A Risk Level Assessment Model for Artificial Light Pollution Based on Risk Field Theory and Entropy Weight TOPSIS Method

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Abstract. In order to better develop a widely applicable indicator to determine the risk level of artificial light pollution in various regions, this paper proposes an artificial light pollution risk level assessment mechanism based on risk field theory and entropy weight TOPSIS method. Firstly, based on the theory of environmental risk field, two major types of light pollution indicators are selected: the intensity of the light pollution source itself (including industrial light pollution level, type of light pollution source, distance of light pollution, density of buildings, degree of residential light pollution, degree of traffic light pollution, etc.) and the vulnerability of light pollution receptors (including vegetation coverage and its type, surface type, building density, etc.). Then, an entropy weight TOPSIS method is used to establish a light pollution risk level assessment model, and regional representatives with different light pollution gradient characteristics from China are selected as reference data. Finally, the scoring results of artificial light pollution risk levels in different regions are obtained to verify the assessment model. The obtained results can provide quantitative results and qualitative analysis for light pollution risk assessment. The innovation of this article lies in the development of a light pollution risk assessment model that provides a reasonable evaluation of the level of light pollution risk in different regions. This model combines quantitative and qualitative analysis of indicators.

Keywords: Risk Level Assessment Model, Artificial Light Pollution, Environmental Risk Field Theory, Entropy Weight TOPSIS Method.

1. Introduction

Light pollution describes any excessive or improper use of artificial light sources, encompassing phenomena such as light disturbance, excessive lighting, and light disorder. These phenomena are most evident as skyglow after sunset in large cities, though they also occur in remote areas [1]. Light pollution alters our perception of the night sky, impacts the environment, and affects human health and safety. For instance, it can delay or accelerate plant maturation and disrupt wildlife migration patterns. Excessive artificial light may disrupt circadian rhythms, reduce sleep quality and potentially cause physical and mental health issues. Glare from artificial sources can also contribute to traffic accidents [2]. Addressing these environmental issues necessitates the development of a widely applicable indicator to assess light pollution risk levels at specific locations.

Extensive research exists on the status and evaluation methods of artificial light pollution. The challenges light pollution poses for both professional and amateur astronomers observing the night sky are detailed in [1]. The environmental problems stemming from increasing light pollution trends were investigated in [2]. Urban nighttime artificial light pollution's current status and trends have been discussed [3]. Drawing on physics field theory, the theory of environmental risk field was proposed in [4], which helps systematically integrate key concepts in traditional environmental risk and provides new approaches for quantifying vulnerability. A regional environmental risk assessment method based on this risk field theory was studied in [5]. Research into the classification and control value exploration for light environment pollution monitoring is presented in [6]. The monitoring, trends, and impacts of light pollution were studied in [7], noting the lack of satellites with high spectral and spatial resolution in existing technologies. Means of obtaining detailed intra-city light pollution distribution characteristics were studied, and nighttime light pollution in Nanjing was monitored using Luojia-1 night light remote sensing imagery in [8]. The assessment of light pollution in protected areas globally from 1992 to 2018 was discussed in [9]. The construction of environmental carrying capacity based on an entropy weight TOPSIS model and the evaluation of ecological-geological environmental carrying capacity were studied in [10], demonstrating the model's feasibility for environmental assessment. The Multi-level Evaluation Model for Light Pollution (MELP) was developed in [11], selecting 14 universal indicators and using the Analytic Hierarchy Process Entropy Weighting Method (AHP-EWM) to determine their weights. Regional light pollution data was simulated using the Normal Cumulative Distribution Monte Carlo method. Finally, based on TOPSIS scoring results, the severity of light pollution is classified into three levels: mild (I-III), moderate (IV-VI), and severe (VII-IX).

Shortcomings of the above research include insufficiently detailed and universally applicable selection of light pollution indicators, limited research on their quantification and characterization, a lack of risk assessment methods for light pollution areas, a scarcity of high-precision evaluation data for regional risk levels, and subjective evaluation model methods with room for improvement.

Considering these shortcomings, to better develop a widely applicable indicator for determining artificial light pollution risk levels across regions, this paper first chooses the environmental risk field theory as the regional assessment method. Based on this method, two major types of light pollution indicators are selected: the intensity of the light pollution source itself and the vulnerability of the receptor. To reflect the hierarchical, differential, and representative nature of the data, reference data is drawn from representative regions across China exhibiting varying light pollution gradient characteristics. Finally, a risk level assessment mechanism for artificial light pollution based on risk field theory and the entropy weight TOPSIS method is proposed.

2. Assessment and Analysis of Light Pollution Risk Level

2.1. Data preprocessing

The data in this article comes from the National Bureau of Statistics of China (www.stats.gov.cn). As shown in Table.1 and Table.2, specific data such as per capita income level, population density, and streetlight ownership of Shanghai(1,5,9,13), Henan(2,6,10,14), Chongqing(3,7,11,15), and Qinghai(4,8,12,16) in China from 2015 to 2021 are used, combined with other factors that do not have specific data scoring factors (light pollution sources, light pollution distance, complex density) based on the entropy weight TOPSIS method to develop a light pollution risk intensity model.

Table 1. Data preprocessing of light pollution source impact indicators.

Numbers	Industrial pollution intensity (1.000)	Light pollution distant	Building complex density (%)	Pollution level of residents (people / km^2)	Traffic pollution (lamps / km)	Types of light pollution
1	59.357	1	66.977	3953	111	10
2	17.652	3	3.504	595	68	7
3	19.820	4	4.120	390	70	6
4	3.657	6	0.012	8	23	2
5	59.357	1	66.977	3953	111	10
6	17.652	3	3.504	595	68	7
7	19.820	4	4.120	390	70	6
8	3.657	6	0.012	8	23	2
9	59.357	1	66.977	3953	88.8	10
10	17.652	3	3.504	595	54.4	7
11	19.820	4	4.120	390	56	6
12	3.657	6	0.012	8	18.4	2
13	59.357	1	53.358	3953	111	10
14	17.652	3	3.154	595	68	7
15	19.820	4	3.708	390	70	6
16	3.657	6	0.011	8	23	2

The data in Table.1 has been integrated based on specific data situations. Randomly select four cities from four different provinces and number them. Table.1 can be clearly used to compare the factors affecting the indicators of light pollution sources in four regions.

Table 2. Preprocessing of Light Pollution Receptor Impact Index Data (Scoring Results).

Index	Vegetation cover	Surface type	Density of building complexes
1	35	93	95
2	70	78	60
3	67	56	40
4	92	35	5
5	52	93	95
6	81	78	60
7	80	56	40
8	96	35	5
9	35	93	95
10	70	78	60
11	67	56	40
12	92	35	5
13	35	93	76
14	70	78	54
15	67	56	36
16	92	35	4.75

Table. 2 shows the scoring results of vegetation cover type, surface type, and building density in China were selected to verify the vulnerability of light pollution receptors.

2.2. Introduction to Risk Field Theory and Entropy Weight TOPSIS Method

The risk field is the spatial distribution of the possibility of different types and degrees of destructive effects on the receptors involved, caused by risk sources. It has four dimensions: risk sources, forms of destructive effects, intensity of destructive effects, and types of destructive consequences. The basic research method of risk field is to analyze the four dimensions of risk field and use field models to model the combination of interested features; After establishing a comprehensive risk field model, it can be integrated into various dimensions according to application needs. The primary task of risk field research is to determine the type classification/standardization specifications for each dimension. The theory of risk field and the study of receptor vulnerability transform risk from probabilistic form to loss value or other quantitative indicators, providing an inductive method for risk field estimation[4].

The TOPSIS method (Technique for Order Preference by Similarity to Ideal Solution) can be translated as a ranking method for approximating ideal solutions. Topsis method is a commonly used comprehensive evaluation method that can fully utilize the information of raw data, and its results can accurately reflect the differences between various evaluation schemes. The limitation of the Analytic Hierarchy Process (AHP) used in the multi-level analysis and evaluation model for light pollution in reference [11] is that it requires us to construct a judgment matrix, which is highly subjective, and the number of decision factors should ideally not exceed 10. The principle of entropy weight method is that the smaller the degree of variation of the indicator, the less information it reflects, and the corresponding weight should also be lower. Therefore, the data itself tells us the weights. So, entropy weight method is an objective method, and this article improves the model method by using the Topsis model based on entropy weight method to objectively judge the weights between various factors.

2.3. Establishment of risk level assessment model for artificial light pollution

The measurement standards should establish widely applicable light pollution indicators, that is, to identify factors that affect the level of light pollution risk. For light pollution, the objects can be mainly divided into two main factors: light pollution sources and light pollution receptors. Subdivide a series of influencing factors under these two categories of factors. According to the theory of environmental risk field, on the one hand, for light pollution sources, the intensity of light pollution risk can be used for regional risk assessment of light pollution sources. Regional Risk Assessment is a method of estimating and comparing environmental impacts across large-scale geographic regions. Further analysis of light pollution factors in different types of regions reveals that factors such as industrial light pollution level, types of light pollution sources, distance of light pollution, density of building clusters, residential light pollution level, and traffic light pollution level appear to have a closer relationship with the intensity of light pollution risk. Among these factors, for better quantitative analysis, per capita income level is used to characterize the degree of industrial light pollution, population density is used to characterize the degree of residential light pollution, and the number of street lamps is used to characterize the degree of traffic light pollution. At the same time, three factors that are difficult to quantify, namely the type of light pollution source, the distance of light pollution, and the density of building clusters, are evaluated using a TOPSIS model based on entropy weight to assess the intensity of light pollution risk at different locations. On the other hand, for the group affected by light pollution, consider using the vulnerability of light pollution receptors to represent the size of the impact of light pollution on a certain group. Through biological analysis of different types of locations, it was found that factors such as vegetation coverage and its type, surface type, and building density have a closer apparent relationship with the vulnerability of light pollution receptors. Due to the difficulty of quantitatively representing these three factors, we used a TOPSIS model based on entropy weight method to score the impact of these three factors on the vulnerability of light pollution receptors at different locations. The reference data is sourced from regional representatives in China with distinct characteristics of light pollution gradients.

Combine the comprehensive results of the two results, and calculate the formula according to the environmental accident risk value, The grid unit（i）of accident risk level (ACL) and accident risk intensity (RW_i) and risk hazards (RA_i) are calculated using the following formula：

(1) ACL, The higher the sum of the grid scores for various factors i, the higher the risk level of light pollution in the area. On the contrary, the lower the risk level of light pollution is. The measurement standard model has been established.

(2) Limited scope of accident risk level (ACL) and accident risk intensity (RW_i) and risk hazards (RA_i).

$$ACL = \sqrt{RW_{\mathrm{i}} \times RA_i} \tag{1}$$

$$\text{s.t.}\begin{cases} \mathrm{RW_i} \geq 0 \\ \mathrm{RA_i} \geq 0 \\ 0 \leq \mathrm{ACL} \leq 1 \end{cases} \tag{2}$$

Table 3. Entropy weight calculation of light pollution source impact indicators.

Item	Information entropy value e	Information utility value d	Weight (%)
Industrial pollution intensity (1.000)	0.821	0.179	15.456
Complex density (%)	0.645	0.355	30.761
Pollution level of residents (person / km^2)	0.727	0.273	23.693
Traffic pollution (lamp / km)	0.901	0.099	8.543
Species of light pollution	0.881	0.119	10.356
Light pollution distance	0.871	0.129	11.150

Analysis process of light pollution intensity (Table.3): The weight calculation results of entropy weight method show that industrial pollution intensity (15.496%), building density (10-3) is 30.761%, residential pollution (person/square kilometer) is 23.693%, traffic pollution (light/kilometer) is 8.543%, and light pollution distance is 10.356%. Among them, building density (10-3) has the highest weight (30.761%), and traffic pollution (light/kilometer) has the lowest weight (8.543%).

Table 4. Entropy weight calculation of light pollution receptor impact indicators.

Item	Information entropy value e	Information utility value d	Weight (%)
Surface type	0.869	0.131	35.762
Complex density	0.874	0.126	34.563
Vegetation coverage	0.892	0.108	29.675

Light pollution receptor analysis (Table.4): The weight calculation results of entropy weight method show that the weight of surface type is 35.762%, the weight of complex density is 34.563%, and the weight of vegetation cover is 29.675%. Among them, the weight of surface type is the highest (35.762%), and the weight of vegetation cover is the lowest (29.675%).

Table 5. TOPSIS Distance Calculation of Light Pollution Source Impact Index.

Index value	Positive ideal solution distance (D+)	Negative ideal solution distance (D-)	Comprehensive score index	sort
1	0	0.47368147	1	1
2	0.38006026	0.14388333	0.27461607	4
3	0.38910805	0.12343623	0.24083037	7
4	0.47214287	0.00608503	0.01272413	10
5	0	0.47368147	1	1
6	0.38006026	0.14388333	0.27461607	4
7	0.38910805	0.12343623	0.24083037	7
8	0.47214287	0.00608503	0.01272413	10
9	0.02936690	0.46694966	0.94083031	2
10	0.38316593	0.13662087	0.26284021	6
11	0.39211850	0.11424203	0.22561401	9
12	0.47367988	0.00000026	0.00000548	12
13	0.05896689	0.44006589	0.88183763	3
14	0.38115881	0.14373177	0.27383187	5
15	0.39035775	0.12319181	0.2398830	8

Table 6. TOPSIS Distance Calculation of Light Pollution Receptor Impact Index.

Index value	Positive ideal solution distance (D+)	Negative ideal solution distance (D-)	Comprehensive score index	sort
1	0	0.41880952	1	1
2	0.18110460	0.25161245	0.58147109	4
3	0.24736882	0.17343203	0.41214753	7
4	0.40909236	0.01617563	0.03803633	10
5	0.06868445	0.38244422	0.84774977	3
6	0.21758516	0.23653083	0.52085994	6
7	0.27844455	0.14328049	0.33974859	9
8	0.41840333	0.00068677	0.00163872	12
9	0	0.41880952	1	1
10	0.18110460	0.25161245	0.58147109	4
11	0.24736882	0.17343203	0.41214753	7
12	0.40909236	0.01617563	0.03803633	10
13	0.05219465	0.39018588	0.88201413	2
14	0.19036825	0.24202723	0.55973579	5
15	0.25422929	0.16754493	0.39723844	8

Chart description of Table.5 and Table.6: D + and D-values, respectively, represent the distance between the evaluation object and the optimal or the worst solution (i. e. A + or A-). The practical significance of the two values is that the distance between the evaluation object and the optimal or worst solution, the greater the value, the farther the distance, the larger the research object D + value, the farther the distance from the optimal solution; the greater the D-value, the farther the distance from the worst solution. The most understood subject is that the smaller the D + value and the larger the D-value.

Comprehensive degree score C are calculated using the following formula:

(3) The molecule is D- value and the denominator is the sum of D + and D-; the larger the D-value, the farther the distance from the worst solution, the better the study object; the greater the C value, the better the study object.

$$C = \frac{D-}{(D+)+(D-)} \tag{3}$$

Table 7. Median display (light pollution source).

Item	Is ideal solution	Negative ideal solution
Industrial pollution intensity (1.000)	0.46679214	$8.4e^{-7}$
Complex density (%)	0.52275756	$7.8e^{-7}$
Pollution level of residents (person / km^2)	0.49230234	e^{-8}
Traffic polltion (lamp / km)	0.41908655	$4.5e^{-7}$
Species of light pollution	0.39035859	$4.9e^{-6}$
Light pollution distance	0.40555099	$8.1e^{-6}$

Table 8. Median display (light pollution receptors).

Item	Is ideal solution	Negative ideal solution
Surface type	0.38567360	$6.6e^{-7}$
Complex density	0.42171297	$4.7e^{-7}$
Vegetation coverage	0.45242283	$7.4e^{-7}$

Chart description of Table.7 and Table.8: Positive and negative ideal solutions (non-distance), these two values represent the maximum or minimum value of the evaluation index (the optimal solution or the worst solution), these two values are used to calculate D + or D-value, the size of these two values does not have much significance.

Based on the above analysis, we know that the comprehensive score index of light pollution risk intensity and light pollution receptor vulnerability in Shanghai, Henan, Chongqing and Qinghai are within the reasonable range of model constraints, and the fitting degree of the data is good. Thus, verifying that the developed metric standard model is widely applicable.

2.4. Regional risk level assessment results

According to the CIE environmental brightness partition system (Table.9)[6], CIE divides the brightness of the earth's light environment into four levels, namely the protected area, countryside, suburb and city, which are highly consistent with the four positions required in the problem. In addition, the four classes each have their subdivisions, and sum of the subpartition categories is 9.

Table 9. Ambient brightness partitioning under the CIE partition system.

Area	Environment characteristics	Subarea	Example
E1	Natural, Dark areas	E1a	Natural reserve
		E1b	Nation park
		E1c	An area with outstanding natural landscapes
E2	Country, Low brightness areas	E2	Periphery of cities and rural settlements
E3	Suburbs, Medium brightness areas	E3a	Residential areas on the outskirts of the city
		E3b	Urban settlements
E4	City, High brightness areas	E4a	Urban commercial areas, industrial areas, mixed residential areas, etc. with appropriate activity functions at night
		E4b	A city business district with a highly active function at night

According to [8], the brightness of the night sky in a certain place can be used to evaluate the light pollution. The night sky brightness rating table shows that the sky brightness level can also be divided into nine levels. Combined with the metrics of the first question, we can get the scoring interval range of the nine grades, and then correspond to the scores of the four types of regions. The correspondence score was evaluated by consulting the corresponding materials in combination with the topsis model based on the entropy weight method.

According to the above information, we know that a protected land location has no light pollution, a rural community is very small, the light pollution of a suburban community is also small but slightly larger than the rural light pollution, and the light pollution of an urban community is very large, increasing sharply compared with the suburbs. Therefore, according to our metric, we consulted a large number of relevant data on four types of locations and concluded that the locations of protected land scores were roughly between 0.002 and 0.05, rural scores between 0.1 and 0.34, suburban scores between 0.36 and 0.52, and urban scores between 0.58 and 1. This data size precisely confirms the relative magnitude of the light pollution at these four types of locations. It shows that the results fit well with the model.

3. Conclusions

This article establishes widely applicable indicators to determine the risk level of artificial light pollution in various regions, proposes an artificial light pollution risk level assessment model based on risk field theory and entropy weight TOPSIS method, and verifies the artificial light pollution risk level scoring table for different regions through regional scoring.

The measurement model developed in this article provides a reasonable assessment of the risk level of light pollution in different regions. This metric combines quantitative and qualitative analysis. The main factors of measurement standards are divided into two categories, one is clearer and the other is more numerous, all of which have a certain impact on the main factors. For uncountable factor data, select direct factor data strongly correlated with that factor as representative data. For factor data that is difficult to quantitatively analyze, appropriate gradients are selected as reference data for sorting, and the data is used for qualitative scoring. The TOPSIS model based on entropy weight method is used to convert the scoring results into the weights of different independent factors, which reflects the degree of influence on the dependent variable and can also obtain the comprehensive score index of different factors. Using analogy method and referring to the formula for calculating environmental risk accidents, derive the formula for calculating the comprehensive score of light pollution. The modeling process of the model is rigorous and scientific, which can more accurately assess the risk level of light pollution in a certain area and provide effective intervention strategies. It has certain reference value for monitoring and preventing light pollution and solving light pollution problems.

In the future, we hope to have more quantitative light pollution data to revise the artificial light pollution assessment model in this area, or to conduct a larger scale artificial light pollution evaluation.

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