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Research on light pollution based on policy intervention optimization model

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Abstract: *Light pollution is not only a threat to non-humans, but also a threat to humans. People gradually realize the harm of light pollution. It is urgent to control and prevent light pollution. In this paper, we propose the light pollution assessment model to evaluate the light pollution risk. We select evaluation indicators from population, economy, transportation and energy to obtain evaluation criteria. We used the entropy weight method to determine the respective weights of the above indicators, and established the TOPSIS comprehensive model to obtain comprehensive scores for 43 countries. We construct policies intervention optimization model, to quantify the policy effect, we consider the policy version time to obtain the policy factor. Then we establish a government control index model and input Population density, GDP Policy Power and Light intensity, etc. The basis of this analysis is the random forest model for regression prediction, that is, we limit the model function form to the relative bias of the variables. The year in which the national light pollution policy was introduced, the longer the version is old, the less effective. Finally, we designed a selection poster advocating limiting light pollution, with the "X" shaped light source on the back of the human body representing the symbol of prohibition, calling for attention to the prevention of light pollution.*

Keywords: *Light pollution, Evaluation index, TOPSIS, Random Forest, Intervention Policy*

1. Introduction

Light pollution problem in addition to wastewater, waste gas, waste residue and noise pollution in addition to new environmental pollution, with the rapid development of night economy and L ED products with its eye-catching characteristics are widely used in shopping malls, construction site lighting equipment and other areas of night lighting time is too long, brightness is too high, most of the world is facing increasingly severe light pollution dilemma. Leaders from the University of Exeter launched a study on light pollution, looking at light emissions from 1992 to 2017. The findings show different regional trends, but emissions are increasing almost everywhere, with only "limited evidence" that improved technologies have reduced light pollution [1].

The definition of light pollution refers to the phenomenon that excessive light exposure in the environment adversely affects the normal survival and development of humans or other organisms. In daily life, the common situation of light pollution is mostly the dizziness of pedestrians and drivers caused by the reflection of mirrored buildings, and the discomfort caused by unreasonable lighting at night. Excessive light radiation adversely affects human life and production environments, including pollution caused by visible, infrared and ultraviolet rays.

In addition to causing interference to humans, light pollution from street lights and other sources can have a significant impact on the natural environment. Artificial light sources at night pose a negative and even fatal threat to many organisms, including amphibians, birds, mammals, insects and plants. For example, exposure from artificial light sources affects amphibians that live wetlands, such as frogs and toads, whose nocturnal calls are part of mating. However, artificial light sources interfere with this nocturnal activity, which interferes with their reproduction and their numbers decrease [2].

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2. The Framework

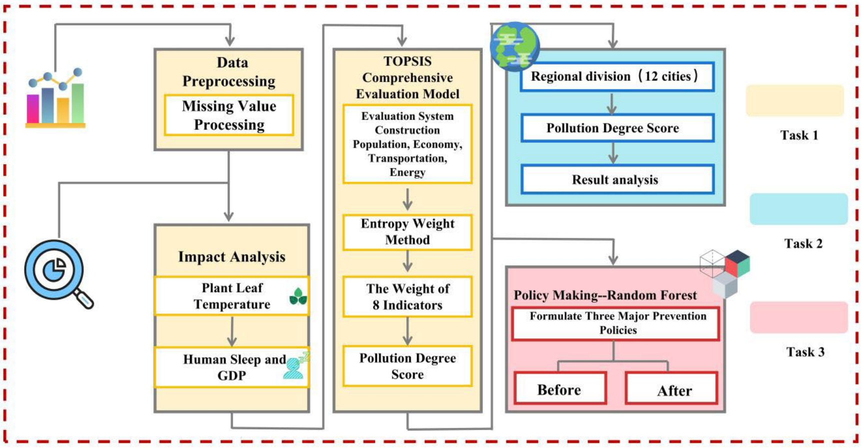

Figure 1: The Framework

As shown in Figure 1, we first use the data on the influence of artificial light on plant leaf temperature and human insomnia and GDP correlation data from the National Bank to study the impact of light pollution on plants and humans, among which GDP is closely related to the degree of nighttime economic development, so we think GDP and light pollution are positively correlated to a certain extent, and the correlation data between GDP and human insomnia is used as a manifestation of the impact of light pollution on human sleep.

After fully realizing the impact of light pollution on human sleep, we built evaluation indicators from the four levels of population, economy, transportation and energy, and finally decided to select eight specific indicators in the middle of the year: population, population density, per capita GDP, final consumption rate of residents, air passenger traffic, carbon dioxide intensity, electricity consumption, and energy use. After collecting a large number of national corresponding index data and preprocessing the data, the TOPSIS evaluation model based on the entropy weight method was used to obtain the weights of the 4 3 countries screened out, and the comprehensive score of the light pollution degree of each country was further obtained.

For the specific question, four major areas in China, namely protected areas, rural areas, suburban areas and urban areas, were selected for research, and 1 2 corresponding cities were selected using population density and regional GDP as evaluation criteria. Then, combined with the six indicators (population, population density, final consumption rate of residents, carbon dioxide intensity, electricity consumption, and energy use) that have a large impact on the light pollution evaluation index, the relevant data of these 1and 2 cities were collected, based on the TOPSIS comprehensive evaluation method. Analyze the levels and causes of light pollution in these four regions.

Then, we draw on the international experience of countries that have achieved good results in light pollution control, and find that the use of national public power to adopt the governance of light pollution can effectively reduce the current situation of light pollution. In this regard, we establish an index model of government control strength, combined with the year and number of light pollution related policies promulgated by the state, compare the effectiveness of policies in past years with the growth coefficient of light pollution prevention and control policies, and use 13 input indicators including policy governance and 1 output index of the average light pollution index of various countries. The feasibility of policy intervention to optimize the current situation of light pollution was analyzed. Finally, we adjust the government's control of light pollution to strengthen, unchanged and weaken, and obtain the changes in pollution indexes in various countries under different assumptions, and finally conclude that government intervention is effective for light pollution control.

2.1 The Notations

For convenience, we introduce some important notations below in Table 1 and Table 2.

(1) Light pollution evaluation model

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Table 1: Model Notations

Notations	Explanations
I_{ij}	The variable value representing the indicator for the first country
$X_{\phi ij}$	Indicates the entropy value of the first indicator for the first country
$Y_{\phi j}$	The composite score for the first indicator
R^{+}、R^{-}	Represents the positive and negative ideal solutions
C_j^{*}	Relative progress for the first indicator

(2) Indicator model of government control strength

Table 2: Model Notations

Notations	Explanations
P	Indicates the government's efforts in light pollution management
y_i	Represents the year in which the national policy on light pollution control was promulgated, indicating the number of relevant policies for light pollution control in that year
a	Indicates the growth coefficient of the country's light pollution policy

3. Model Based on the evaluation system of light pollution risk level

The experimental data is the accurate values of eight indicators of population, population density, per capita GDP, final consumption rate of residents, air passenger traffic, carbon dioxide intensity, electricity consumption, and energy use in 43 countries collected in the past year. The hardware environment for numerical experiments is: software Matlab2022a.

The observed data can find that there are a large number of missing values (too many NAN values) in some influencing factors in the data of some countries, or the features are not duplicated, that is, irrelevant features, so find for NAN values and duplicates for the data, and round off the missing and irrelevant dimensions.

3.1 TOPSIS Evaluation Model Based on Entropy Weight Method

As a common method in the objective empowerment method, the entropy weight method can avoid subjectivity and use the real data obtained from objective investigation to determine the weight of indicators.

In order to avoid the impact caused by the difference of index units between data and enhance the accuracy and reliability of data processing, the original data is first **dimensionless**. In view of the positive and negative contribution direction of the measurement index to the target layer, the extreme value method is used to standardize the data. Set the entropy weight algorithm used in this question as the first model, that is, i represents the number of the first i country. The eight evaluation indicators are the number of population, population density, per capita GDP, final consumption rate of residents, air passenger traffic, carbon dioxide intensity, electricity consumption, and energy usage in the middle of the year, which are expressed as j(j=1, 2,...,8) respectively The formula (1)-(8) are as follows:

The metric attribute is positive:

$$\mathrm{I}_{\Phi ij}{}' = \frac{I_{\Phi ij} - \min(\mathrm{I}_{ij})}{\max(\mathrm{I}_{ij}) - \min(\mathrm{I}_{ij})} + 1 \tag{1}$$

The metric attribute is negative:

$$\mathrm{I}_{\Phi ij}{}' = \frac{\max(\mathrm{I}_{ij}) - \mathrm{I}_{\Phi ij}}{\max(\mathrm{I}_{ij}) - \min(\mathrm{I}_{ij})} + 1 \tag{2}$$

Secondly, calculate the proportion of the indicator value:

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$$Q_{\Phi ij} = \frac{I_{\Phi ij}{}'}{\sum_{\Phi}^{m}\sum_{i}^{z} I_{\Phi ij}{}'} \tag{3}$$

Again, calculate the entropy values of each indicator:

$$X_{\Phi ij} = -K\sum_{\Phi}^{m}\sum_{i}^{z}(\mathrm{Q}_{\Phi ij}\ln(\mathrm{Q}_{\Phi ij})) \qquad (k=\frac{1}{\ln(\mathrm{mz})} \text{ and } k>0) \tag{4}$$

Next, calculate the redundancy of indicator j:

$$\mathrm{E}_j = 1 - X_{\Phi ij} \tag{5}$$

Then, measure the weights of each indicator:

$$W_j = \frac{E_j}{\sum_{j}^{n} E_j} \tag{6}$$

Finally, calculate the composite score of each indicator:

$$Y_{\Phi i} = \sum_{j}^{n} W_j I_{\Phi ij}{}' \tag{7}$$

We used the preprocessed data to calculate the weights of each indicator in 43 countries using the above method, as shown in the Figure 2.

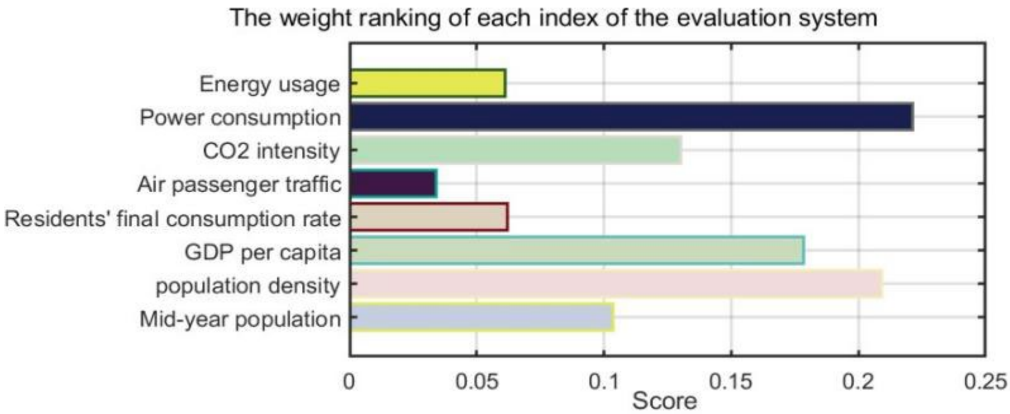

Figure 2: The Weight Ranking of 8 Index

TOPSIS comprehensive evaluation method is used to solve the problem of multi-attribute decision-making of objects, and its basic idea is to select the optimal solution and the worst solution under all indicators of the evaluation object as positive and negative ideal solutions, detect the distance between the value of each index of the evaluation object and the positive and negative ideal solution, and sort and evaluate the existing objects by calculating the relative fit [3][4]. The optimal result is the closest to the affirmation of the ideal goal and the furthest to the negation of the ideal goal. This method fully considers the distance between the value of a certain index of the research object and the highest and lowest values in the sample, and represents a relative concept.

We applied the model to 43 countries and obtained their light pollution degree scores as shown in the Figure 3.

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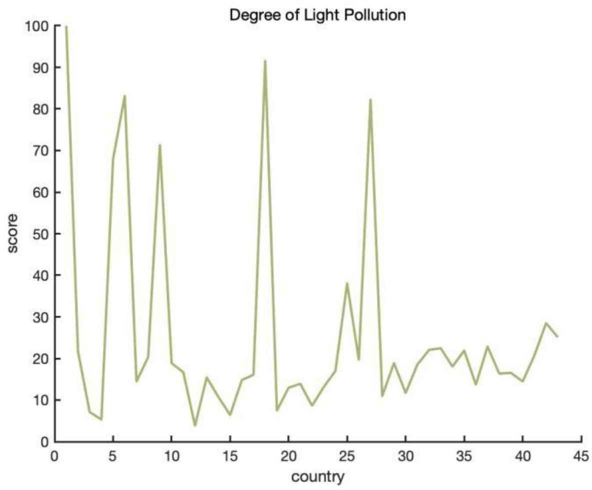

Figure 3: The Score of 43 Countries

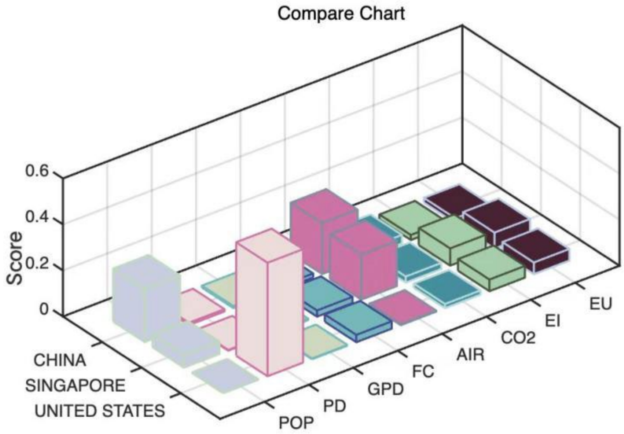

Figure 4: Comparison of Indicators of the Three Countries

As shown in the Figure 4: Based on the TOPSIS comprehensive model, we can analyze the 3 countries with the highest light pollution scores: China (100), Singapore (91.58), United States (82 29), the three countries also scored relatively high on the eight evaluation indicators.

According to the light pollution map, we can observe that the areas with more serious light pollution (higher brightness in the light pollution map) in the three countries are mostly in the coastal area, which basically coincides with the economically developed areas of the three countries. According to the above evaluation system, we can see that the four indicators of electricity consumption, population density, per capita gross national product and carbon dioxide intensity play a major role in the degree of light pollution. The two indicators of electricity consumption and carbon dioxide intensity belong to the energy level, the population density belongs to the population level, and the per capita GDP belongs to the economic level, so it can be inferred that the area with a large degree of light pollution has the characteristics of large population (mostly more than 1000), developed economy and large energy efficiency.

4. Model Based on the evaluation system of light pollution risk level

For prediction problems, it is actually a regression and classification problem. There are many traditional classification machine learning algorithms, such as decision trees (DTC), Bayesian (BC), support vector machine algorithms (SVM), etc. However, due to the low accuracy of these traditional classifiers, the performance is difficult to break through the bottleneck, and overfitting problems are prone to occur [5]. Therefore, methods of integrating multiple classifiers to improve prediction accuracy have emerged, and these methods are called classifier combination methods. That is, Ensemble Learning. The construction of combinatorial classifiers is usually divided into two categories: Bagging and Boosting, and the Bagging method is suitable for parallelization methods that do not have a strong relationship between individual learners and can be generated at the same time, and Boosting vice versa is a serially generated serialization method. Random Forests is the most representative algorithm of the Bagging ensemble method.

Random Forest (RF) is a machine learning algorithm published by American scientist Leo Breiman in 2001, RF is usually an ensemble learning model with decision trees as the basic classifier, it contains multiple machine learning patterns made by Bagging After entering the training data, each decision tree votes according to the results, and the random forest outputs the average results with high accuracy according to the voting.

4.1 Indicator model of policy control strength

Set the government's management of light pollution as P, the year of the national policy promulgating light pollution is $y_i(i=1,2,\cdots,\mathrm{N})$, representing that the country has promulgated N light pollution-related policies in the past, a is the growth coefficient, the longer the version of the age, we can consider its effectiveness to be lower. By adding up the effectiveness of past years, we can get the following indicators of policy strength in formula (8), and we can model them.

$$P=\sum_{i=1}^{N}\frac{(2023-y_i)^2}{a} \tag{8}$$

Incorporate Population density, GDP, Consume rate, Air passenger volume, Carbon dioxide intensity, Power consumption, Energy consumption, Population, Area, Trend. The 13 indicators of Rad, Policy Power, and Light intensity were used as input variables, and the national average light pollution index (**Avg. mean**) as the output variable.

The importance parameter indicators obtained by the random forest model are shown in the following Figure 5.

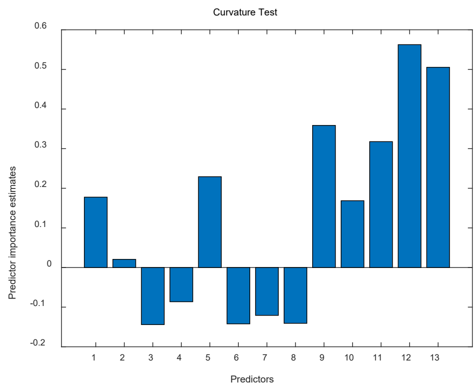

Figure 5: Curvature Test

From the perspective of the importance analysis index, indicator 12, that is, the influence of relevant policies, is the largest, followed by night light intensity, which can be called up through the result analysis chart 1, 5, 9, 10, 11, 12, 13. These indicators are important indicators that affect the light pollution coefficient.

We used the first 80% of national data for training and the last 20% of national data for testing.

We use random forest regression prediction. Since the dataset is relatively small, the use of random forest without parameters is prone to overfitting, and the selection error will be relatively large, so SSA (Sparrow Search Algorithm) is chosen to optimize the parameters of the model.

The optimization parameters are as follows:

"SSA Sparrow Search Algorithm" "Optimized TreeBagger: " "tree_num:" "10" " "Min Leaf Size: ""1"

The results after optimization are as follows in Figure 6 and Figure 7:

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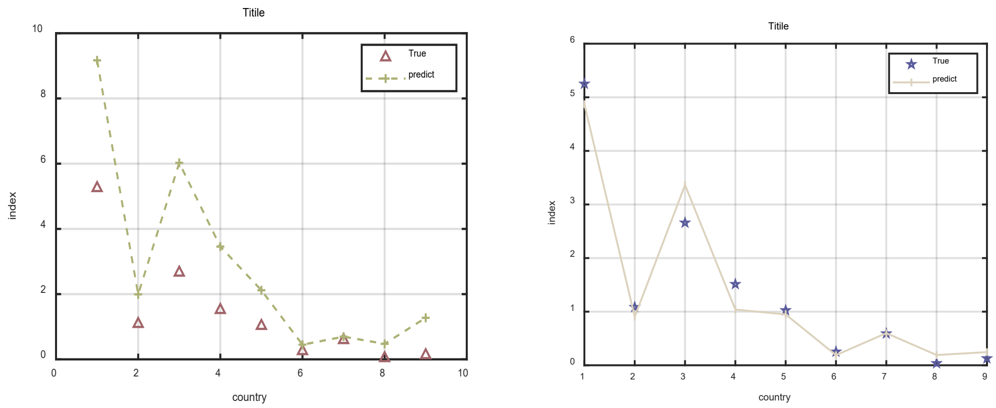

Figure 6: Comparison of predicted values before and after optimization

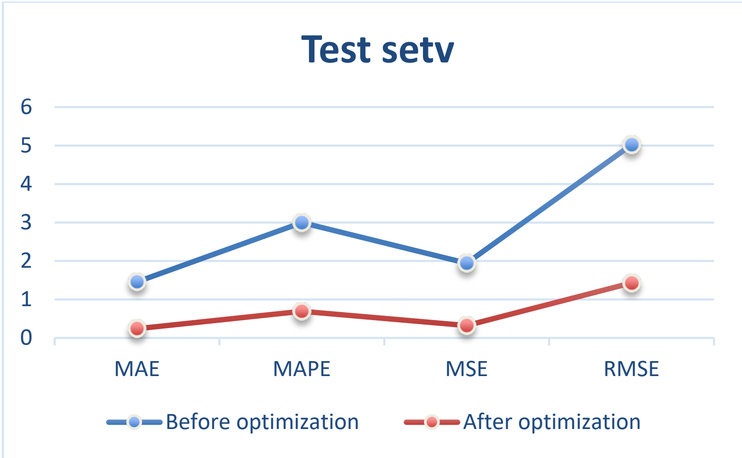

Figure 7: Test set

From the above modeling tests, it can be obtained that the average absolute error (MAE), mean relative error (MAPE), and root mean square error (MSE and RMSE) of the training set, verification set and test set are significantly smaller than before optimization after optimization. Thus, the random forest model after optimizing the parameters can achieve better results, and verify the feasibility of optimization.

From the above model, it can be concluded that the policy strength and the average intensity of night light are the most important indicators affecting the light pollution indicators, and now we change the values of these two indicators respectively, call the optimized stochastic network model we established, and observe the changes of the coefficients of light pollution indicators in various countries

Let's assume the following 6 cases:

1) The value of policy strength is increased by 10%, and the average intensity of night light is reduced by 10%.

2) The value of policy strength is increased by 10%, and the average intensity of night light remains unchanged

3) The value of policy strength is reduced by 10%, and the average intensity of light at night remains unchanged

4) The value of policy strength remains unchanged, and the average intensity of night light is reduced by 10%.

5) The value of policy strength remains unchanged, and the average intensity of night light increases by 10%. The value of policy strength is reduced by 10%, and the average intensity of night light is increased by 10%.

Using the model, we can get how the pollution index changes in each country under six scenarios

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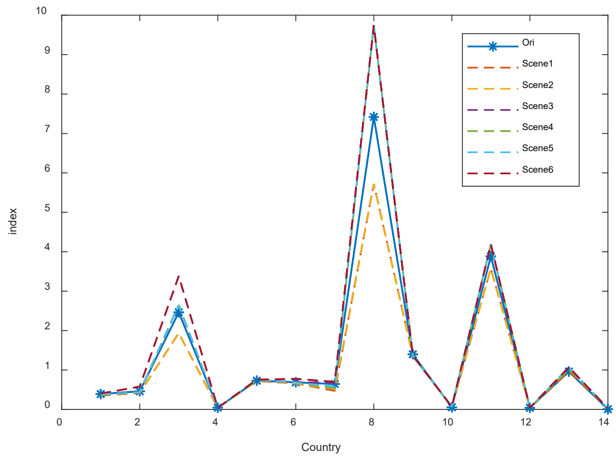

Figure 8: The experimental results.

According to the above Figure 8, taking the light pollution coefficient of the original countries as a reference, the increase in the value of policy intensity (assumptions 1 and 2) will reduce the light pollution index of all countries, while the decrease in government support by 10% (assumption 6) will lead to a large increase in the light pollution index. Therefore, it can be concluded that the strength of the policy affects the light pollution index.

5. Conclusion

In this paper, we used the TOPSIS evaluation model based on the entropy weight method to measure the light pollution evaluation system and evaluation, and obtained a composite score of the light pollution index of 4 3 countries and 4 regions, which can objectively evaluate the given data, and It can clearly show the comprehensive influence of the 4 levels and 8 impact indicators we constructed, which is more flexible and convenient; We use the random forest model to optimize the policy control index model, and obtain better optimization results to verify the feasibility of optimizing government control light pollution, and the random forest model can exclude irrelevant variables in complex data processing, and the unified standardization of data can achieve twice the effect with half the effort, which not only greatly improves the accuracy, but also shortens the calculation time; We establish an index model of policy control strength, which links the number of laws and regulations related to the control of light pollution with the promulgation period, which can effectively quantify the government's control of light pollution into measurable data, and facilitate the evaluation of the effectiveness of local light pollution intervention by promulgating governance policies with the government as the main body.

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