Research on Light Pollution System Based on Innovative Evaluation Method and Particle Swarm Optimization Grey Prediction Method

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Abstract. The control of light pollution is an important part of people's urban health. An accurate index system of quantitative light pollution level is of great significance for controlling light pollution, saving energy, and improving social happiness index. After obtaining the combined weight evaluation model, in order to verify the reliability of the index system in various regions, based on the grey prediction theory, combined with the advantages of PSO algorithm in model accuracy and predictability, the light pollution risk level in Shanghai was evaluated and predicted, and specific intervention strategies for light pollution remediation were proposed.

Keywords: Light Pollution, PSO-GM (1, 1), Evaluating Indicator, Intervention Strategy.

1. Introduction

With the development of urbanization and social economy, artificial lighting devices are widely used in all corners of the city at night. However, too much artificial lighting is beyond the actual demand, bringing light pollution to the city's night sky [1]. People are becoming more concerned about the safety, health, and environmental protection of the living environment. Simple "brightening" can no longer meet people's needs. Light pollution like water pollution, and air pollution is more and more people concerned. How to develop accurate quantitative methods and evaluation standards, scientific monitoring and management of light pollution has become an urgent problem [2].

In this paper, we review and summarize the literature on light pollution monitoring and the model results of existing studies on light pollution and influencing factors, and find that the factors affecting light pollution levels are mainly related to the level of urban development (population density, urban scale, functional zoning, GDP), the natural environment, quantitative indicators such as nighttime lighting index, and non-quantitative indicators such as psychological factors [3]. Ge Lou et al. found that the correlation between nighttime light data and urban centralization [4]. Some scholars added climatic and geographical factors such as aerosol parameters, light scattering, and observational geographic location to refine the model of nighttime sky brightness in relation to population distribution [5-8]. Rabaza observed the local nighttime sky brightness in Spain and obtained a sky brightness model by Stellarium software, which can analyze the nighttime sky light pollution by comparing the brightness of known sky stars. It is also able to provide accurate background skylight fluxes. Light pollution levels are closely related to regional functional zoning [9]. Falchi et al. found that by comparing the relationship between GDP and light pollution in European and American regions, the difference in light flux per unit GDP between the most and least light-polluted regions in Europe was 267 times[10].

The dataset used in this paper is derived from the 2023 U.S. Collegiate Mathematical Modeling Contest Problem E. In this paper, based on the above literature research, we will select the indicators affecting light pollution levels from multiple dimensions, establish a light pollution level indicator evaluation system with wide applicability, and verify its accuracy. Then, based on the weights of the

evaluation indicators, we will propose effective and feasible intervention strategies for the management of light pollution in areas with different environmental characteristics.

2. Basic Assumption and Glossary

2.1. Basic assumption

The level of risk from light pollution depends on a variety of factors. In order to make the model more practical, this paper makes several reasonable assumptions as follows.

Assumption 1: The main internationally recognized forms of light pollution include white bright pollution, artificial daylight, and colored light pollution. In order to enhance the relevance and operability of the model, this paper assumes that the light environment is independently evaluated according to nighttime.

Assumption 2: Because the actual data is not easy to obtain when calculating the brightness level, this paper assumes that the impact of each light source in the selected area on the selected area follows a uniform distribution, and the same light intensity can be observed at any location.

Assumption 3: In this paper, it is assumed that all stars in the sky are within the observable range.

2.2. Glossary

This paper constructs the following index system to quantify the level of light pollution in a region. The index system includes many important factors to measure the risk level of light pollution, such as economic factors, meteorological factors and geographical factors, which makes the model widely applicable.

Population Density (PD): For convenience and safety considerations, people have been improving the level of urban lighting as much as possible, the population density will become an important factor affecting the level of light pollution.

City Size ($\boldsymbol{CS}$): City size is the scale of population, economy and technology gathering in the city. The larger the scale of the city, the scope and level of its outdoor lighting will also increase accordingly.

Vegetation Cover ($\boldsymbol{VC}$): Vegetation can use light to photosynthesize, reducing the degree of light pollution. However, the lighting at night can disrupt the life rhythm of plants. Therefore, vegetation cover can indirectly reflect the level of light pollution risk.

Air Quality Index ($\boldsymbol{AQI}$): Air pollutants in the atmosphere affect the propagation and distribution of light in the air, which in turn affects the light pollution level in the area.

Sky Magnitude Brightness ($\boldsymbol{SMB}$): Magnitude brightness is the degree of observed brightness level of stars per unit of time, which can visually reflect the light pollution risk level of the region. The ancient Greeks Hipparchus divided the stars into 6 levels according to the brightness of the stars, with the brightest star of the 1st magnitude and the faintest of the 6th magnitude. The team quantified the brightness of 6 magnitudes from 1 to 6 and constructed a large Causy distribution and logarithmic function as a membership function.

$$f(x) = \begin{cases} [1 + \alpha(x - \beta)^{-2}]^{-1}, 1 \le x \le 3 \\ a\ ln\ x + b, 3 \le x \le 6 \end{cases} \tag{1}$$

When the magnitude is 1, $f(1) = 0.01$ When it is 3, $f(3) = 0.08$ and f(6)=1. When it is 6, $f(6) = 1$ Using Matlab to calculate that

$$\begin{cases} \alpha = 1.1086 \\ \beta = 0.8942 \\ a = 0.2885 \\ b = 0.483 \end{cases} \tag{2}$$

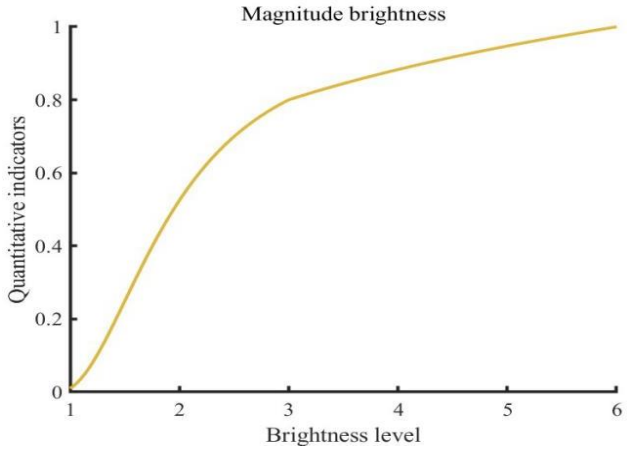


Figure 1. The continuity index of the magnitude brightness figure

From Figure 1, the higher the quantitative index, the stronger the degree of light pollution.

Gross National Income (***GNI***) & Gross Domestic Product (***GDP***): GNI & GDP is an important indicator to measure the level of economic development of cities and is closely related to the level of light pollution.

Digital Number (***DN***): Nocturnal remote sensing data represented by DMSP and OLS can enable people to obtain accurate information of light pollution and has been widely used in light pollution monitoring.

Luminosity (***L***): Luminosity is the luminous flux received per unit area, which is mainly used in this paper to reflect.

3. Light Pollution Combination Weighting Integrated Evaluation

3.1. Model Preparation

(1) Data Processing

First, principal component analysis was performed on the nine indicators listed. Perform KMO and Bartlett's tests.

$$KMO = \frac{\sum\sum_{i \neq j} r_{ij}^{\ 2}}{\sum\sum_{i \neq j} r_{ij}^{\ 2} + \sum\sum_{i \neq j} a_{ij}^{\ 2}} \tag{3}$$

Table 1. The results of the model parameter value table

KMO test and Bartlett's test		
KMO Value		0.436
Bartlett's sphericity test	Approximate cardinality	280.175
	df	36
	P	0.000***

Note: ***, **, * represent 1%, 5%, 10% significance levels, respectively

The result of the KMO and Barlett test shows in Table 1. It shows that the KMO value is 0.436 less than 0.6, indicating that there is no correlation between each index, and there is no need to conduct principal component analysis for data dimensionality reduction.

The results of the correlation coefficient analysis of the nine indicators were then shown in Figure 2.

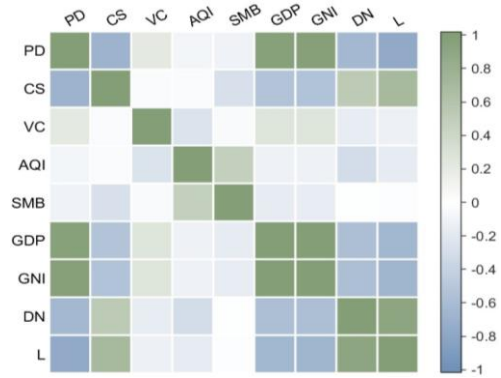


Figure 2. thinking research paper figure

It can be seen that the correlation between the 9 indicators is weak. In summary, no deletion is required for the nine indicators that determine the level of light pollution risk.

(1) Selection of quantitative indicators

Positive indicators: Population Density (*PD*), City Size (*CS*), Sky Magnitude Brightness (*SMB*), Gross National Income (*GNI*), Gross Domestic Product (*GDP*), Digital Number (*DN*), Luminosity (*L*)

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{4}$$

Negative indicators: Vegetation Cover (*VC*), Air Quality Index (*AQI*)

$$x'_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \tag{5}$$

(2) The matrix is normalized to eliminate the magnitude

$$r_{ij} = \frac{x'_{ij}}{\sqrt{\sum_{i=1}^{n} x'^{2}_{ij}}} \tag{6}$$

3.2. Model Establishment

Step 1: The judgment matrix of the hierarchical analysis method was established by reviewing the information.

$$\begin{bmatrix} 1 & 2 & 3 & \frac{1}{3} & 3 & 3 & 3 & \frac{1}{5} & \frac{1}{3} \\ \frac{1}{2} & 1 & 1 & \frac{1}{5} & 3 & 2 & 2 & \frac{1}{7} & \frac{1}{5} \\ \frac{1}{3} & 1 & 1 & \frac{1}{5} & 5 & 2 & 2 & \frac{1}{7} & \frac{1}{5} \\ 3 & 5 & 5 & 1 & 3 & 5 & 5 & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{5} & \frac{1}{3} & 1 & \frac{1}{3} & \frac{1}{3} & \frac{1}{3} & \frac{1}{2} \\ \frac{1}{3} & \frac{1}{2} & \frac{1}{2} & \frac{1}{5} & 3 & 1 & 1 & \frac{1}{7} & \frac{1}{7} \\ \frac{1}{3} & \frac{1}{2} & \frac{1}{2} & \frac{1}{5} & 3 & 1 & 1 & \frac{1}{7} & \frac{1}{7} \\ 5 & 7 & 7 & 2 & 3 & 7 & 7 & 1 & 2 \\ 3 & 5 & 5 & 2 & 2 & 7 & 7 & \frac{1}{2} & 1 \end{bmatrix} \tag{7}$$

Step 2: Weights were obtained by hierarchical analysis.

$$w_1 = [0.0900, 0.0540, 0.0601, 0.1745, 0.0382, 0.0381, 0.0381, 0.02934, 0.2136] \tag{8}$$

Step 3: Obtain weights by entropy weighting method.

$$E_i = -\frac{1}{\ln m}\sum_{i=1}^{m} p_{ij} \ln p_{ij} \tag{9}$$

$$p_{ij} = \frac{r_{ij}}{\sum_{j=1}^{n} r_{ij}} \tag{10}$$

The weight is

$$w_{ij} = \frac{(1-E_j)}{\sum_{j=1}^{n}(1-E_j)} \tag{11}$$

Get weights w_2:

$$w_2 = [0.0628, 0.2824, 0.0619, 0.0233, 0.0618, 0.1146, 0.1039, 0.0973, 0.1920] \tag{12}$$

Step 4: Weights are obtained by the coefficient of variation method.

$$A_j = \frac{1}{n}\sum_{i=1}^{n} r_{ij} \tag{13}$$

Mean square error (MSE):

$$S_j = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(r_{ij} - A_j)^2} \tag{14}$$

Coefficient of variation of each index:

$$V_j = \frac{S_j}{A_j} \tag{15}$$

The weight:

$$w_j = \frac{V_j}{\sum_{j=1}^{n} V_j} \tag{16}$$

Net weight w_3:

$$w_3 = [0.0755, 0.2367, 0.0792, 0.0421, 0.0746, 0.1026, 0.1114, 0.1702] \tag{17}$$

Step 5: The weights obtained from the three methods form the combined weights.

$$\begin{bmatrix} 0.0900 & 0.0540 & 0.0601 & 0.1745 & 0.0382 & 0.0381 & 0.0381 & 0.2934 & 0.2136 \\ 0.0628 & 0.2824 & 0.0619 & 0.0233 & 0.0618 & 0.1146 & 0.1039 & 0.0973 & 0.1920 \\ 0.0755 & 0.2367 & 0.0792 & 0.0421 & 0.0746 & 0.1076 & 0.1026 & 0.1114 & 0.1702 \end{bmatrix} \tag{18}$$

Step 6: Assign weights to the weight matrix using the CRITIC method.

$$T_{ij} = \sum_{i=1}^{n}(1-r_{ij}) \tag{19}$$

$$C_i = \delta_i \sum_{i=1}^{n} (1 - r_{ij}) \tag{20}$$

The weight coefficient obtained is

$$w_y = \frac{C_j}{\sum_{j=1}^{m} C_j} \tag{21}$$

The matrix weights $[0.5726\ 0.2509\ 0.1765]$ were obtained. Multiply the matrix weights with the combination weights to get the final weights $w_c w_y$:

$$w_c w_y = [0.0806, 0.1436, 0.0639, 0.1132, 0.0506, 0.0696, 0.066, 0.2121, 0.2005] \tag{22}$$

3.3. Light pollution risk level formula

$$\text{light pollution risk level} = \sum_{i=1}^{2} w_i x_i + \sum_{i=5}^{9} w_i x_i - \sum_{i=3}^{4} w_i x_i \tag{23}$$

Table 2. Partial symbols used in this formula

Symbol	Definition
X_1	PD
X_2	CS
X_3	VC
X_4	AQI
X_5	SMB
X_6	GDP
X_7	GNI
X_8	DN
X_9	L

Table 2 shows the meanings of each independent variable indicator.

4. Application of Light Pollution Combination Weighting Integrated Evaluation Model

4.1. Application Preparation

(1) Location Selection

Four regions were selected to assess the risk level of light pollution, the Greater Khingan Range, Yangshuo, Taizhou, and Shanghai.

(2) Data Processing

Firstly, the nighttime lighting data of four areas were acquired through the Luojia 1-01 satellite.

- Greater Khingan Range & Yangshuo

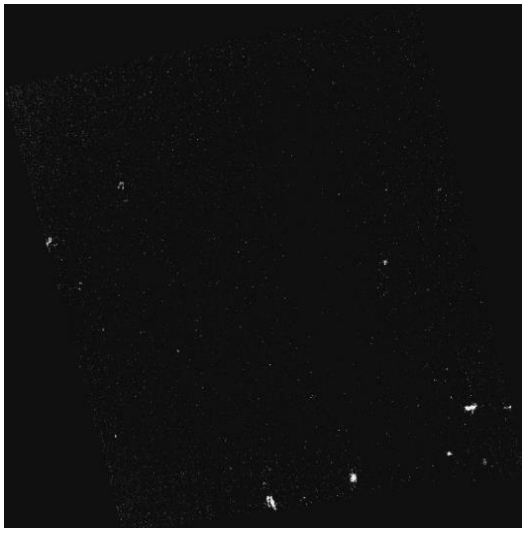


Figure 3. Greater Khingan Range Night Light Data

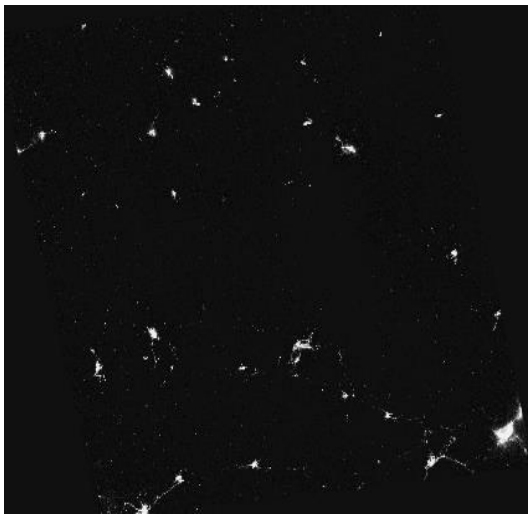


Figure 4. Yangshuo Night Light Data

- Taizhou & Shanghai



Figure 5. Taizhou Night Light Data



Figure 6. Shanghai Night Light Data

Figure 3-6 shows the Digital Number of the four areas.

Afterward, we obtained data on population density, city size, star brightness, GDP, GNI, nighttime light index, illuminance level, forest coverage, and AQI for four regions: Greater Khingan Range, Yangshuo, Taizhou, and Shanghai.

4.2. Model Test Results

The final results for the four regions were calculated by bringing in the light pollution risk level model.

The risk level of light pollution in the four regions is 0.2249 0.2268 0.9342 3.7582 . Showed in Figure 7 below.

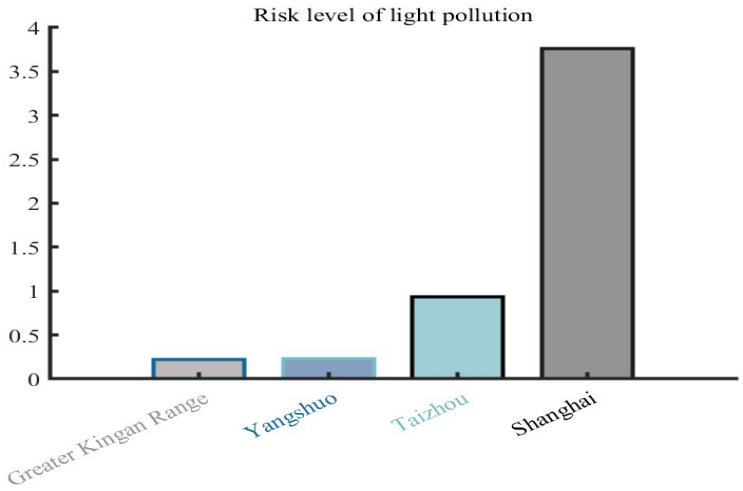


Figure 7. Risk Level of Light Pollution

You can see that the risk level of light pollution is ranked from high to low in Shanghai, Taizhou, Yangshuo, and the Greater Khingan Range.

5. Analysis and Implementation of Light Pollution Intervention Strategies

5.1. Model Preparation

(1) Data Processing

We subjective screening of three indicators that can be used to implement the policy: population density, vegetation cover, nighttime light index. Selected regions 2013, 2015, 2017, 2019, and 2021 data.

5.2. Model Establishment

Three indicators by the entropy weighting method (Positive and negative processing of the data) are listed in Table 3.

Table 3. Intervention Strategy Metric Weight Table

PD	VC	DN
0.21	0.28	0.51

$$\text{Light pollution risk level}=0.21*PD-0.28VC+0.51*DV \tag{24}$$

6. Effective Intervention Strategy Analysis

Our team choose three effective intervention strategy analysis. First is reducing night light index. Second is reducing the population density in some areas. Third is increasing vegetation coverage.

The locations chosen in this article are urban neighborhoods in Shanghai. The corresponding intervention strategy were proposed for the variables within the index according to $\mathrm{PD}, \mathrm{VC}, \mathrm{DN}$. Get the following formula.

$$\text{Light pollution levels without lntervention strategy}=0.21*PD-0.28*VC+0.51*DN \tag{25}$$

The $\mathrm{PSO}-\mathrm{GM}\,(1,1)$ prediction model was constructed to predict the risk level of light pollution under no intervention policy and three policy intervention conditions. $\mathrm{GM}(1,1)$ prediction formula

$$\widehat{\mathrm{X}}^{(1)}(\mathrm{k}+1)=\left[\mathrm{X}^{(0)}(1)-\frac{\mu}{\alpha}\right]\mathrm{e}^{-\mathrm{ak}}+\frac{\mu}{\alpha} \tag{26}$$

Analysis the PSO optimization algorithm formula

$$X_i^{t+1}=X_i^{t}+V_i^{t+1} \tag{27}$$

$$V_i^{t+1}=\bar{\omega}V_i^{t}+c_1r_1(P^{t}{}_{ibest}-X_i^{t})+c_2r_2\left(G^{t}{}_{best}-X_i^{t}\right) \tag{28}$$

Combining PSO with $\mathrm{GM}\,(1,1)$), optimizes the $\mathrm{GM}\,(1,1)$ model parameters through PSO to improve the advance of the $\mathrm{GM}\,(1,1)$ model measure accuracy. Level of light pollution risk without the intervention strategy.

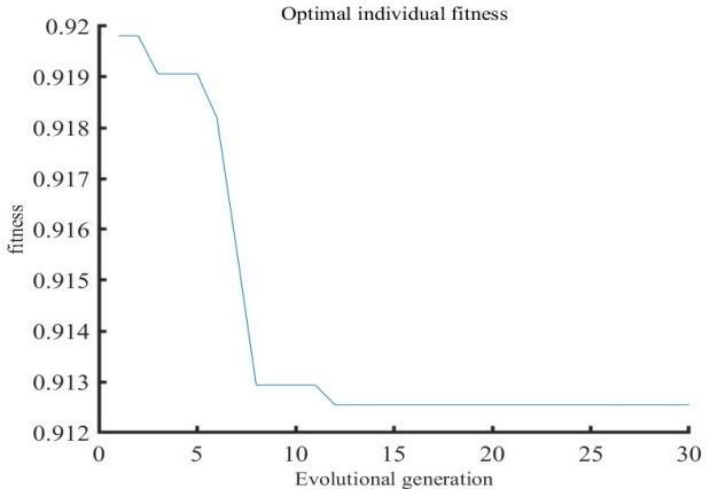


Figure 8. Global optimal fitness value

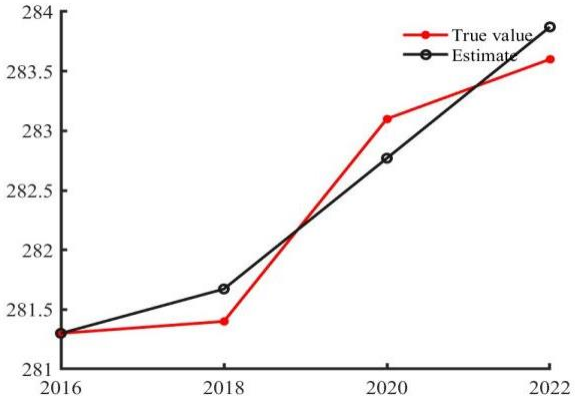


Figure 9. Prediction accuracy

Figure 8 displays the optimization process of PSO. Figure 9 displays the prediction accuracy of PSO-GM (1, 1). The PSO optimized the $GM\ (1,1)$ parameter after the prediction equation: $a = -0.0039, u = 279.9602.$ $-a < 0.3$ can be used for medium and long-term prediction.

The ratio of mean variance is C = 0, 1398. And for a small error probability P = 1.

6.1. Analysis of Strategy One: Reduce night light index

(1) Date Processing

The team has compiled the night light index data of Shanghai for consecutive years, and the data of each year is X_i, the average annual growth rate is V.

(2) Level of light pollution risk with the intervention strategy

The average annual growth rate after the policy adjustment V_g is

$$V_i = X_i + \frac{1}{X_i} - 1 \tag{29}$$

$$V = \frac{\sum_{i=1}^{n} V_i}{n} \tag{30}$$

$$X_i + 1 = X_i * (1 + V) \tag{31}$$

$$X_{g(i+1)} = X_{g(i)} * (1 + V_g) \tag{32}$$

$$DN' = X_{g(i+1)} - X_i + 1 \tag{33}$$

$$\text{Light pollution risk level } (1) = 0.21 * PD - 0.28 * VC + 0.51 * (DN - DN') \tag{34}$$

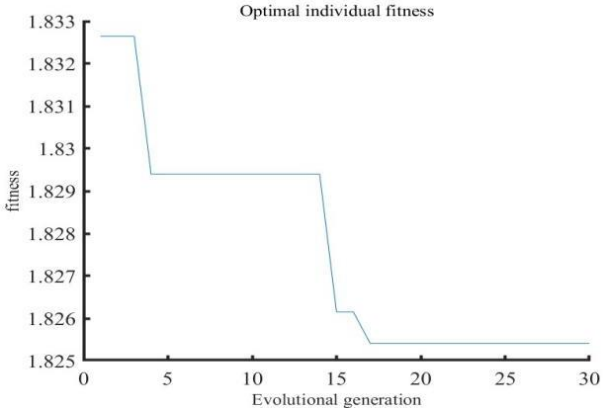


Figure 10. Global optimal fitness value

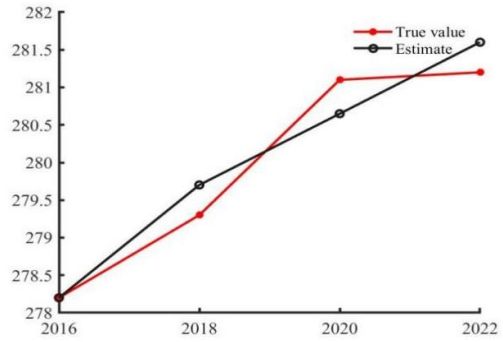


Figure 11. Prediction accuracy

Figure 10 displays the optimization process of PSO. Figure 11 displays the prediction accuracy of PSO-GM (1, 1). The PSO optimized the $GM\ (1,1)$ parameter after the prediction equation: $a = -0.0034,\ u = 278.1708.\ -a < 0.3$ can be used for medium and long-term prediction.

The ratio of mean variance is *C =0.1591*. And for a small error probability *P = 1*.

6.2. Analysis of Strategy Two: Reduce the population density in some areas

(1) Assumptions

Urban communities are single core population distribution, and big cities are only composed of commercial land and densely populated areas, the population density decreases with the increasing distance from the city center.

(2) Population Density Model Establishment

$$D_{(r)} = D_0 e^{-br} \tag{35}$$

$D_{(r)}$ is population density in *r* miles from downtown. D_0 and *b* are parameters.

The larger D_0, the higher the downtown population density. When D_0 decreases, the downtown population density decreases. The population density decrease is defined as *D′*.

$$D' = \Delta D_0 \tag{36}$$

$$\text{Light pollution risk level } (2) = 0.21 * (PD - D') - 0.28 * VC + 0.51 * DN \tag{37}$$

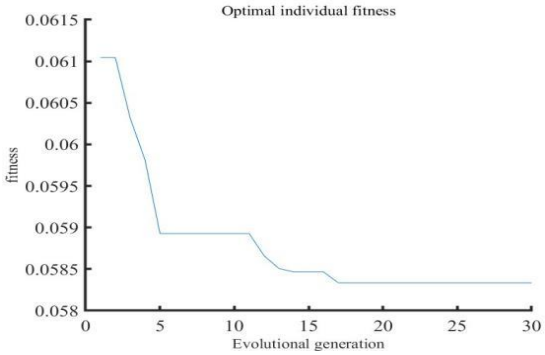


Figure 12. Global optimal fitness value

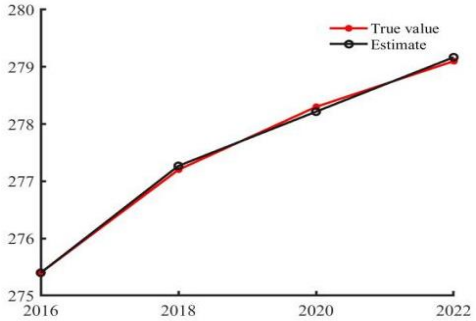


Figure 13. Prediction accuracy

Figure 12 displays the optimization process of PSO. Figure 13 displays the prediction accuracy of PSO-GM (1, 1). The PSO optimized the $GM\ (1,1)$ parameter after the prediction equation: $a = -0.0034,\ u = 275.8372.\ -a < 0.3$ can be used for medium and long-term prediction.

The ratio of mean variance is C =0.0258. And for a small error probability P = 1.

6.3. Analysis of Strategy Three: Increase vegetation coverage

Define the normalized vegetation index NDVI:

$$NDVI = f_g NDVI_g + (1 - f_g) NDVI \tag{38}$$

To construct a density model of vegetation coverage f_g

$$f_g = \frac{NDVI - NDVI_0}{NDVI_g - NDVI_0} \tag{39}$$

To construct a non -density model of vegetation coverage f_g

$$f_g = \frac{NDVI - NDVI_0}{NDVI_g - NDVI_0} \tag{40}$$

The vegetation classification can be determined according to the size of f_g

Table 4. Vegetation Cover Grading Table

$f_g = 0$	No vegetation cover
$0 < f_g < 25\%$	Low vegetation cover
$25\% < f_g < 50\%$	Middle vegetation cover
$50\% < f_g < 95\%$	High vegetation cover
$95\% < f_g$	Full vegetation cover

Table 4 shows the various intervals of vegetation cover. The area increased from low to middle vegetation coverage, and the amount of f_g increase was defined as f'_g.

$$\text{Light pollution risk level } (3) = 0.21 * PD - 0.28 * (VC + f_g') + 0.51 * DN \tag{41}$$

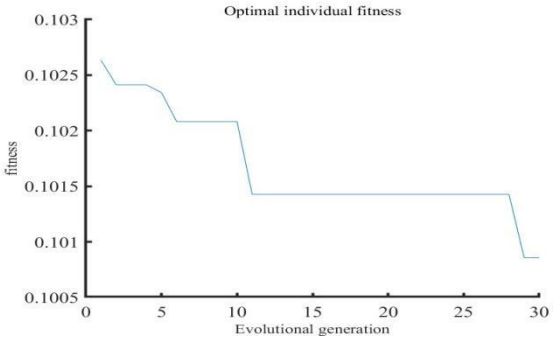


Figure 14. Global optimal fitness value

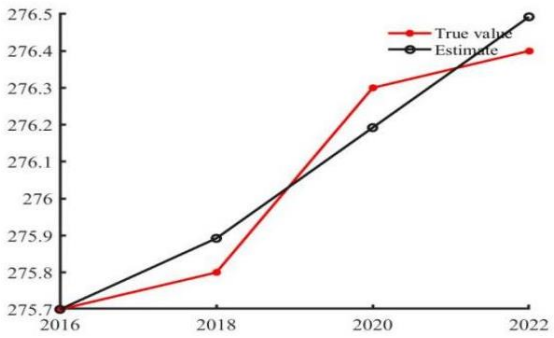


Figure 15. Prediction accuracy

Figure 14 displays the optimization process of PSO. Figure 15 displays the prediction accuracy of PSO-GM (1, 1). The PSO optimized the $GM(1,1)$ parameter after the prediction equation: $a = -0.0011,\ u = 275.4176.\ -a < 0.3$ can be used for medium and long-term prediction.

The ratio of mean variance is *C =0.1552*. And for a small error probability *P = 1*.

6.4. Result

The light pollution risk level in urban communities from 2016 - 2020 was calculated through the light pollution risk level without policy intervention and the light pollution risk level formula of three strategy interventions.

Table 5. Summary Table of Light Pollution Risk Level

Year	No Intervention	Reduce DN	Reduce PD	Reduce VC
2016	281.3	278.2	275.4	275.7
2018	281.4	279.3	277.2	275.8
2020	283.1	281.1	278.2	276.3
2022	283.6	281.2	279.1	276.4
2024	284.9052	282.4365	280.1048	276.767
2026	286.0152	283.3936	281.0628	277.0678
2028	287.1294	284.3539	282.024	277.3689

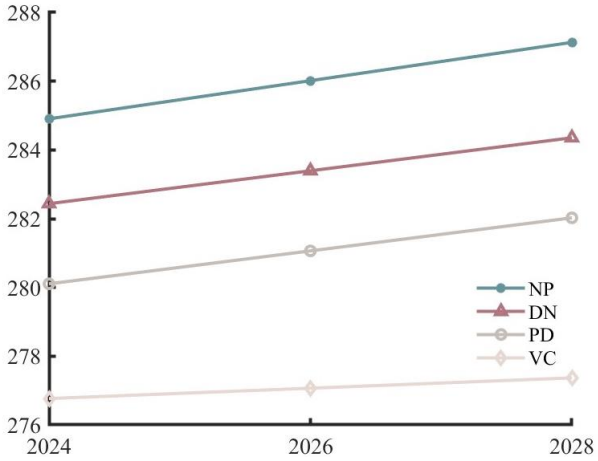


Figure 16. Comparison of predicted results

From Table 5 and Figure 16 we can know that the final conclusion is: For urban communities, night light index intervention policy, population density intervention policy and vegetation coverage intervention policy can be reduce.

7. Conclusion

For exploring how to effectively reduce global light pollution levels. This paper uses a combined weight evaluation model to calculate the weight of the core indicators of light pollution. This model combines subjective and objective methods and is scientific. A light pollution risk level evaluation system is established to measure the regional light pollution level. After taking into account the three external factors of reducing Digital Number, reducing Population Density and improving Vegetation Cover, a light pollution risk level evaluation system was established with external factors taken into account. The PSO-GM (1, 1) prediction model was used to predict the light pollution risk level evaluation system in Shanghai. The key coefficient of gray prediction was optimized by PSO algorithm. The accuracy of the model is improved, and the model has good predictability and stability. The results show that increasing vegetation coverage has the lowest predicted light pollution risk level, and planting more trees and plants should be considered to increase the green space in the city, which has practical value.

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