Modelling and Researching Light Pollution Risk

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Abstract. With the acceleration of urbanization, the negative impact of light pollution on human production and life and biological growth is increasing. This paper develops four models to quantify the intensity of light pollution, formulate effective strategies to mitigate the negative impact, and improve human awareness. The STNLP model is developed for light pollution by firstly using AHP to determine the indicator weights and concluding that geography is a widely applicable indicator to describe the risk level of light pollution, then building the STNLP model between geography and light radiation brightness, and finally using the Erdos-Renyi model to test the effect of the STNLP model. This paper proposes three intervention strategies, builds a stepwise regression wavelet neural network model, and concludes that policy adjustments can effectively mitigate light pollution by comparing the three-dimensional scatter plots before and after the corrections.

Keywords: Light pollution, STNLP, Neural Network, Erdos-Renyi, Policy.

1. Introduction

As economies grow, so does the problem of light pollution. Using VIIRS observations, scientists have found that global light pollution is increasing by about 2% per year. Light pollution is a phenomenon in which excessive light radiation adversely affects the productive life of plants and humans. More and more countries are aware of the impact of light pollution and have introduced a series of policies one after another.[1].

Research has shown that most animals, with the exception of a very small number of nocturnal animals, are quiet and immobile at night and do not like bright light. However, the skylight, spill light, trespass light, and reflected light produced by outdoor lighting at night often illuminates the environment in which animals live and rest, disrupting the rhythm of their circadian biological clock and preventing them from sleeping and resting. For wildlife and fish, in addition to the effects of visible light, luminaires emitting radiant energy also affect the life and growth of animals; due to the photophobic nature of insects, outdoor lighting at night can attract a large number of pests, especially during the egg-laying period when large numbers of insects are concentrated in the illuminated area and the eggs quickly develop into larvae and adults, causing infestations. For beneficial insects and birds, it is said that excessively bright outdoor lighting at night can cause a number of beneficial insects and birds to fly directly into the light and die[2, 3] . The effect of outdoor lighting on plants at night: disrupting the rhythm of the plant biological clock Plants, like other organisms, are long in the day and in the night, with obvious growth cycles, the specific performance of plants according to the rhythm of the biological clock in the body, if outdoor lighting at night, plants will disrupt the rhythm of the biological clock in the plant, which will hinder its normal growth, especially at night for a long time, high radiation energy effect on plants. This will cause the leaves or stems of the plant to change color and even die[4].This paper builds on the research of scientists such as Smith-Siabiha, Ramli-No-Azam, and others.[5] Since the traditional prediction methods based on linear regression, such as the time series method, analytical method, and pattern recognition method respectively, have shortcomings, this paper further investigates the influencing factors of light pollution and finds out the strategies to effectively mitigate the effects of light pollution by building a spatio-temporal network model of light pollution (STNLP) and a stepwise regression wavelet neural network model.

2. Materials and methods

2.1. Data acquisition and pre-processing

Light pollution is becoming more and more serious and more countries are aware of all the pernicious effects of light pollution, therefore, the light pollution data are from a wide range of sources, and the data in this paper were obtained from organisations such as the Light Pollution Map, the National Atmospheric Administration (NOAA)https://www.noaa.gov/ and the Light Pollution Science Institute .

After removing outliers, the data were normalised as a way to remove the effects of magnitude,. The normalisation formulae applied are shown below.

$$x_{i'} = x_i / \sum_{i=1}^{n} x_i \tag{1}$$

Where is the $\sum_{i=1}^{n} x_i$ sum of the column in which x_i is located and x_i is the value of x_i after normalisation.

2.2. Method Introduction

Spatio-temporal network data is a geological data model that effectively organises and manages temporal geological data, spatial, thematic, and temporal semantic integrity, emphasising not only the spatial and thematic characteristics of geological objects but also the change of these characteristics over time, both temporal characteristics[7-9].

The basic idea of stepwise regression analysis is to introduce independent variables into the regression equation in descending order of their significance on the dependent variable and to eliminate the first independent variable from the original equation if it loses significance due to the newly introduced variable, to ensure that only significant factors are included in the regression equation.

The BP network structure is the most widely used class of neural networks.,with Rumelhart and McClelland lleading the way in the mid-1980s with the BP - Back Propagation learning algorithm for multilayer feedforward networks[10].

2.3. Model evaluation metrics

The advantages of the model in this paper are as follows:

Through the stepwise regression analysis (SRA) method, the optimal regression equation includes only those factors that have a significant effect on the seepage pressure value, while the remaining factors that do not have a significant effect are eliminated altogether. Compared to multiple regression, where all factors are included in the regression model, stepwise regression highlights the most important influencing factors while improving the stability of the regression equation.

Combined with wavelet analysis, the model has the ability to characterise the local features of the signal in both the frequency and time domains.

3. Model building

3.1. STNLP Model and Erdos-Renyi Model Testing

3.1.1 STNLP Model

Based on a network and graph theory, we propose definitions and notations necessary for the design and study of light pollution spatio-temporal networks, and then study the concept of light pollution spatio-temporal network (STNLP) as a model for characterising the variation in radiant brightness of satellite images, and relate their spatial relationships for study. [6] This means that given

a graph G, where n(G) and m(G) denote the number of vertices and edges respectively, or simply n and m, in a given graph we say that the graph is weighted if each edge e$^{\epsilon}$ e is associated with a real number.

We represent the spatiotemporal network of light pollution (STNLP) as a weighted graph, as shown below. Given a set C of geographical points ci with latitude and longitude xi and yi , we consider a sequence of vectors $P_1\ P_2\ P_3 \cdots P_t$ indexed in time (e.g. $p_i \epsilon P_j$) equal to the radiance value associated with a given geographical point ci , with the dimension of each Pj equal to the vector of the total number of points in the set c with the difference in brightness over two consecutive years, from which we obtain a new sequence of vectors $d_i \epsilon D_j$ equal to the change in brightness over two consecutive years at point ci .Two examples of vectors P1 and P2, whose terms are radiance and a vector of synthetic values as shown in Table 1 .Note that from P1 to P2 only the radiance at point D decreases, while the radiance at all other points increases, but with different intensities, which will be taken into account in the following calculations.

Table 1: Radiation values at each point

	Vectors		**New Vectors**
Points	**P_1**	**P_2**	**D_1**
A	11.08	52.64	40.56
B	2.05	31.44	28.38
C	20.18	53.33	32.14
D	28.60	27.23	−2.37
E	4.64	37.97	32.32
F	12.33	58.02	44.68
G	23.03	33.79	9.76
H	4.39	29.75	24.35
I	16.52	37.45	19.92
J	17.03	56.45	38.41

We compute the joint variation between and for each pair of points and for each.

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

Where μ_k and σ_K denote the mean and variance of the vector Dk and n denote the total number of points. $S(c_i, c_j)_k$ is the spatial correlation of light pollution between two geographical points on the Earth (SCLP).

Given a set of geographical points C and their $S(c_i, c_j)_k$, the spatio-temporal network of light pollution is a weighted graph. In this way $E\{(c_i, c_j)_k > \epsilon\}$ and $\epsilon > 0$, this definition means that if we connect two points ci and cj, then the spatial correlation of their light pollution is greater than that of the column winding, using this to ensure a threshold for the presence of edges. We note that the connection between the two points represents a strong simultaneous increase (or decrease) in light pollution at both locations.

Figure 1 shows STNLP using the data in Table 1, clearly nodes D and Gare disconnected, the former because of the decrease in brightness and the latter because its change is not significant relative to the mean of the thresholds used in SCLP.

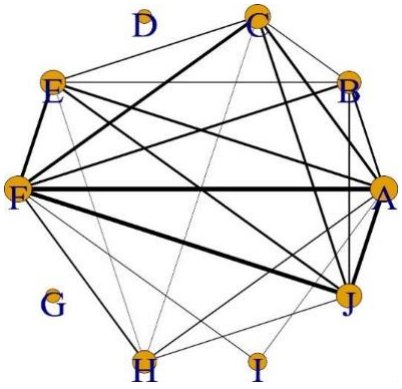


Figure 1: Weighted graph

3.2. Erdos-Renyi model test

To complement the characteristics of the spatio-temporal network of light pollution, this paper assesses the significance of a number of measures, such as mean path length, transmissibility, and maximum clump size.[] For this purpose, the Erdos-Renyi model was used and 1000 random plots were constructed every 5 years from 1995 onwards, comparing the mean distributions of the real and random networks, and the following figure summarises the total illuminance for all smoothed time series associated with each illuminance. An example of a single smoothed data process is shown in Figure 2:

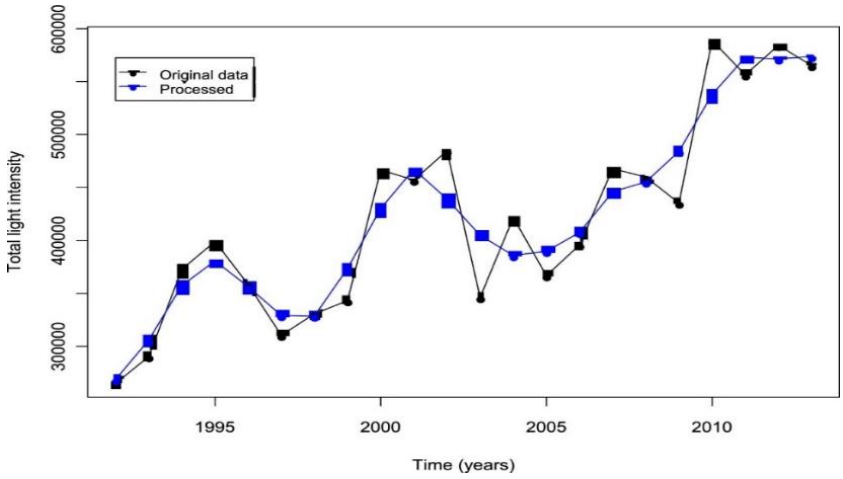


Figure 2: Comparison of original and improved light intensity

Some measurements have similar values in a random network. This could be a change in the size of the largest clusters or in the value of transmissibility. As noted in this paper, the changes in light pollution have many similar points at the same time, which obviously does not happen on a random graph. Box line diagram as shown in the Figure 3.This is also true for transmissibility, where the light pollution network has higher values of transmissibility than the random graph, and the random graph has higher mean path averages. These measures are therefore statistically significant, based on the fact that their network structure is not insignificant.

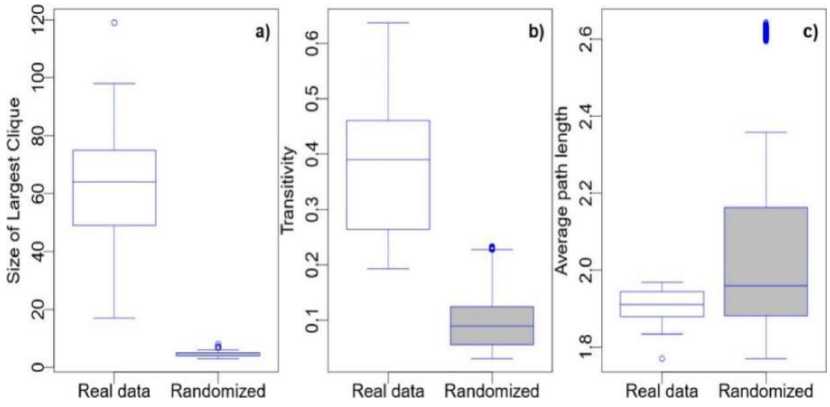


Figure 3: Random graph

In summary, the analysis shows that the latitude, longitude, and mean path of the geographical points are affected by the main geographical factors of the STNLP, and significantly so that they can be used as widely applicable indicators of the effects of light pollution.

3.3. Stepwise regression wavelet neural network model

3.3.1 Modelling and Optimisation

The factors with significant correlation with the seepage pressure values obtained by stepwise regression analysis are used as input factors for the wavelet neural network, a model is built in the plane, and the training sample data corresponding to the factors with significant correlation is used for network training, and the predicted results are obtained by inputting the predicted samples

3.3.2 Model Solution

Based on the analysis of the grey correlation method, and the determination of correlation significant factors. In order to predict future trends, time, longitude, and latitude are taken as influence factors in this paper and labelled as $X_1\ X_2\ X_3$ respectively. The optimal regression equation for the level of temperature historical data was obtained separately using stepwise regression analysis as follows:

$$W_1 = -0.95X_1 - 0.42X_2 + 0.03X_3 \tag{3}$$

$$W_2 = 0.08X_1 + 0.14X_2 + 0.09X_3 \tag{4}$$

In this paper, the data corresponding to the initial factor and the correlation significant factor are input into the model $SRA-WNN$ for training respectively, and then input into the prediction sample for prediction, while using stepwise regression for prediction analysis, and after several times of data training and prediction,.Stepwise regression results are shown in the Figure 4.the better prediction results of each model are obtained.

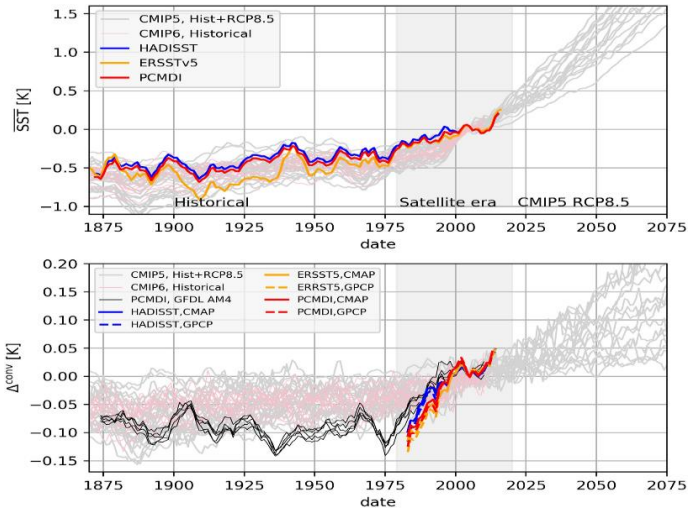


Figure 4: Model prediction results

Before the multiple regression, a three-dimensional scatter plot of location, light pollution and time is drawn to facilitate the validation of this paper in subsequent regressions.The three-dimensional scatter plot is shown in the Figure 5.

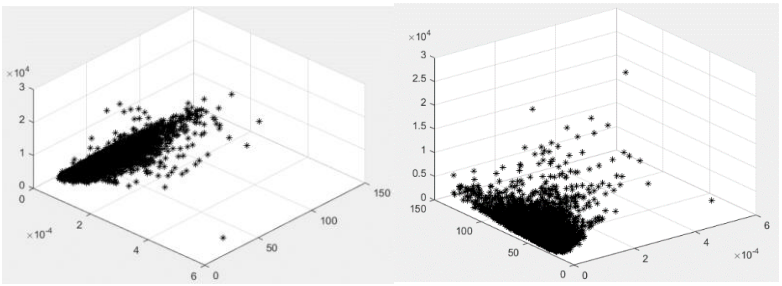


Figure 5: Three-dimensional scatter plot

This gives a regression equation $y = 0.024 - 0.024x_1 - 2.394x_2 + 0.075x_3$ of which x_1, x_2, x_3 Temperature, Economy and Power.

The variables were tested for joint significance. Original assumptions H_0:β_0、β_1、β_2、β_3 all zeros. Alternative assumptions H_1:β_0、β_1、β_2、β_3 at least one of them is not zero and the result is as shown in Table 2:

Table 2: Significances test results

Risk Degree of impact	Coef.	St.Err.	t-value	p-value	[95%	Interval]	Sig
A	-0.024	0.020	-1.17	0.241	-0.063	0.016	**
B	-2.394	0.079	-30.11	0.000	-2.550	-2.238	***
C	0.075	0.027	2.74	0.006	0.021	0.128	***
D	0.024	0.001	28.63	0.000	0.022	0.025	***
E	-3.526	0.048	-3.33	0.000	-3.594	-2.856	***
F	0.185	0.046	3.64	0.000	0.052	0.005	***

Prob > F= 0.0000<0.05, Therefore, the original hypothesis is rejected and the coefficient is considered to be non-zero. Therefore, at the 95% confidence level, the original hypothesis is rejected and the alternative hypothesis that the coefficient is non-zero is accepted. The joint significance test is passed.

$$SSR = 0.87$$
$$SSE = 0.911$$
$$SST = 0.998$$
$$R - squared = 0.0875$$
$$Adj\ R - squared = 0.0872$$

For judging the impact of policy adjustment on light pollution, this paper needs to make a correction to the multiple regression. Before the correction of multiple regression, another kind of quantitative data corresponding to it, assuming that its impact on light pollution shows a uniform distribution pattern, realize the imputation of the data through simulation and bring it back into the multiple linear regression.The following results were obtained as shown in the Figure 6:

$$F_1 = 3.55E^{-11}x_1 - 8.51E^{-11}x_2 + 6.48E^{-11}x_4 + 0.019x_5 - 2.66E^{-11}x_6 - 3.33 \quad (5)$$

$$F_2 = -4.98E^{-12}x_1 + 2.26E^{-11}x_2 - 9.39E^{-11}x_4 + 0.028x_5 + 4.10E^{-11}x_6 - 14.33 \quad (6)$$

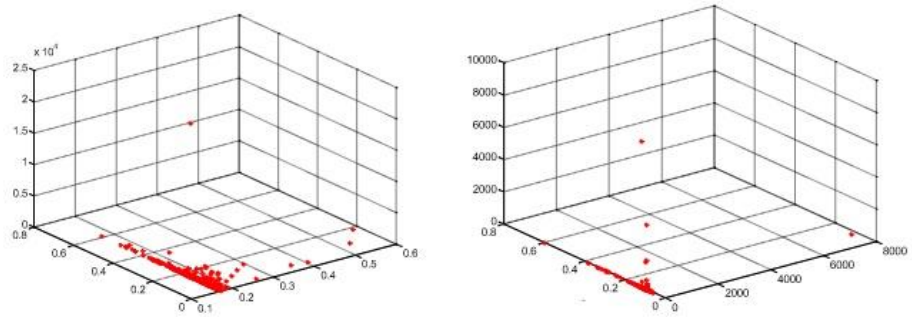


Figure 6: 3D scatter plot after intervention

As can be seen from the figure, the policy adjustment will greatly reduce the level of light pollution, light pollution space is reduced, saving energy, reducing the temperature, the effect is good, thus this paper can be seen that the strategy policy is better, the model fitting effect is better.

4. Conclusion

Measure light pollution and mitigate its effects. The problem is addressed by building a model and suggesting improvements to the model. This paper uses AHP to conclude that geography is a widely applicable indicator to describe the risk level of light pollution, and establishes the STNLP MOLDE between geography and light radiation brightness. Through the Erdos-Renyi model test, the latitude, longitude and mean path of geographical points in the main geographical factors of STNLP are affected and have a significant impact, and it is used as a widely applicable indicator to have a significant impact on the effect of light pollution. Intervention intensity and light pollution levels were modelled, and aerial monitoring led to the conclusion that the policy has a significant affects on light pollution. The results suggest that the effects of light pollution can be reduced by zoning urban areas for lighting by latitude and longitude, policies to encourage the use of solar lighting, and the expansion of three-dimensional green spaces.

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