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Models for Measuring Light Pollution Risk

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Abstract: *With the development of social economy, light pollution becomes more serious. In order to deal with double carbon policy and promote sustainable development of green economy, the reduction of light pollution has become an important task in today's society. This paper established a measurement model for evaluating the degree of light pollution (Model I) by integrating a large amount of data and principal component analysis, and applied it to four different types of areas. Combined with clustering algorithm, three strategies to solve the problem of light pollution were proposed (Model II), and the effect of each strategy on the prevention and control of light pollution was discussed. Finally, this paper applies these three measures to two different areas of Beijing and New York to get the most effective intervention strategies.*

Keywords: *Light pollution, PCA, Intervention strategies, Clustering*

1. Introduction

1.1 Background

Artificial light sources have increased the brightness of the night sky so much over the past decade that the number of stars visible to the naked eye has dropped dramatically, according to a report in the US journal Science. If this continues in less than 20 years, the number of stars visible to the naked eye will be less than half what it is today. Some studies also point out that light pollution will not only affect the natural life of plants and animals, and destroy the balance of the ecosystem, but also disrupt the balance of human body clock and endocrine, resulting in physical and mental problems, so the management and control of light pollution is very important.

1.2 Notations

The key mathematical notations used in this paper are listed in Table 1.

Table 1: Notations used in this paper

Symbol	Description	Unit
IL	Illumination	lx
IL_O	The optimized illumination[2]	lx
ZB	Zenith brightness	cd/m^2
EI	Effective illumination	$\%$
EI_O	The optimized effective illumination	$\%$
UR	Urbanization rate	$\%$
EC	Per capita electricity consumption	$kW{\cdot}h$
EC_O	The optimized per capita electricity consumption[3]	$kW{\cdot}h$
GDP	Per capita GDP	
IT	Illumination time	h/day
IT_O	The optimized illumination time	h/day

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FRL	Fitted light pollution risk level	/
FRL_O	The optimized light pollution risk level	/
ARL	Actual light pollution risk level	/
PL	Protected land location	/
RC	Rural community	/
SC	Suburban community	/
UC	Urban community	/

2. Model I: Light Pollution Risk Level Measurement Model

Light pollution is determined by a variety of factors, such as illumination, illumination time, per capita electricity consumption, urbanization rate, etc., so the method of multivariate analysis should be adopted to solve it. Principal component analysis can eliminate the correlation between evaluation indicators, reduce the mathematical spatial dimension studied, and facilitate the subsequent evaluation of schemes and models. Therefore, this paper establishes a light pollution measurement model based on principal component analysis.

2.1 Light Pollution Risk Level Standard

This paper divides the risk of light pollution into four levels: no pollution, light pollution, moderate pollution and heavy pollution[1]. The specific scores are shown in Table 2.

Table 2: Level standard

Levels	Score Interval
No Pollution	[0 , 20)
Light Pollution	[20 , 60)
Moderate Pollution	[60 , 90)
Heavy Pollution	[90 , 100]

According to the above scoring criteria, several typical samples corresponding to the four regions around the world are selected, namely, environmentally protected areas correspond to no pollution, rural areas correspond to light pollution, suburban areas correspond to moderate pollution, and urban areas correspond to heavy pollution.

2.2 Principal Component Analysis Level Modeling

In this paper, the average parameter values of 8 samples are calculated through statistical analysis based on relevant data, as shown in Table 3[1].

Table 3: Parameters for 8 different regions

	IL	*ZB*	*EI*	*IT*	*EC*	*GDP*	*UR*	*ARL*
UC_1	500	150	30	14	8500	65000	100	95
SC_1	200	50	70	10	6000	35000	90	85
RC_1	50	10	90	8	3500	20000	50	50
PL_1	1	1	100	2	80	800	7	5
UC_2	200	50	10	12	5000	20000	85	80
SC_2	50	20	40	7	3000	10000	60	45
RC_2	1	1	50	4	1000	2500	30	20
PL_2	0.01	0.01	60	1	20	40	1	2

The second to seventh columns of data in the table were independent variables, and ARL was the dependent variable. Principal component analysis was conducted on these eight groups of data, and the following results were obtained after data standardization and principal component extraction, IL=83.47%,ZB=94.27%,EI=99.37%,IT=99.75%,EC=99.94%,GDP=98.99%,UR=98.68%,

[1]Data sources: NOAA https://www.noaa.gov/, CNKI https://kns.cnki.net/,
NBS http://www.stats.gov.cn/,Light Pollution Map https://www.lightpollutionmap.info/

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ARL=99.78%.

Table 4: Cumulative contribution rate

	IL	***ZB***	***EI***	***IT***	***EC***	***GDP***	***UR***	***ARL***
Rate	83.4677	94.2728	99.3696	99.7544	99.9381	98.9882	98.6785	99.7783

It can be seen from the Table 4 that the cumulative contribution rate of EI has reached 99.37%, so we select the third principal component and express the extracted three principal components with the following formula according to the calculated coefficient[6].

$$Z_1=0.3987IL+0.3918ZB-0.2434EL+0.3968IT+0.4070EC+0.3930GDP+0.3883UR$$

$$Z_2=0.1210IL+0.1161ZB+0.9176EI-0.0530IT+0.1223EC+0.3272GDP-0.0713UR$$

$$Z_3=-0.3970IL-0.5005ZB+0.2097EI+0.4168IT+0.2245EC-0.1610GDP+0.5458UR$$

So for the principal component Z1, all variables except EI play a role. For Z2 EI plays a major role. For principal component Z3, both IT and UR play major roles. Finally the fitting risk level can be calculated according to the calculated principal component and cumulative contribution rate $FRL=83.4677Z_1+10.8105Z_2+5.1187Z_3$

2.3 Application of Model I and Analysis of results

2.3.1 Apply

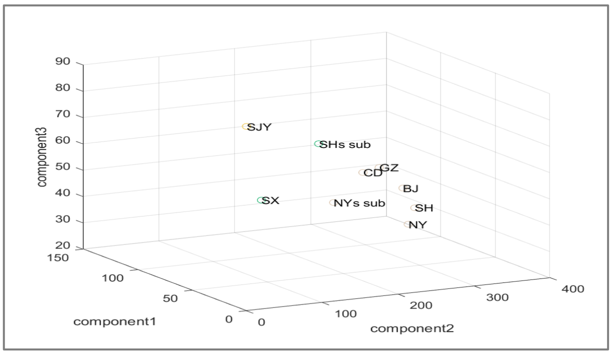

Figure 1: Cluster analysis results

In this paper, nine different regions were respectively applied to the light pollution risk model, in which NY represents New York, NYs sub represents suburban New York, BJ represents Beijing, SH represents Shanghai, SHs sub represents suburban Shanghai, GZ represents Guangzhou, CD represents Chengdu, SJY represents Sanjiangyuan, SX represents Yamagata County. Through cluster analysis, the three principal component scores of each sample were used to divide the nine sites into three categories, as shown in Figure 1.

As can be seen from the figure above, the third principal component of SHs sub and SX is higher than that of other regions except SJY, and the first and second principal components also account for a certain proportion, so they are classified into the first category. NY, NYs sub, BJ, SH, GZ and CD have high first and second principal components, while the third principal component is relatively low, so they are divided into the second category. The third principal component of SJY is relatively high, and the first and second principal components almost have no effect on SJY, so SJY is classified into the third category.

Next, the actual parameters of 9 regions are substituted into the expression of FRL obtained by us, and the results are shown in Table 5.

Compared with the FRL calculated from the above table and the existing ARL, it can be seen that the model established by us well reflects the actual light pollution risk level, and the conclusion reached at last is consistent with the conclusion reached by the statistical analysis of the data: Protected land location and rural community are rated as light polluted, and suburban and urban community are rated as moderately polluted. Their scores increase in turn, and there are few areas with no pollution or heavy pollution. However, due to the special geographical conditions of the protected land, we do not rule out the problem of incomplete collection of relevant parameters or partial distortion of parameters.

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Table 5: Parameters for 9 different regions

	IL	ZB	EI	IT	EC	GDP	UR	FRL
NY	400	130	20	13	8300	63000	100	93
NYs sub	240	87	40	10	8000	51000	96	83
BJ	350	100	40	12	5000	16000	85	70
SH	380	110	30	13	5400	22000	84	74
SHs sub	170	52	70	8	2900	11000	57	45
GZ	310	94	50	10	4500	18000	84	63
CD	280	88	50	10	3000	10000	76	55
SX	30	7	60	10	3500	21000	50	52
SJY	0.5	0.2	90	2	60	540	3	3

2.3.2 Analysis of results

The above results are mainly due to different development strategies in different regions. For New York, Shanghai, Beijing and other national central cities, economic development is the first priority, a large number of resources and talents gathered here, so the number of enterprises and families using light is huge; For suburban Shanghai and Japan's Yamagata prefecture, economic development is less of a priority, and businesses and homes will use less light; Finally, for nature reserves like Sanjiangyuan, which are developed to ensure that the environment is not damaged, the economy is relatively backward, so the light pollution index of such areas is very low.

3. Model II: Intervention Strategy Optimization Model

3.1 Intervention Strategy

3.1.1 Improved Light Source

By using shielding and directional lighting to direct the light from the existing light source to the desired place, or using voice controlled lights, light sensitive lights to make it glow for the desired period of time, etc. This strategy can reduce IL and EC to a certain extent, but these two factors do not play an important role in the principal component, so it may not achieve a good effect in the end[4]. In order to verify this point, this paper established the relationship between t and IL and the linear model of EC.

$$IL_O = IL\left(1 - \frac{\pi}{2}\arctan(t)\right)$$

$$EC_O = 0.92EC$$

According to the above expression, the score pair optimized by strategy 1 can be obtained. The analysis shows that with the continuous optimization of light source, the regional light pollution index will continue to decline, but with the passage of time, the influence of improved light source on light pollution gradually reaches the threshold.

3.1.2 Legislative Limit

Laws need to be enacted at the national level to limit lighting hours. This paper puts forward the following concrete measures[5]:

A. Urban communities should not be lit for more than 12 hours a day and effective illumination should not be less than 30%;

B. Suburban communities lighting should not exceed eight hours a day, and effective illumination should not be less than 50%;

C. Rural communities and protected lands are not restricted.

This strategy can improve and reduce, but has no obvious effect .For this, we modeled:

For urban communities,

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$$EI_O=\begin{cases} 30\ ,\ EI<30 \\ EI\ ,\ EI\geq 30 \end{cases} \quad IT_O=\begin{cases} 12\ ,\ IT>12 \\ IT\ ,\ IT\leq 12 \end{cases}$$

For suburban communities,

$$EI_O=\begin{cases} 50\ ,\ EI<50 \\ EI\ ,\ EI\geq 50 \end{cases} \quad IT_O=\begin{cases} 8\ ,\ IT>8 \\ IT\ ,\ IT\leq 8 \end{cases}$$

One of the most effective strategies is government policies to reduce light pollution, which will guide enterprises to improve production methods and compete reasonably. In addition, it can affect education to let residents know the seriousness of light pollution.

3.1.3 Intensify Publicity

At present, the public's understanding of light pollution is relatively shallow, so it is necessary to increase the publicity of the harm of light pollution and call on people to use light energy rationally[7]. This strategy will affect both EI and IT factors, but IT will take a long time for the strategy to achieve effect. Therefore, this paper establishes models between EI and t, and between IT and t.

Publicity and education can influence people's way of life imperceptibly, thus stimulating the broad consciousness of the masses. In addition, publicity and education should be implemented to make people really aware of the seriousness of light pollution.

$$EI_O=100-\frac{EI(100-EI)}{(100-EI)\ (e^t-1)\ +EI}$$

$$IT_O=7+e^{(-t+\ln(IT-7))}$$

3.2 Model Application and Analysis

After comparative analysis, this paper finally applied the two typical regions of New York and Beijing into the optimization model of intervention strategy. At the same time, in order to reach a more accurate conclusion, this paper defined an optimization rate[8] $\eta=1-\frac{FRL'}{FRL}$.

3.2.1 Location I: New York

After applying New York to the intervention model, the light pollution risk score of strategy 1 was 91.69, strategy 2 was 86.78, and strategy 3 was 83.05[9]. Based on the above data, the optimal ratio of light pollution risk score for New York can be calculated:

$$\eta_1=1.8624\%,\eta_2=7.1176\%,\eta_3=11.1099\%$$

Due to $\eta_1<\eta_2<\eta_3$, we can know that intervention strategy III is the most effective for reducing light pollution risk levels in New York.

3.2.2 Location II: Beijing

Then, after applying Beijing to the model, the light pollution risk score of strategy 1 was 69.48, strategy 2 was 57.33, and strategy 3 was 62.36. Based on the above data, the optimal ratio of Beijing's light pollution risk score is calculated:

$$\eta_1=1.4188\%,\eta_2=18.6578\%,\eta_3=11.5210\%$$

Due to $\eta_1<\eta_3<\eta_2$, we can know that intervention strategy II is the most effective for reducing light pollution risk levels in Beijing.

3.3 Result Description

As can be seen from the above, New York initially belongs to the heavily polluted area with a score of 93.43. However, through the intervention strategy proposed by us, its light pollution risk score can be reduced to 83.05 points, thus restoring to the moderately polluted area. For Beijing, it was initially a moderately polluted area with a score of 70.48, but after intervention strategies, its light pollution risk score could be reduced to 57.33, making it revert to a mildly polluted area. Because for New York, the economy is highly developed and the income level of its residents is very high[10]. So reaching out to residents through advocacy and education can work well. For Beijing, the political center of China, government policy plays a key role in social development. By formulating relevant policies, the government can influence the behavior of enterprises and individuals to effectively deal with the problem of light pollution. Therefore, the optimal intervention strategies for different sites may be different, but strategies 2 and 3 optimize the light pollution risk score far better than strategy 1, and it can be inferred that areas with lower initial scores within a certain range are more likely to reduce the degree of light pollution.

4. Conclusion

4.1 Strengths

Based on the analysis of the existing literature on the influence factors of light pollution, the model adopts the method of principal component analysis to eliminate the influence of correlation among evaluation indicators, and integrates the principal component analysis and clustering algorithm to get better results. Most of the data used in the model is basic data, which is easy to collect and easy to use. The model is highly distinguishable and can well separate the light pollution risk situation in different regions.

4.2 Weakness

However, due to the lack of statistical data and errors in some fields, the model established in this paper may be different from the ideal model. In addition, there are some subjective factors in light pollution that are difficult to quantify, such as the impact on sleep quality, so the model is not inaccurate in measuring the impact of light pollution on these factors.

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