Evaluation and intervention of light pollution risk level

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Abstract: With the prosperity of cities, problems such as global light pollution are becoming more prominent, hence the need for scientific monitoring and assessment. This paper mainly studies the comprehensive evaluation index and intervention strategy of light pollution, and establishes the evaluation and prediction model based on TOPSIS and wavelet neural analysis. This paper first defines the concept of light pollution risk level. Secondly, based on the ERA5 data, the TOPSIS model optimized by AHP and entropy weight method is used for the preliminary assessment of the risk level. Then, based on the night remote sensing data of Luojia No. 1 satellite, the VIIR map was deeply analyzed by using graph theory algorithm, and the evaluation index was further optimized. Finally, an evaluation system based on luminosity, radiation, spectrum, perspective, space time and region is established. At the same time, for the prevention and control of light pollution, based on the established index system, this paper adopts the stepwise regression analysis algorithm to obtain the factors significantly related to the risk level of light pollution, and input them into the wavelet neural network. Since different intervention measures correspond to different parameters, this paper predicts the change of light pollution risk level under different measures by modifying the parameters. Further development of optimal intervention models.The results showed that the risk levels of light pollution were urban community, suburban area, rural area and protected area. In particular, over the past few decades, regions such as Europe have suffered higher levels of light pollution, mainly between 30° and 60° north latitude.

1. Introduction

With the continuous development of lighting technology, light pollution has become a problem that cannot be ignored. Light pollution originates from the use of artificial light sources, which is closely related to urbanization and the expansion of human activities[1]. Internationally, light pollution is generally divided into three categories, namely white light pollution, artificial daylight pollution and color light pollution. In addition, the monitoring and evaluation index system of the light environment includes illuminance, brightness, brightness, irradiation, illuminance uniformity, glare index, etc.

Light pollution is increasingly affecting people's production and life, seriously endangering people's health and destroying the human ecological environment. Therefore, we must attach great importance to improving the awareness of preventing and reducing light pollution, and take various effective prevention and control measures to take precautions and prevent problems before they occur.

2. Notations

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

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Table 1 Notations used in this paper

Symbol	Description	Unit
A	Photometric elements	/
B	Light pollution elements	/
C	Spectral feature	/
D	Perspective features	/
E	Space-time features	/
F	Regional features	/

3. Model I: Light Pollution Risk Level Assessment Model

Definition of light pollution risk level: It is classified according to the actual impact degree of excessive optical radiation (including visible light, infrared light and ultraviolet light). Generally speaking, the risk level is proportional to the impact degree.

3.1 Model Construction

Use graph theory and grid algorithm to penetrate VIIRS images: this paper analyzed images from the Visible Infrared Imaging Radiometer Suite (VIIRS) using graph theory. In this approach, pixels are represented as nodes (vertices) and changes in brightness are represented as edges. The study of optical data through a complex network approach represents an innovative opportunity in the study of urban processes[2].

Given a set, the latitude and longitude of the geopoints are related to x_i and y_i.This paper considers a vector sequence P_1, P_2…The index of P_t in time (e.g. t years), such as $P_i \in P_j$ is equal to the radiance value associated with a particular geographical point c_i, for each P,the dimension of j is equal to n, and the total number of points in the set c is a vector of brightness difference for two consecutive years, from which this paper get a new vector sequence; D_j is equal to the change in brightness at point C_i for two consecutive years. The table 2 shows examples of two vectors P_1 and P_2, whose terms are radioactivity and the composite value of a vector; This paper notes that from P_1 to P_2, only the radiance at point D decreases, while the radiance at the other points increases, but with different intensities, which is taken into account in the calculations below.

Table 2 Ventors

Points	P_1	P_2	D_1
A	12.08	53.64	41.56
B	3.05	32.44	29.38
C	21.18	54.33	33.14
D	29.60	28.23	−1.37
E	5.64	38.97	33.32
F	13.33	59.02	45.68
G	24.03	34.79	10.76
H	5.39	30.75	25.35
I	17.52	38.45	20.92
J	17.03	56.45	39.41

This paper calculates the joint variation between each pair of point ci sums, and for each di cj we calculate:

$$S(c_i, c_j)_k = \frac{d_i d_j - \mu_k^2}{n\sigma_k} \tag{1}$$

Where μ_k and σ_k represent the mean and variance of the vector Dk, and n represents the total number of points. $S(c_i, c_j)_k$ represents a change in the spatial correlation (SCLP) of light pollution between two geographic points on Earth.

Given a set of geographic points C and their $S(c_i,c_j)_k$, the spatiotemporal network of light pollution is a weighted map

$$E=\left\{(c_i,c_j)\mid S(c_i,c_j)_k>\varepsilon\right\},\varepsilon>0 \tag{2}$$

This definition means that if we connect two points c_i and c_j,then their light pollution is spatially related more than the column winding, which is a threshold used to ensure the presence of edges. We note that the link between the two points represents a strong increase (or decrease) of light pollution in both places at the same time[3].

3.2 The solution to the model I

A key part of light pollution research is the quantification of spatial heterogeneity in relation to lighting systems, and since satellite imagery is a visual representation of the information captured by sensors, it can be used to obtain information data for artificial nighttime radiation.

To complement the characteristics of the spatiotemporal network of light pollution, we evaluate the significance of measures such as mean path length, transmittability, and maximum cluster size. To do this, we used the Erdos-Renyi model to build 1,000 random graphs per year. We compare the mean distribution of real and random networks.

The graph 1 below summarizes the total illumination of all smoothed time series associated with each illuminance.

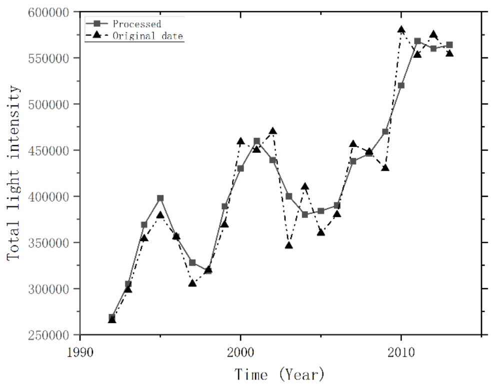

Fig.1 Time series analysis

Some measurements have similar values in a random network. This could be that the size of the largest clump or the transitivity values have changed and they cannot significantly represent the network. To that end, we assess their importance. The results of comparing the built network with a random graph are shown. As we have noticed, there are many similar points in light pollution changes at the same time, and obviously this does not happen on a random chart. The same is true for transitivity, where the transmittability value of the light pollution network is higher than that of the random graph, and the average path average of the random graph is higher than that of the STNLP. Therefore, these measures are statistically significant, and the network structure based on them is not insignificant[4].

3.3 Results

This paper first takes photometric theory, radiometric theory, spectral theory, etc. as the guide, establishes the database required by the relevant theory, and then solves the data through the model algorithm. At the same time, we establish a correspondence network between the graph theory algorithm and the VIRS system, and then build a spatiotemporal network of light pollution. The results show that maximum clumps and transmittability are a good explanatory method based on structural models to identify aspects of light pollution that may be relevant to urban processes. Therefore, we hope that this document will inspire future research to link urban processes to the increase in artificial lighting at night.

Finally, a light pollution risk rating system is obtained through comprehensive analysis, as shown in Table 3.

Table 3 Schematic diagram of the evaluation system

Objective	Level 1 indicator layer	Level 2 indicator layer
Global light pollution risk level assessment	A	Light color
		Light type
		Night illuminance value
		Temperature
	Radiance features	Night illumination
		Night light
		Average light intensity
	spectrum element	Light intensity
		wavelength
	visual angle element	Light angle
		Light range
		Pole height
		Number of living floors
	spacetime element	Lighting period
		Lighting duration
		Neon height
		Billboard height
	region element	Level of development
		geographical location
		Biodiversity
		Number of people

4. Model II: Light pollution intervention Model

According to the light pollution assessment system constructed by model I., we summarize it into three intervention strategies for reducing light pollution: Reduce light time,Reduce light intensity,Reduce the effective light range.

To discuss the impact of these intervention strategies on light pollution, this paper translate the problem into a stepwise regression + wavelet neural network prediction model with correction (SRA-WNN) to establish and solve.

4.1 The Establishment of Model II

Stepwise regression-wavelet neural network (SRA-WNN) model:Stepwise regression analysis (SRA) is a method for establishing the optimal regression equation, which contains only the factors that have a significant impact on light pollution, while the remaining factors that do not have a significant impact are eliminated。

SRA is based on the initial regression equation and statistical model. According to the above analysis and modeling of the influence factors affecting the light pollution level, first let the light pollution level to each influence factor one by one, and then according to the partial regression square sum (namely contribution), the influence factors are introduced into the regression equation from large to small. Then, the index is tested for significance F. Then this index is introduced; Among the factors introduced at present, the factor with the smallest sum of partial regression squares is found to conduct F significance test. If it is not significant, the index is removed from the regression equation. The cycle of introduction and elimination should be repeated until no significant factors are introduced and no insignificant factors are eliminated, and the cycle is stopped. Then we get the optimal regression equation. The factor contained in the optimal regression equation is the factor that has significant influence on the light pollution level, and can be used as the input factor of the wavelet neural network[5].

Wavelet analysis is proposed in response to the shortcomings of traditional Fourier analysis, which is considered a breakthrough in Fourier analysis.

The wavelet transform means that after selecting a basic wavelet function (also called parent wavelet function) ψ(t) to translate τ, the inner product is performed with the signal x(t) to be analyzed under different scale a. The equivalent time-domain expression is

$$f_x = (a,\tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(\omega)\psi(a\omega)e^{jw} dt \tag{3}$$

Wavelet analysis can study the frequency domain characteristics of signals in local time through the transformation of wavelet basis functions, so it has the ability to characterize the local characteristics of signals in both frequency and time domains. The topology of wavelet neural network is shown in the figure.2.

SRA-WNN model prediction process:The factors with significant correlation with light pollution obtained after stepwise regression analysis are used as the input factors of wavelet neural network, and the training sample data corresponding to the correlation significance factors is used for network training, and the prediction samples are input to obtain the predicted results. Its operation flow chart is shown in Figure.3.

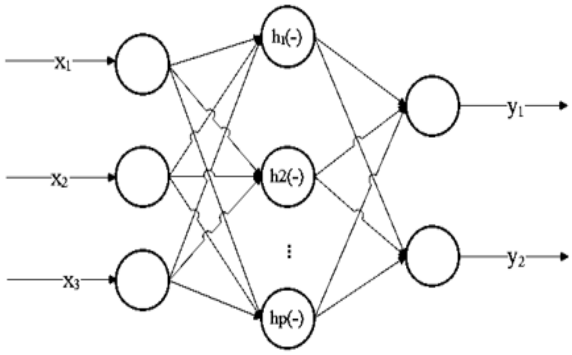

Fig.2 Topology diagram of a wavelet neural network

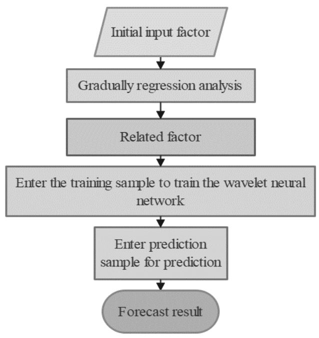

Fig.3 SRA-WNN model prediction process

4.2 Results

According to the analysis of the modulus gray correlation method, and the determination of the correlation significance factor. In order to predict the trend of light pollution under the intervention strategy, we took time, light intensity and light range as the influencing factors,They are respectively labeled as X_1,X_2,X_3.

The stepwise regression analysis method was used to obtain the optimal regression equation for the historical data level of light pollution。

$$W_1 = -0.95X_1 - 0.42X_2 + 0.03X_3 \tag{4}$$

$$W_2 = 0.08X_1 + 0.14X_2 + 0.09X_3 \tag{5}$$

The data corresponding to the initial factor was input into the WNN model and the data corresponding to the correlation significance factor into the SRA-WNN model for training, and then the prediction samples were input for prediction. Stepwise regression is also used for predictive analytics. After multiple data training and prediction, the best prediction results of each model are obtained. The result is shown in Figure 4.

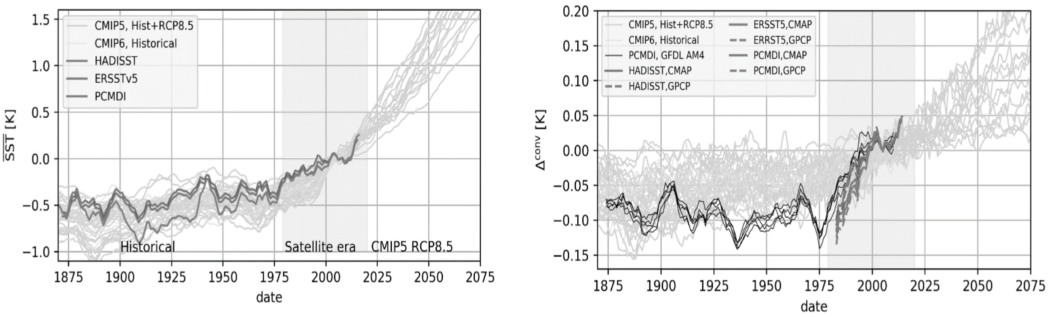

Figure.4 Predictive outcome plot of intervention strategy impact

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