Evaluation Model Based On Optimized EWM Identifying Light Pollution

Hengzhi Xie*, Mingxuan Jiang, Zihao Wang

Department of Software, Northeastern University, Shenyang, China

*Corresponding author: xhzadrianlin@163.com

Abstract. Light pollution has negative impacts on wildlife, human health and the environment, disturbing the natural darkness of the night sky. However, there lacks an objective and feasible method measuring the risk level of light pollution. Therefore, we establish a mathematical evaluation model based on the integration of optimized EWM and TOPSIS to measure the light pollution of representative locations. According to the results, we conclude that the risk level of light pollution is positively correlated to the prosperity of commerce.

Keywords: EWM, TOPSIS, Evaluation Model, Algorithm optimization.

1. Introduction

1.1. Motivation

Light pollution is used to describe any excessive or poor use of artificial light and include varieties of phenomena.It alters our view of the night sky and exerts negative impacts on both natural environment and human health [1-2]. The accurate measurement of light pollution is of great significance for the analysis of light environment and the strategy to control light pollution, but inconsistencies between different research disciplines can cause confusion [3-4]. Therefore, we establish mathematical evaluation model based on optimized EWM and TOPSIS.

1.2. Related Work

Current research about light pollution mainly focuses on two aspects, the intensity and spectra [5]. The result shows that the spectra may have greater influence on residents [6]. Many light pollution measurements and modelling works have been reported around the world.

In 2011, Kocifaj et al. [7] proposed a numerical model analysing the influence of different light sources on light pollution. In this paper, a contribution of distant sources to the light pollution might be essential under specific conditions.

In 2016, Yali Katz and Noam Levin [8] compared ground measurements using SQM devices and space-borne measurements using EROS-B night light imagery.They examined the use of the SQM for evaluating artificial light in different view directions and provided evidence for the correspondence between field and space-borne measurements of artificial lights. Besides, this paper emphasized the need for taking into account of the three dimensional nature of light pollution.

In 2017, Jin et al. [9] measured light pollution levels and their damage at the neighborhood scale by a light pollution assessment method which is easy to perform, low-cost and has a short data processing cycle. This paper analysed the connection between the spatial variation pattern of light intensity and light pollution in a commercial place in Beijing.They found that the vertical illumination at the windows of residential buildings in some areas is far higher than the value recommended by CIE.

In 2018, Jiangtao Du et al. [10] presented an investigation into the risk of light pollution caused by indoor artificial lighting in a fully glazed office building. They found that a shining façade with large glazing might be a source of light pollution and external positions at middle and lower façade heights can be impacted more by indoor lighting than positions at higher levels while significant effects can be found within a distance of 20m to the façade.

In 2018, Lim et al. [11] proposed a model measuring the light pollution in Seoul and investigated vertical luminance values in different locations. This model was based on field measurement.They found that all locations were experiencing light pollution to different degrees.

In 2018, Xavier Ges at el. [12] selected sea as a stage for evaluating light pollution propagation models. In this work, they presented a proof-of-concept of a gimbal measurement system. After calculation, data recorded in Mediterranean coastal waters are compatible with predictions.

In 2020, Jimmy C. K. Tong et al. [13] quantitatively evaluate light pollution in Hong Kong through measurement and numerical modelling. They developed measurement protocols and conducted site measurement in Mong Kok district. They found an average level of 250 lx for the vertical illuminance, which was 3-4 times higher than the recommended brightness for normal activity.

In 2021, Zihao Zhen et al. [14] quantified the light pollution dynamics of African reserves from 1992 to 2018. They conducted long-term monitoring and evaluation of light pollution in African protected areas using aligned multi-sensor NTL data. They found that the number of light-polluted areas rapidly increased and human activity intensity surrounding the areas was highly correlated with light pollution within them.

1.3. Main Work

In this paper, we develop a broadly applicable metric to identify the light pollution risk level and use this metric to analyse light pollution in different areas in Shenyang. We divide Shenyang into two kinds of areas and select the typical communities in each area. Our work is mainly targeted at proposing a evaluation model based on the criteria relevant to light pollution we choose and data of representative locations are input into this model to get the results describing light pollution risk level.

2. Model Preparation

2.1. Data Collection

Table 1. Data Sources Collection

Database Names	Database Websites
Light Pollution Map	https://www. lightpollutionmap. info/
Geographic Information Monitoring Cloud Platform	http://www. dsac. cn/
CHINA CITY STATISTICAL YEARBOOK	http://www. stats. gov. cn/
China National Knowledge Infrastructure	https://www. cnki. net/
ScienceDirect	https://www. sciencedirect. com/

2.2. Notations

Table 2. Notations

Symbol	Description	Unit
e	Information entropy	bit
D	The distance of each alternative from the solution	-
S	The final scores calculated by TOPSIS	-
P	Criterion pollution index	-

3. Model Construction

The light pollution risk level of a location is determined by various factors.The light pollution risk level of a location is a dependent variable coming from independent variables and the rationality of the selection of those independent variables determine that of metric. Therefore, the first priority should be given to the selection of criteria determining or relevant to right pollution risk level. Next, we should propose a method to manipulate selected criteria and acquired data, which makes a request for an appropriate and applicable evaluation model.

3.1. Criterion Selection

We select seven criteria targeted at the main human social activity environments in the city, where environment, health, ecology and many other factors are taken into account. Seven criteria are divided into commercial areas and residential areas. They represent three parts of illumination: illumination time, illumination brightness and illumination range. In residential area, we select Average Road Surface Illumination, Indoor Window Vertical Illumination and Uniformity of Illumination. In commercial area, we select The Brightness of Advertising Light Boxes, The Brightness of LED Screen, Color Contrast of LED Screen and Average Illumination. Specific description of these criteria are as follows [15]:

·Average Road Surface Illumination: The average value of the illumination of each point chosen on the road surface

·Indoor Window Vertical Illumination: The illumination of vertical light through indoor windows

·Uniformity of Illumination: The ratio of the minimum illumination to the average illumination on a specified surface

·The Brightness of Advertising Light Boxes: The degree to which light emitted or reflected by advertising light box is perceived by the human eyes

·The Brightness of LED Screen: The degree to which light emitted or reflected by LED screen is perceived by the human eyes

·Color Contrast of LED Screen: The ratio of the illumination values of two adjacent colors

·Average Illumination: The energy of visible light received per unit area

3.2. Entropy Weight Method

EWM is a method objectively empowering criteria based on the variance calculation of known data. This method is a popular multi-criteria decision-making approach and can be used to solve problems in which multiple criteria are involved. The basic principle of EWM is to calculate the weight of each criterion based on its relative entropy value, which measures the degree of uncertainty or randomness associated with each criterion.

3.2.1 Implementation

Step 1: Criteria Normalization

We need to change all the other criteria into maximum criteria. The bigger maximum criteria values are, the better the alternative is. We can normalize criteria data using reciprocal if all the criteria data are positive.

Step 2: Construct a decision matrix

Construct a decision matrix X in which the row amount represents the number of evaluation objects and the column amount represents the number of criteria. Let x_{ij} denote the performance score of evaluation objects i on criterion j. Let n and m denote the number of evaluation objects and criteria respectively. The decision matrix is as follows:

$$\begin{bmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{bmatrix}$$

Step 3: Normalize the decision matrix

The decision matrix needs to be normalized so that errors due to differences between criteria or dimensions can be balanced. Normalization can be done by dividing each element in a column by the square of the sum of elements in that column if the data chosen are all positive, i. e.,

$$z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} {x_{ij}}^2}}, i = 1,2,\cdots,n;\ j = 1,2,\cdots,m \tag{1}$$

The resulting normalized decision matrix Z is an $n \times m$ matrix, whose elements are z_{ij}.

Step 4: Calculate the proportion of elements

Calculate the proportion of evaluation object i under criterion j and regard it as the probability used in the entropy calculation. To achieve this, Equation (2) is used:

$$p_{ij} = \frac{z_{ij}}{\sqrt{\sum_{i=1}^{n} z_{ij}}}, i = 1,2,\cdots,n;\ j = 1,2,\cdots,m \tag{2}$$

Step 5: Calculate the weight of each criterion

First, we should use Equation (3) to calculate the entropy value of each criterion:

$$e_j = -\frac{\sum_{i=1}^{n} p_{ij}\, ln\, p_{ij}}{ln\, n}, j = 1,2,\cdots,m \tag{3}$$

Then, we can use Equation (4) to calculate the weight of each criterion:

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{m}\left(1 - e_j\right)}, j = 1,2,\cdots,m \tag{4}$$

The entropy value e_j measures the degree of diversity or heterogeneity in the performance scores of criterion j. A higher entropy value indicates greater diversity, which means greater uncertainty or risk. The weight w_j is a measure of the relative importance of criterion j in the decision-making process. A higher weight indicates greater importance.

3.3. Technique for Order of Preference by Similarity to Ideal Solution

TOPSIS is a decision analysis method that is commonly used when there are multiple criteria to consider and there is no obvious or clear-cut solution. This technique allows the evaluation of a set of alternatives based on multiple criteria, whose results can accurately reflect the gap between the evaluation schemes because of full use of the information contained in raw data.

3.3.1 Implementation

Step 1: Criteria Normalization

We need to change all the other criteria into maximum criteria. The bigger maximum criteria values are, the better the alternative is. We can normalize criteria data using reciprocal if all the criteria data are positive. Actually, this step is the same with that of the implementation of EWM.

Step 2: Construct a decision matrix.

Construct a decision matrix X in which the row amount represents the number of evaluation objects and the column amount represents the number of criteria. Let x_{ij} denote the performance score of evaluation objects i on criterion j. Let n and m denote the number of alternatives and criteria respectively. Actually, this step is the same with that of the implementation of EWM.

Step 3: Normalize the decision matrix.

The decision matrix must be normalized to ensure that each criterion is measured on a comparable scale. The normalization process involves dividing the value of each cell in the decision matrix by the squares of the sum of values in the corresponding columns. The result is a normalized decision matrix, where each criterion has a value between 0 and 1. Actually, this step is the same with that of the implementation of EWM as well.

Step 4: Determine the ideal and worst solutions.

The ideal and worst solutions are determined by calculating the largest and the smallest performance scores for each criterion across all the evaluation objects in the decision matrix, which means selecting the largest and the smallest number from every column and make them composed of two vectors respectively:

$$z_j{}^{+} = max\, z_{ij}, z = 1,2,\cdots,n \tag{5}$$

$$z_j{}^{-} = min\, z_{ij}, z = 1,2,\cdots,n \tag{6}$$

where z_j^+ represents the ideal solution while z_j^- represents the worst solution. The ideal solution represents the best possible performance of each criterion while the worst solution represents the worst possible performance of each criterion.

Step 5: Calculate the distance of each alternative from the ideal and from worst solutions

The distance of each alternative from the ideal and worst solutions is calculated using a distance metric, such as the Euclidean distance or the Manhattan distance. The distance of each alternative from the ideal solution is calculated using the following formula:

$$D_i^+ = \sqrt{\sum_{j=1}^{m} w_j\left(z_{ij} - z_j^+\right)^2}, i = 1,2,\cdots,n \tag{7}$$

The distance of each alternative from the worst solution is calculated using the following formula:

$$D_i^- = \sqrt{\sum_{j=1}^{m} w_j\left(z_{ij} - z_j^-\right)^2}, i = 1,2,\cdots,n \tag{8}$$

In the two formulas mentioned above, the weight w_j should reflect the relative importance of the criterion j, to which the results of EWM can be assigned. In some cases, the values of weight w_j can also be uniformly set as 1.

Step 6: Calculate the scores and rank the alternatives

The final scores are calculated using the following formulas which are based on distance metric:

$$S_i = \frac{D_i^-}{D_i^+ + D_i^-}, i = 1,2,\cdots,n \tag{9}$$

The value of S_i represents the relative closeness of alternative i to the ideal solution as well as the relative distance to the worst solution. Therefore, the alternative with the highest value of S_i is the most preferred alternative while the alternative with the lowest value of S_i is the least preferred alternative.

3.4. Optimized EWM

According to Equation (4), it indicates that a criterion can play a more significant role in evaluation if the information entropy of this criterion is smaller, thus increasing weight value of this criterion. On the contrary, the greater the information entropy of a criterion is, the smaller role it plays in evaluation, resulting in less corresponding weight value.

The criterion pollution index P reflects the severity of light pollution. When P is greater than 1, it can be considered to suffer from light pollution. Then, assuming a situation where the criterion pollution index of each sample is greater than 1 but the difference between criteria values is small, the information entropy value will be very close to 1. For example, provided that the criterion pollution index value of two samples is 5 and its information utility value is 0 after calculation, the weight of the criterion calculated by EWM is also 0. Although it is obvious that both samples suffer from light pollution(up to 5 times of allowed maximum value) under this criterion, the weight used to calculate light pollution comprehensive evaluation index is 0, which is very unreasonable. We take the following hypothetical data in Table 3 as an example:

Table 3. Hypothetical Data

	Criterion 1	Criterion 2	Criterion 3
Sample 1	5	3	0.8
Sample 2	5	2.8	0.2

If the weight is calculated by the original EWM and input into the comprehensive evaluation model, weights and light pollution comprehensive indexes are shown in Table 4:

Table 4. The Results Calculated by EWM

	Criterion 1	Criterion 2	Criterion 3	Score
Sample 1	5	3	0.8	0.806766
Sample 2	5	2.8	0.2	0.207996
Weight	0.0	0.003076	0.996924	

The final result shows that not only the weights are inconsistent with the reality but also the comprehensive light pollution indexes are less than 1, indicating that neither sample 1 or sample 2 are subject to light pollution when the criterion pollution index 1 and the criterion pollution index 2 greatly exceed the maximum light allowed, which is inconsistent with the real situation as well.

Given this situation and calculation characteristics of the EWM, a standard group is added when calculating, which is composed of samples whose criterion values are all 1. By this means, erroneous results can be avoided when the pollution index values are large and the differences of criterion values is small, which makes the model more objective and reasonable.

After adding the standard group, weights and light pollution comprehensive indexes calculated by EWM and comprehensive evaluation model are shown in Table 5:

Table 5. The Results Calculated by Optimized EWM

	Criterion 1	Criterion 2	Criterion 3	Score
Sample 1	5	3	0.8	2.966061
Sample 2	5	2.8	0.2	2.694409
Standard Sample	1	1	1	1
Weight	0.400163	0.220625	0.379211	

The light pollution comprehensive indexes of two samples both exceed 1 and the light pollution situation of two samples are well reflected, which is well consistent with the reality. Therefore, we well establish the comprehensive index evaluation model targeted at light pollution based on the optimized EWM, whose schematic diagram is shown in Figure 1:

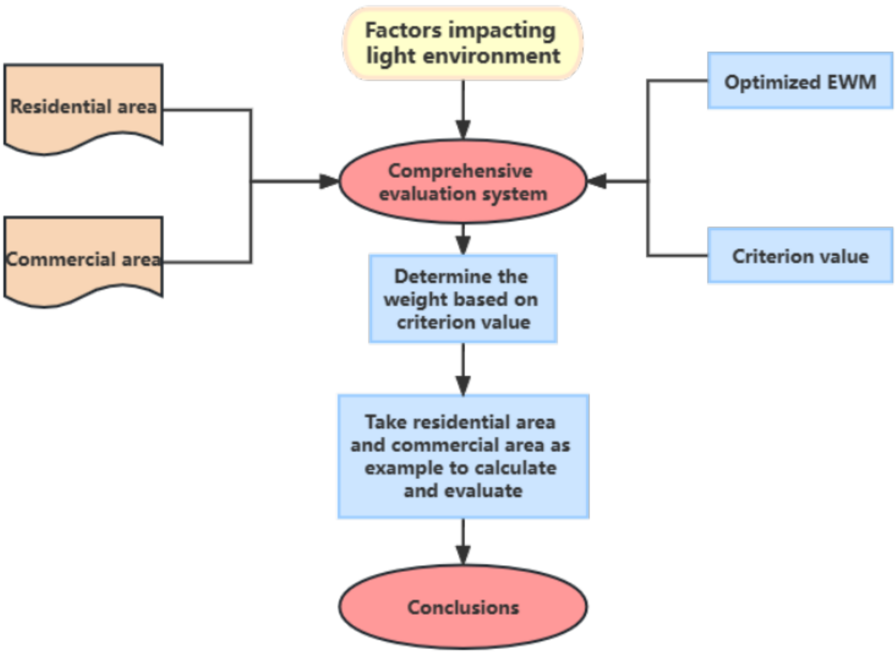

Figure 1. The Schematic Diagram of Comprehensive Evaluation Model Based On EWM

4. Results

4.1. Data Acquisition

The values of criteria from Table 6 and Table 7 are as follows [15]:

Table 6. The Data of Residential Area

Measurement Point	Average Road Surface Illumination	Indoor Window Vertical Illumination	Uniformity of Illumination
The First Town In Tiexi	1.04	0	0.269
Nanba Road Community	19.03	0	0.028
Wulihe City	5.13	30.57	0.252

Table 7. The Data of Commercial Area

Measurement Point	The Brightness of Advertising Light Boxes	The Brightness of LED Screen	Color Contrast of LED Screen	Average Illumination
Taiyuan Street	211.8	797.675	2.53	22.55
Middle Street	225.3	786.95	2.93	38.53

4.2. Quantification of Light Pollution In Residential Area

According to the model we propose, the weight of every criterion concerning residential area and the scores of every alternative can be calculated, whose results are shown in Table 8, Figure 2 and Table 9:

Table 8. Residential Area Criterion Weight

Criterion	Weight
Average Road Surface Illumination	0. 306566
Indoor Window Vertical Illumination	0. 567280
Uniformity of Illumination	0. 126154

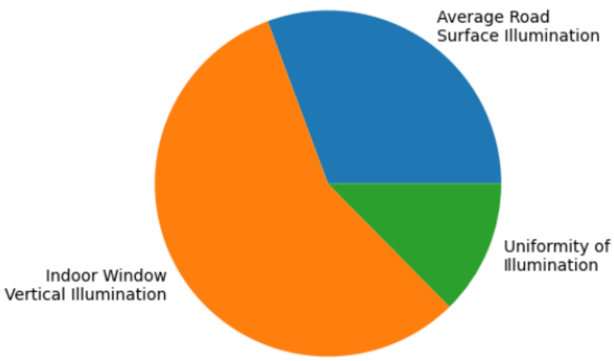

Figure 2. Residential Area Criterion Weight

Table 9. Residential Area Scores

Measurement Point	Scores
The First Town In Tiexi	0. 176656
Nanba Road Community	1. 179370
Wulihe City	2. 029310

4.3. Quantification of Light Pollution In Commercial Area

According to the model we propose, the weight of every criterion concerning commercial area and the scores of every alternative can be calculated, whose results are shown in Table 10, Figure 3 and Table 11:

Table 10. Commercial Area Criterion Weight

Criterion	Weight
The Brightness of Advertising Light Boxes	0. 186411
The Brightness of LED Screen	0. 619580
Color Contrast of LED Screen	0. 012069
Average Illumination	0. 181939

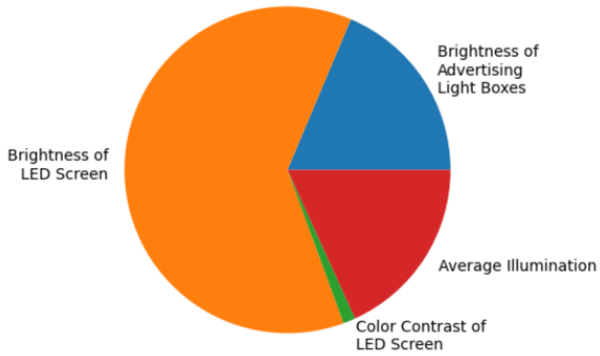

Figure 3. Commercial Area Criterion Weight

Table 11. Commercial Area Scores

Measurement Point	Scores
Taiyuan Street	3. 084050
Middle Street	3. 280254

4.4. Analysis of Results

According to the results, the scores of light pollution risk level in Shenyang range from 0.176656 to 3.280254. The light pollution in The First Town In Tiexi is the smallest, which is considered non-polluting. The light pollution in Nanba Road Community and Wulihe City are relatively high. Taiyuan street and Middle Street are experiencing severe pollution. Overall, the light pollution in residential area is much smaller than that in commercial area. This may be related to the difference of light facilities used and various needs of illuminating.

5. Strengths and Possible Improvements

5.1. Strengths

·Optimized EWM improves the objectivity of results.

5.2. Possible Improvements

·EWM ignores the importance of the criteria themselves, which is likely to make weight value far from expected results.

·Accuracy may be reduced in the context of too many decision-making levels for evaluation.

6. Conclusion

In this paper, we propose a model based on the integration of TOPSIS and optimized EWM to identify the risk level of light pollution and use this model to analyse the light environment in Shenyang. We can conclude that the light pollution risk level of residential area is much less severe than that in commercial area, but most of them are confronted with light pollution to different degrees. In the future, we plan to expand this model to other cities in China and make a comprehensive evaluation of light environment in China.

Acknowledgements

The authors gratefully acknowledge the financial support from Northeastern University in Shenyang.

References

[1] Svechkina, A. , Portnov, B. A. , Trop, T. The impact of artificial light at night on human and ecosystem health: A systematic literature review[J]. Landscape Ecology, 2020, 35(8): 1725–1742.

[2] Cinzano, P. , Falchi, F. , Elvidge, C. D. The first world atlas of the artificial night sky brightness. Mon. Not. R. Astron. Soc. 2001, 328: 689–707.

[3] Jechow, A. , Hölker, F. How dark is a river? Artificial light at night in aquatic systems and the need for comprehensive night-time light measurements[J]. Wiley Interdisciplinary Reviews: Water, 2019, 6(6).

[4] Susan Mander, Fakhrul Alam, Ruggiero Lovreglio, Melanie Ooi. How to measure light pollution - a systematic review of methods and applications. Sustainable Cities and Society, 2023, 104465.

[5] Caddick, Z. A. , Gregory, K. , Flynn-Evans, E. E. Sleep environment recommendations for future spaceflight vehicles[J]. Advances in Human Aspects of Transportation, 2017, 923–933.

[6] Lewy, A. J. , Wehr, T. A. , Goodwin, F. K. , Newsome, D. A. , Markey, S. P. Light suppresses melatonin secretion in humans[J]. Science, 1980, 210: 1267–1269.

[7] Kocifaj, M. . A numerical experiment on light pollution from distant sources[J]. Mon. Not. R. Astron. Soc, 2011, 415 (4): 3609–3615.

[8] Yali Katz, Noam Levin. Quantifying urban light pollution - A comparison between field measurements and EROS-B imagery[J]. Remote Sensing of Environment, 2016, 177: 65 - 77.

[9] Jin, X. , Li, Y. , Zhang, J. , Zheng, J. , Liu, H. , An approach to evaluating light pollution in residential zones: a case study of Beijing[J]. Sustainability, 2017, 9 (4): 652.

[10] Jiangtao Du, Xin Zhang, Derek King. An investigation into the risk of night light pollution in a glazed office building: The effect of shading solutions[J]. Building and Environment, 2018, 145: 243 - 259.

[11] Lim, H. , Ngarambe, J. , Kim, J. , Kim, G. . The reality of light pollution: a field survey for the determination of lighting environmental management zones in South Korea[J]. Sustainability, 2018, 10 (2): 374.

[12] Xavier Ges, Salvador Bará, Manuel García-Gil, Jaime Zamorano, Salvador J. Ribas, Eduard Masana. Light pollution offshore: Zenithal sky glow measurements in the mediterranean coastal waters[J]. Journal of Quantitative Spectroscopy and Radiative Transfer, 2018, 210: 91 - 100.

[13] Jimmy C. K. Tong, Edmond S. L. Lau, Melody C. Y. Hui, Enoch Kwong, Morgan E. White, Arthur P. S. Lau, Light pollution spatial impact assessment in Hong Kong: Measurement and numerical modelling on commercial lights at street level[J]. Science of The Total Environment, 2022, 837: 155681.

[14] Zihao Zheng, Zhifeng Wu, Yingbiao Chen, Guanhua Guo, Zheng Cao, Zhiwei Yang, Francesco Marinello, Africa's protected areas are brightening at night: A long-term light pollution monitor based on nighttime light imagery[J], Global Environmental Change, 2021, 69: 102318

[15] Qin Wei. Typical areas of light environmental assessment and analyze. Northeastern University, 2015.