravated in the case of no control.

4. Conclusions and outlooks

In this paper, the light pollution risk level assessment model established by the combination weighting method is used to evaluate the light pollution level in China and the United States, and the results after applying different strategies are simulated. In the three light pollution prevention strategies proposed in this paper, combined with the predicted results of the data of China and the United States, strategy one has a better control effect than the other two strategies, that is, reducing unnecessary artificial lighting. It should be noted that the optimal strategy is based on several light pollution prevention strategies proposed in this paper. When a new strategy appears, the evaluable system can be applied to the comparison between multiple strategies and the prediction of implementation effect.

In the combination process, the effect of the multiplication synthesis selected is close to that of a simple arithmetic average, and its combination precision is poor. In the process of combination weighting, the linear weighting group method can be used to improve the combination accuracy of multiple weighting methods based on the rank correlation coefficient group method. The first-order grey prediction model based on the Metabolic GM (1,1) model relies on the historical comparison of the data. The accuracy of the prediction results is low when the data do not meet the application conditions of the model. The first-order gray prediction model may cause slight deviation in the results, so a variety of prediction methods can be used at the same time, such as the combination of the Metabolic GM (1,1) model and backpropagation, which can improve the accuracy and credibility of the prediction results.

References

[1] Lapostolle D, Challéat S. Making darkness a place-based resource: how the fight against light pollution reconfigures rural areas in France[J]. Annals of the American Association of Geographers, 2021, 111(1): 196-215.
[2] Briolat E S, Gaston K J, Bennie J, et al. Artificial nighttime lighting impacts visual ecology links between flowers, pollinators and predators[J]. Nature communications, 2021, 12(1): 4163.
[3] Czaja M, Kołton A. How light pollution can affect spring development of urban trees and shrubs[J]. Urban Forestry & Urban Greening, 2022, 77: 127753.
[4] Walker W H, Bumgarner J R, Walton J C, et al. Light pollution and cancer[J]. International Journal of Molecular Sciences, 2020, 21(24): 9360.
[5] Owens A C S, Cochard P, Durrant J, et al. Light pollution is a driver of insect declines[J]. Biological Conservation, 2020, 241: 108259.

[6] Zielińska-Dabkowska K M, Xavia K, Bobkowska K. Assessment of citizens' actions against light pollution with guidelines for future initiatives[J]. Sustainability, 2020, 12(12): 4997.
[7] Meier J M. Contentious light: an analytical framework for lighting conflicts[J]. International Journal of Sustainable Lighting, 2018, 20(2): 62-77.
[8] Gokhale V, Goins J, Herdmann A, et al. Sky brightness measurements and ways to mitigate light pollution in Kirksville, Missouri[J]. arXiv preprint arXiv:1908.05234, 2019.
[9] Barentine J C. Methods for assessment and monitoring of light pollution around ecologically sensitive sites[J]. Journal of Imaging, 2019, 5(5): 54.
[10] Hölker F, Moss T, Griefahn B, et al. The dark side of light: a transdisciplinary research agenda for light pollution policy [J]. Ecology and Society, 2010, 15(4).
[11] Li Jiangyun. Evolutionary analysis of the temporal and spatial patterns of technological innovation and regional economic development: based on NPP/VIIRS night light data [J]. Areal Research and Developmen, 2022, 41(03):1-5+11.
[12] Yang Yu. The evaluation and analysis of weighting methods in multi-index comprehensive evaluation [J].Statistics and Decision, 2006(13): 17-19.
[13] Huang Songqian, Wang Weimin, Zeng Cong et al. Prediction of total annual aquatic product production in China based on grey metabolism GM(1,1) mode [J]. Chinese Agricultural Science Bulleti, 2012,28(17): 126-131.
[14] Terrich T, Balsky M. The Effect of Spill Light on Street Lighting Energy Efficiency and Light Pollution[J]. Sustainability, 2022, 14(9): 5376.
[15] Zhang Haoran. Sunshine spacing constraint, population density and urban growth in China [J]. China Economic Quarterly, 2018, 17(01): 333-354. DOI: 10.13821/j.cnki.ceq.2017.04.13.
[16] Wang L, Feng Z, Yang Y. The change in population density from 2000 to 2010 and its influencing factors in China at the county scale [J]. Journal of Geographical Sciences, 2015, 25: 485-496.
[17] Muñoz-Gil G, Dauphin A, Beduini F A, et al. Citizen science to assess light pollution with mobile phones[J]. Remote Sensing, 2022, 14(19): 4976.
[18] Zhu F J M .Comprehensive energy saving evaluation of circulating cooling water system based on combination weighting method[J].Applied thermal engineering: Design, processes, equipment, economics, 2019, 157.
[19] Yakushina Y. The response of the Bonn Convention on Migratory Species to light pollution[C]//IOP Conference Series: Earth and Environmental Science. IOP Publishing, 2022, 1099(1): 012048.