Problem Chosen	2023 MCM/ICM Summary Sheet	Team Control Number
E		**2306750**

Light Pollution Evaluation and Recommendation Model Based on Factor Analysis and GBDT

Summary

As human communities and lighting technologies develop, artificial light is increasingly encroaching on dark refuges in space, time, and across wavelengths, posing a great threat to human health and biological rhythms as well as the survival of local species. This article extensively collected global data and compared different algorithms to establish an optimal light pollution evaluation model, which provides targeted intervention measures for different types of regions. The study can comprehensively evaluate the level of light pollution in different regions and propose the most effective measures for light pollution prevention and control based on regional types.

For question one, after completing data collection and processing, we used both entropy weight-TOPSIS and factor analysis methods to comprehensively evaluate the level of light pollution in different regions, and through visual analysis of the evaluation results, we selected the factor analysis method which performed better in this context to establish the final evaluation model. In the factor analysis method, we synthesized the eighteen light pollution indicators into fewer factors, thereby simplifying the construction of the light pollution evaluation system.

For question two, based on the established model, we evaluated the level of light pollution in four types of regions and presented the evaluation results using visualization methods such as chord diagrams.

For questions three and four, we further constructed a Gradient Boosting Decision Tree (GBDT) regression model to find the main factors affecting the light pollution scores of the four types of regions through multiple decision tree regressions. Based on these main factors, we proposed three intervention measures for each of the four types of regions. After implementing these measures, the light pollution degree of protected land decreased by 18.4468%, rural community decreased by 18.4468%, suburban community decreased by 23.2254

For question five, we created a light pollution prevention and control poster for urban areas based on the established model and the main factors affecting urban light pollution.

Finally, we conducted a sensitivity analysis of the factor parameters obtained by the factor analysis method in the model.

The highlights of this article are: first, the extensive selection of light pollution-related indicators and global data, which makes the model universal; second, the comparison of two algorithms and the establishment of an optimal evaluation model; third, the extensive use of data visualization, which makes the model results more intuitive and clear; and finally, the innovative use of GBDT to identify the main influencing factors of various regions and propose targeted intervention measures.

Keywords: Light pollution evaluation model, Entropy weight topsis method, Factor analysis method, GBDT, Interventions

Contents

1 Introduction

1.1 Background

Light pollution refers to the pollution caused by glare on the environment. As human communities and lighting technologies develop, artificial light increasingly modifies natural light regimes by encroaching on dark refuges in space, in time, and across wavelengths.It is a phenomenon in which artificial nighttime light changes the form of brightness and darkness in natural areas such as protected land and rural community, has become a global concern due to its threat to our circadian rhythms as well as global biodiversity. With ongoing global urbanization and climate change, the light pollution status in global deserves attention for mitigation and adaptation.

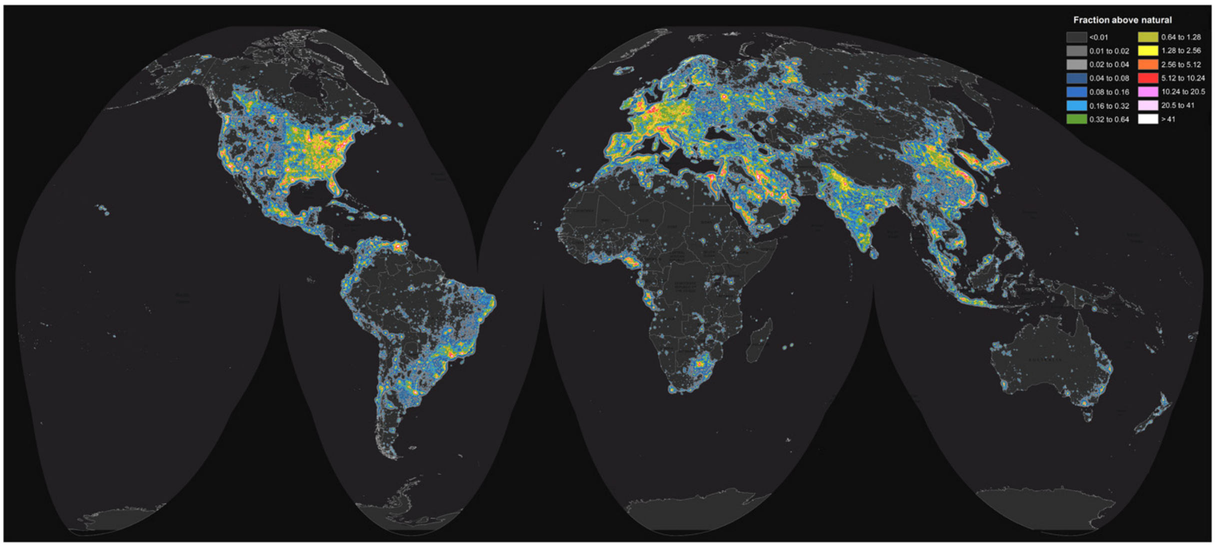


Figure 1: World map of artificial sky brightness

1.2 Restatement of the Problem

In order to address this issue, We were asked to developed a light pollution assessment model to evaluate the level of light pollution in different regions, and to propose targeted intervention policies based on the assessment results.

Strategies to address light pollution, specific actions and associated impacts are also required. To find the most effective measures to address light pollution, we were asked to weigh the effectiveness of interventions.At the same time, it is also necessary to produce leaflets to make the public aware of the dangers of light pollution and what we should do to avoid it.

1.3 Our work

We have developed a new model to assess global levels of light pollution, and based on the data we have proposed several interventions to address light pollution.Then, we apply the established model to evaluate the degree of light pollution in different locations, and put forward reasonable prevention and control suggestions. Finally, we perform a sensitivity analysis of the model.

We need the following work to solve the problem:

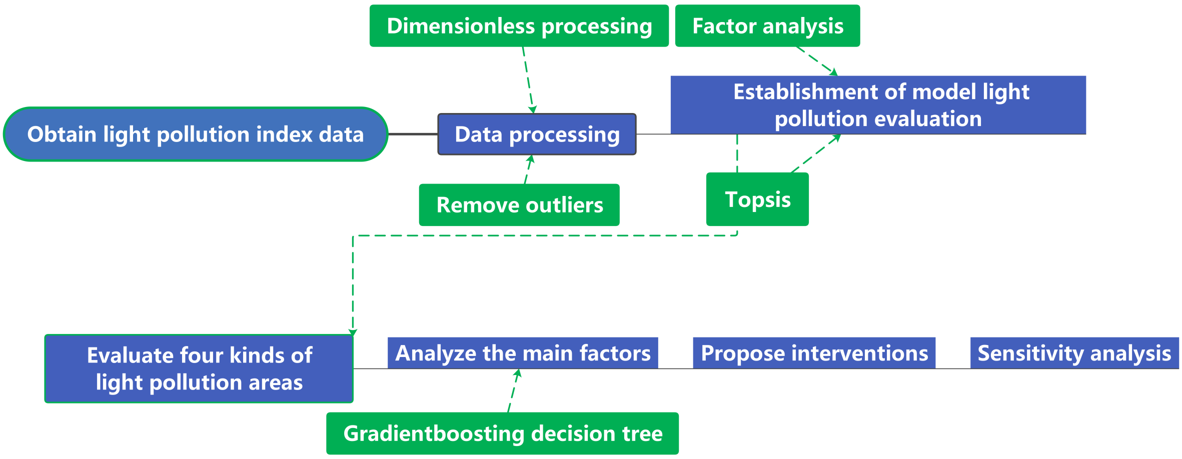


Figure 2: Mind map of our work

2 Assumptions and Justifications

The level of light pollution is influenced by many factors, and each factor has a different impact on it. In order to ensure the accuracy of the light pollution evaluation model we have established, we have to make several assumptions:

1.The level of light pollution is almost entirely related to the 18 indicators proposed in the model, and these 18 indicators are sufficient to describe the level of light pollution in a certain area.

Justification: We have conducted extensive research and selected 18 light pollution indicators based on comprehensive analysis. The range of indicators is broad enough to provide a comprehensive description of the level of light pollution in an area even in the absence of other data.

2.There are 18 indicators that can be subject to manual intervention, and each intervention can be successfully implemented.

Justification: The intervention measures we have proposed have been implemented in reality with good results, and in terms of proposing measures, we have put forward targeted recommendations for four regions, all of which are in line with the actual situation of each region. This proves the validity of this assumption.

3.There should be a certain correlation between various light pollution indicators, and no requirements are made for the correlation, so factor analysis can be used.

Justification: In the following text, we conducted a correlation analysis on the 18 indicators and visualized it through the use of a heat map of causal relationships, which proves the validity of this assumption.

4.Assuming that all indicators can be quantified reasonably, meeting the prerequisite for the use of the TOPSIS method.

Justification: Following the principle of data availability, we replaced all qualitative indicators with quantitative indicators and used the efficiency coefficient method to make the quantitative indicators dimensionless. This proves the validity of this assumption.

3 Notations

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

Symple	Description
DN value	Digital Number
GBDT	Gradient Boosting Decision Tree
Topsis	Technique for Order Preference by Similarity to Ideal Solution
KMO	Kaiser-Meyer-Olkin
UN Date	United Nations database
F1	factor weights
F2	factor weights

Figure 3: Notations used in this paper

4 Data Description

4.1 The acquisition of data and indicators

Regarding these questions, we utilized light pollution maps to capture images of global nighttime light pollution levels. The maps are created from various sources, including satellite imagery, remote sensing measurements, and data from local governments and public institutions. These sources are integrated into an interactive map that displays light pollution levels and brightness zones, as well as provides specific location data. After capturing images from different regions globally, we analyzed the map information using ArcGIS software, which enables the extraction of geometric shapes and attributes from complex map layers and the merging of different data layers through overlay analysis. Finally, we obtained radiance information from different regions globally and, after unit conversion, obtained DN values for major regions globally.

We have used UNdata to find indicators related to GDP, population, and regional development levels for major regions around the world. We have also gathered data related to biodiversity from multiple rural communities around the globe through the Biodiversity Information Network and the Global Biodiversity Information Facility. We have collected multiple indicators related to light pollution by consulting the statistical websites of various rural communities. These include metrics such as brightness partitioning, interference of light with air, sea, and land traffic, distribution of light control over time, and more.

The specific indicators are as follows.

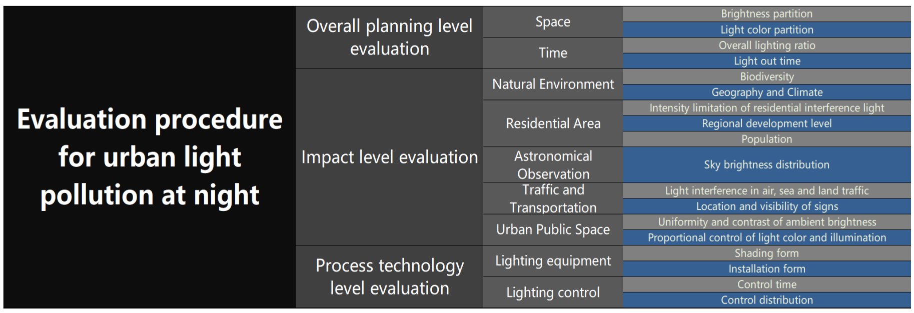


Figure 4: Eighteen indicators affecting the degree of light pollution

To facilitate the next description, we use a combination of index and ordinal to represent different impact indicators.

Index 1	Index 2	Index 3
Overall lighting ratio	*Shading form*	*Control distribution*
Index 4	Index 5	Index 6
Light out time	*Geography and Climate*	*Control time*
Index 7	Index 8	Index 9
Proportional control of light color and illumination	*Sky brightness distribution*	*Uniformity and contrast of ambient brightness*
Index 10	Index 11	Index 12
Installation form	*Population*	*Intensity limitation of residential interference light*
Index 13	Index 14	Index 15
Location and visibility of signs	*Light interference in air, sea and land traffic*	*Light color partition*
Index 16	Index 17	Index 18
Regional development level	*Biodiversity*	*Brightness partition*

Figure 5: Indicator factor comparison table

4.2 Normalization processing

Following the principle of data availability, this article attempts to replace qualitative indicators with quantitative ones and uses the efficacy coefficient method to normalize the quantitative indicators. The efficacy coefficient method is based on the principle of multi-objective programming, which determines the satisfactory and non-allowable values for each evaluation indicator, with the satisfactory value as the upper limit and the non-allowable value as the lower limit. It calculates the degree to which each indicator approaches or reaches the satisfactory value and converts it into a corresponding evaluation score. In this article, the maximum value of a certain indicator is set as the satisfactory value, and the minimum value is set as the non-allowable value. The specific operation of the efficacy coefficient method is as follows:

- Set five standard values. The evaluation levels of each indicator are divided into five levels: excellent (A), good (B), medium (C), low (D), and poor (E).
- Assign five standard coefficients to the corresponding five standard values: 1, 0.8, 0.6, 0.4, and 0.2.
- Score each indicator according to the following method:

  (1)Upper-level base score = Indicator weight x Upper-level standard coefficient;

  (2)This-level base score = Indicator weight x This-level standard coefficient;

  (3)Adjustment score = (Actual value - This-level standard value) / (Upper-level standard value - This-level standard value) x (Upper-level base score - This-level base score);

  (4)Single indicator score = This-level base score + Adjustment score.

4.3 Preliminary processing of data and indicators

After normalizing the 18 indicators, we conducted a correlation analysis and found that there is a strong correlation between the various indicators that measure light pollution. To visualize these correlations, we used a correlation heatmap. This helps us better understand the relationships between the different indicators and how they relate to overall levels of light pollution.

As can be seen from the correlation heatmap, the correlation between each indicator is above 90%,which explains the rationality of indicator selection and effectively reflects the

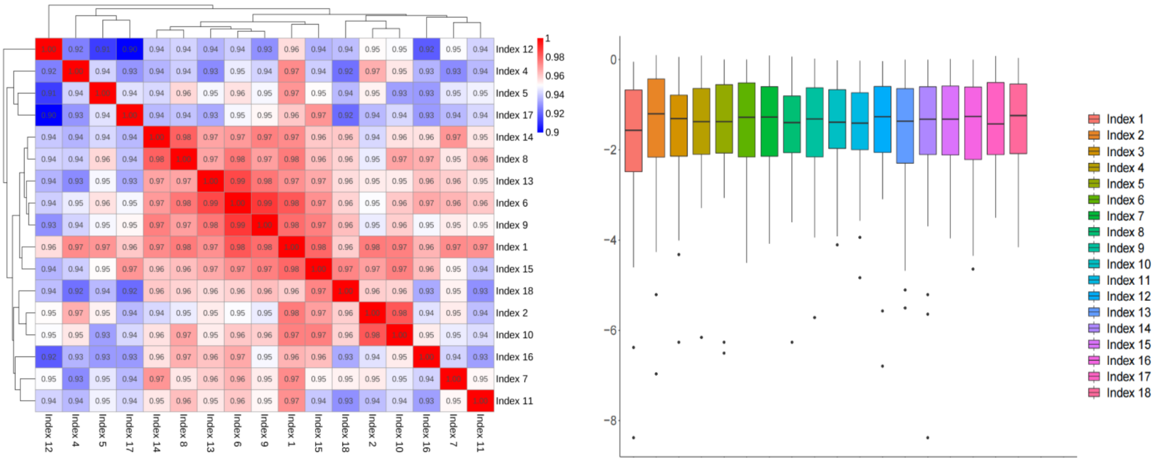


Figure 6: CorHeatmap and Boxplot

degree of light pollution from different perspectives. In summary, this method assigns standard coefficients to different levels of standard values for each indicator and calculates the scores based on the actual values of the indicators. It is a way to normalize quantitative indicators, making them dimensionless and facilitating comparison and evaluation.

5 Model I:Comprehensive Evaluation Model of Light Pollution

5.1 Entropy Topsis Method

TOPSIS is a statistical analysis method that ranks evaluation objects based on the ideal solution and negative ideal solution of multiple attribute problems. The ideal solution is a virtual optimal solution in which each indicator value reaches the optimal value among the evaluation objects, while the negative ideal solution is a virtual worst solution in which each indicator reaches the worst value among the evaluation objects.

Suppose there are m evaluation objects (light pollution evaluation degree of various regions) and n evaluation indicators (18 light pollution indicators selected in this article). The evaluation indicator matrix X composed of each influencing factor represents xij as the jth light pollution indicator value of the ith region.

Normalization of the data is necessary because each indicator usually has different dimensions and cannot be directly compared. Therefore, the indicator value matrix must be normalized and trend-consistent. There are many methods for normalization, and only commonly used standardization methods are given here.

$$y_{ij} = x_{ij} / \sum_{i=1}^{m} x_{ij} . (j = 1, 2, \cdots, n)$$

Entropy weighting, a weight allocation method based on information entropy, is used to evaluate the importance of multiple indicators in decision-making.The definition of information entropy

$$S\left(y_j\right)=-\sum_{i=1}^m y_{ij}\ln y_{ij},$$
$$0\ln 0\equiv 0.$$

where m is the number of evaluation objects

In general, in a comprehensive evaluation, the greater the variability of an indicator's value, the smaller the information entropy $S\left(y_j\right)$, and the greater the information provided by the indicator, the greater the weight of the indicator should be. Conversely, if the information provided by the indicator is smaller, the weight of the indicator should be smaller. Therefore, the weight of each indicator can be calculated using the tool of information entropy based on the variability of each indicator's value. This weight is called entropy weight.

First, solve for the output entropy:

$$S_j=S\left(y_j\right)/\ln m.$$

Second, solve for the degree of difference of the indicator:

$$G_j=1-S_j.\quad(1\leqslant j\leqslant n)$$

Finally, the entropy weight is calculated:

$$a_j=G_j/\sum_{i=1}^n G_i.\quad(j=1,2,\cdots,n)$$

Metric weight calculation:

Construct a weighted normalized matrix by considering the entropy weight of each factor, as the importance of each factor varies. Weight the normalized data to form a weighted normalized matrix:

$$\boldsymbol{V}=\left(v_{ij}\right)_{m\times n}=\left[\begin{array}{cccc} a_1y_{11} & a_2y_{12} & \cdots & a_ny_{1n}\\ a_1y_{21} & a_2y_{22} & \cdots & a_ny_{2n}\\ \cdots & \cdots & & \cdots\\ a_1y_{m1} & a_2y_{m2} & \cdots & a_ny_{mn}\end{array}\right].$$

Determine the positive ideal solution and negative ideal solution of the evaluation object. It should be noted that in this case, the positive ideal solution and negative ideal solution refer to the maximum value of light pollution level and the minimum value of light pollution index, respectively. A higher score for a region indicates a more severe level of light pollution in that region.

$$\boldsymbol{V}^+=\left\{\left(\max_i v_{ij}\mid j\in J_n\right),\right.$$

$$V^-=\left\{\left(\min_i v_{ij}\mid j\in J_n\right),\right.$$

Entropy weight method			
Index	Information entropy (e)	Information utility value(d)	weight(%)
Index17	0.926	0.074	6.961
Index18	0.944	0.056	5.291
Index 1	0.941	0.059	5.57
Index9	0.948	0.052	4.909
Index4	0.952	0.048	4.541
Index7	0.93	0.07	6.63
Index6	0.931	0.069	6.535
Index 2	0.944	0.056	5.239
Index5	0.949	0.051	4.79
Index8	0.948	0.052	4.901
Index13	0.937	0.063	5.978
Index16	0.936	0.064	6.053
Index15	0.93	0.07	6.553
Index14	0.946	0.054	5.064
Index12	0.952	0.048	4.543
Index3	0.943	0.057	5.418
Index10	0.937	0.063	5.968
Index11	0.946	0.054	5.057

Figure 7: Indicator factor comparison table

Figure 8: Wordcloud:The larger the indicator text, the greater the weight.

Calculate distance: The distance between the evaluation object and the ideal solution and the negative ideal solution is :

$$\begin{cases} d_i^+ = \left[\sum_{j=1}^n \left(v_{ij} - v_j^+\right)^2\right]^{1/2} \\ d_i^- = \left[\sum_{j=1}^n \left(v_{ij} - v_j^-\right)^2\right]^{1/2} \\ (i = 1, 2, \cdots, m) \end{cases}$$

Determine relative proximity. The relative proximity of the evaluation object to the ideal solution is :

$$C_i = \frac{d_i^-}{d_i^+ + d_i^-}. \quad (i = 1, 2, \cdots, m)$$

According to the relative proximity, the light pollution of the evaluation object can be scored.

Positive ideal solution distance(D+)	Negative ideal distance(D-)	Composite score index	Rank	Positive ideal solution distance(D+)	Negative ideal distance(D-)	Composite score index	Rank	Positive ideal solution distance(D+)	Negative ideal distance(D-)	Composite score index	Rank
0.047645457	0.967767023	0.953077732	1	0.505698422	0.495056794	0.494683202	21	0.736575159	0.264961135	0.264554701	41
0.063171402	0.964885084	0.938552596	2	0.520181196	0.482720604	0.481323898	22	0.749113959	0.263749447	0.260399819	42
0.081222978	0.926739343	0.919418637	3	0.526561704	0.480628669	0.477197442	23	0.764357187	0.240445949	0.239296575	43
0.093667112	0.933759552	0.908833287	4	0.527989198	0.479586338	0.47598053	24	0.769845271	0.23348304	0.232708513	44
0.105758544	0.924632044	0.897360724	5	0.538363015	0.468053772	0.46506952	25	0.785797959	0.216737803	0.216189598	45
0.11532659	0.901609482	0.886594061	6	0.542326543	0.463565927	0.46085038	26	0.815315231	0.193580136	0.191873352	46
0.123396308	0.90260364	0.879730688	7	0.541193319	0.460590172	0.459770176	27	0.825577336	0.18536498	0.183358612	47
0.12585505	0.887967598	0.875860881	8	0.569171463	0.451382085	0.442291427	28	0.830681567	0.177511204	0.176068714	48
0.127451199	0.893626787	0.87517976	9	0.561343726	0.438816361	0.438746123	29	0.868840572	0.175867751	0.168341486	49
0.143831058	0.903984272	0.862732435	10	0.595552172	0.408162621	0.406651993	30	0.868957212	0.152439894	0.149246452	50
0.140678262	0.877322453	0.86180927	11	0.667126566	0.33722018	0.335760713	31	0.874617386	0.152556751	0.148520825	51
0.145588254	0.8567989	0.85475846	12	0.703157969	0.323136185	0.314857279	32	0.878038593	0.151629819	0.147260824	52
0.167569062	0.85686957	0.836428404	13	0.720544688	0.288377696	0.285827434	33	0.915317444	0.132004975	0.126040437	53
0.181814638	0.838264693	0.821764217	14	0.718195012	0.287274621	0.285711882	34	0.901052416	0.128577391	0.124877301	54
0.211121494	0.799921712	0.791184498	15	0.719859903	0.281535751	0.281143372	35	0.902620413	0.110772447	0.109308494	55
0.459714295	0.557081601	0.547879474	16	0.72480846	0.275070889	0.27510408	36	0.894743904	0.106598706	0.106455777	56
0.47216614	0.531221636	0.529428052	17	0.732194456	0.274996029	0.273032791	37	0.919364877	0.109331563	0.106281658	57
0.488361753	0.514785287	0.513170319	18	0.735832419	0.272070173	0.269936971	38	0.931844818	0.097899676	0.095071813	58
0.489383543	0.514314453	0.512419527	19	0.750502785	0.273596635	0.267158275	39	0.922561682	0.095679706	0.093965642	59
0.502752422	0.503333604	0.500288833	20	0.742868933	0.268978454	0.265829074	40	0.929256607	0.085598694	0.084345713	60

Figure 9: TOPSIS evaluation method calculation results

According to the entropy weight TOPSIS evaluation model, we have obtained scores for light pollution in various regions, and have generated a discounted weighted composite graph that includes the positive ideal solution distance (D+), negative ideal solution distance (D-), overall score index, and ranking. It should be noted that the higher the overall score and ranking for light pollution, the more severe the light pollution is.

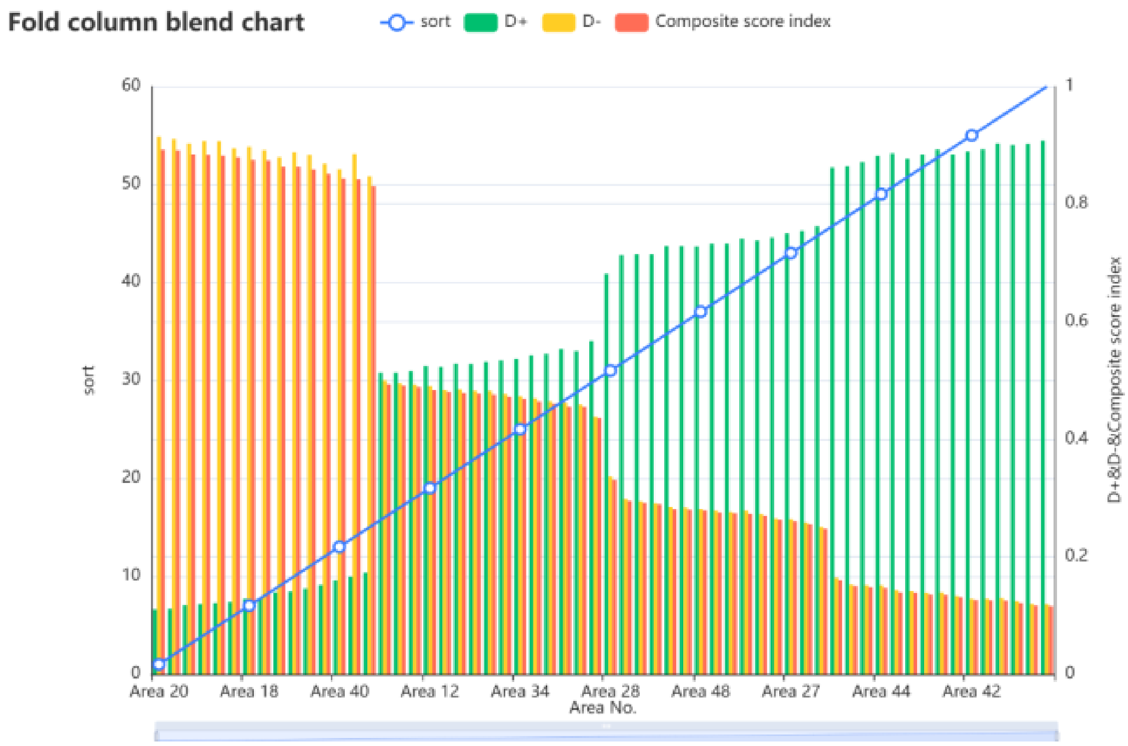


Figure 10: D+Positive ideal solution distance D-Negative ideal solution distance

In order to understand the superiority of the entropy weight TOPSIS method for the evaluation of light pollution, we made a comprehensive evaluation score and ranking of the kernel

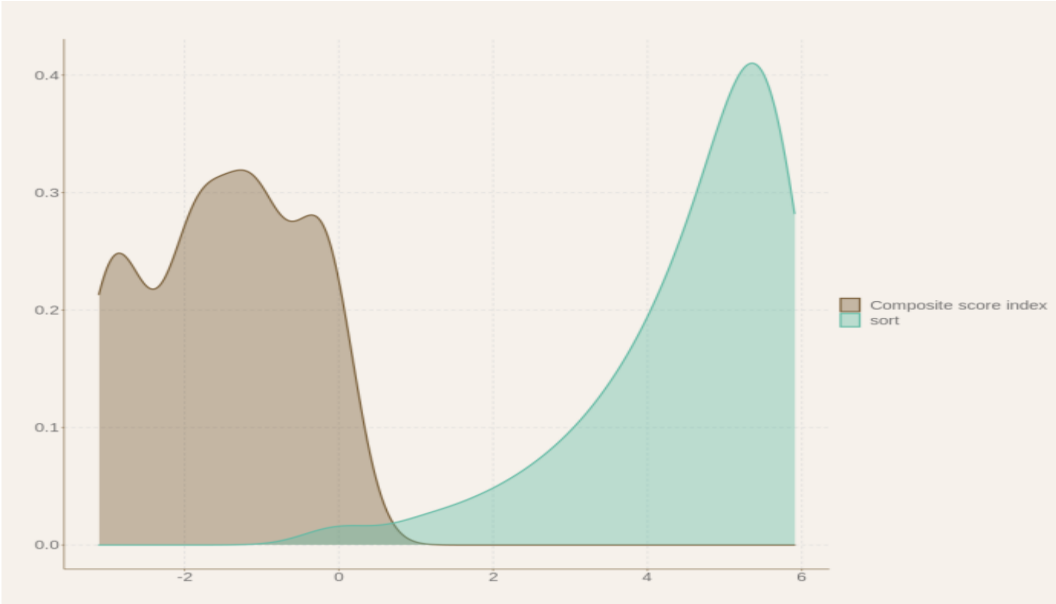


Figure 11: Density curve

density curve: As shown in the graph, the curves of the overall score index and ranking are significantly concentrated in a certain area of the chart, indicating that the evaluation results are too concentrated. In addition, the curves exhibit a "tail" phenomenon, indicating that some data deviate from the evaluation score standard. Therefore, it can be concluded that using the entropy weight TOPSIS method to evaluate the degree of light pollution is not very suitable.

The deep underlying reason for this is that too many indicators (18) were selected in this model, which may have diluted the impact of some important indicators on the evaluation. Moreover, with too many indicators, it is very likely that the line connecting the indicator values of two evaluation objects with respect to the optimal and worst-case scenarios may be symmetric, leading to inaccurate results. Considering multiple factors, the sensitivity of the entropy weight TOPSIS method is not high in this light pollution model.

5.2 Factor Analysis Method

To address the issue of having too many evaluation indices for light pollution, we have constructed a factor analysis model based on the previous work. The basic purpose of factor analysis is to use a few factors to describe the relationships between many indicators or factors, i.e., to group several variables that are closely related into the same category, with each group of variables becoming a factor. Through this approach, a small number of factors can reflect most of the information in the original data. Our analysis has shown that this method is highly suitable for constructing a light pollution evaluation model.

5.2.1 Explanation of factor analysis

1.Tag aggregation processing on raw data

Suppose there are p indicator variables for factor analysis: $\mathrm{x}_1, x_2, \cdots, x_p$

There are n evaluation subjects.The value of the jth indicator of the ith evaluation object is

x_{ij}. The value of each indicator x_{ij} is converted into the standardized indicator $\tilde{x}_{ij}$,

$$\tilde{x}_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j}, \quad (i = 1, 2, \cdots, n; \quad j = 1, 2, \cdots, p)$$

thereinto $\bar{x}_j = \frac{1}{n}\sum_{i=1}^{n} x_{ij}, s_j = \frac{1}{n-1}\sum_{i=1}^{n}(x_{ij} - \bar{x}_j)^2, (j = 1, 2, \cdots, p)$That is, $\bar{x}_j, s_j$ is the sample mean and sample standard deviation of j indicators. Correspondingly, weighed

$$\tilde{x}_i = \frac{x_i - \bar{x}_i}{s_i}, \quad (i = 1, 2, \cdots, p)$$

is a standardized metric variable.

2. Calculate the correlation number matrix R

$R = (r_{ij})_{p\times p}$

$$r_{ij} = \frac{\sum_{k=1}^{n} \tilde{x}_{ki} \cdot \tilde{x}_{kj}}{n-1}, \quad (i, j = 1, 2, \cdots, p)$$

where $r_{ii} = 1, r_{ij} = r_{ji}, r_{ij}$ is the number of correlations between the ith indicator and the j. 3. Calculate the elementary loading load matrix

Calculate the eigenvalues $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p \geq 0$ of the correlation number matrix $R$and the corresponding feature vectors

$$u_1, u_2, \cdots, u_p, \text{ and } u_j = (u_{1j}, u_{2j}, \cdots, u_{nj})^T \text{, elementary load matrix}$$
$$A = \begin{bmatrix} \sqrt{\lambda_1}u_1 & \sqrt{\lambda_2}u_2 & \cdots & \sqrt{\lambda_p}u_p \end{bmatrix}$$

$$\begin{cases} \tilde{x}_1 = b_{11}F_1 + \cdots + b_{1m}F_m \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ \tilde{x}_p = b_{p1}F_1 + \cdots + b_{pm}F_m \end{cases}$$

4. Select m $(m \leq p)$ as a principal factor to rotate the factor

According to the elementary load matrix, the contribution rate of the common factors is calculated and the m principal factors are selected. The extracted factor loading matrix is rotated to obtain matrix $B = \hat{A}T$ (where $\hat{A}$ is the first m column of A and T is the orthogonal matrix), and the factor model is constructed. 5.Calculate the factor score and conduct a comprehensive evaluation

We use the regression method to find the single factor score function

$$\hat{F}_j = b_{j1}\tilde{x}_1 + \cdots + b_{jp}\tilde{x}_p, j = 1, 2, \ldots, m$$

6.Use the comprehensive factor score formula to calculate the comprehensive score of each sample

5.2.2 Analysis steps

1. First, KMO and Bartlett tests to determine whether factor analysis can be performed.

For KMO values: 0.9 is very suitable for factor analysis, 0.7-0.9 is suitable, 0.6-0.7 is acceptable, 0.5-0.6 means poor, 0.5 should be abandoned; the KMO value test can show whether factor analysis is suitable.

For Bartlett's test, if $((p \geq 0.05))$, the null hypothesis is rejected, it means that factor analysis can be done, if the null hypothesis is not rejected, then these variables may provide some information independently and are not suitable for factor analysis.

KMO Inspection and Bartlett Inspection		
KMO Value		0.97
Bartlett bartlett sphericity test	Approximate chi-square	2549.296
	df	153
	P	0.000***
Note: ***、**、* Representing 1%, 5%, 10% significance level respectively		

Figure 12: KMO test and Bartlett's test

The results of the KMO test show that the value of KMO is 0.97, and the results of the Bartlett spherical test show that the significance P value is 0.000***, the significance is displayed at the level, the null hypothesis is rejected, the variables are related, the factor analysis is effective, and the degree is suitable.

2. Determine the number of factors by analysis. The gravel plot is plotted based on how well each principal component interprets the variation in the data. Its function is to confirm the number of factor principal components to be selected according to the slope of the decreasing feature value, and the combination of the variance explanation table can be used to confirm or adjust the number of factor principal components. It can be seen from the figure that when the

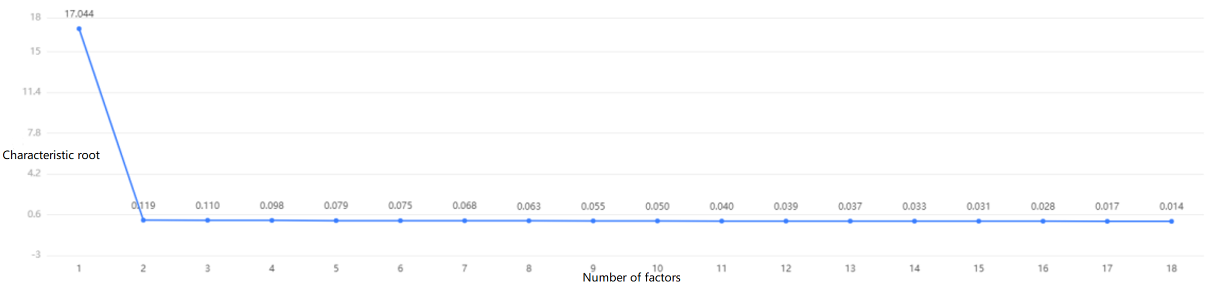


Figure 13: Gravel diagram

number of light pollution comprehensive factors is 2, most of the information is included, and the slope of the gravel plot tends to be flat, and the number of principal components of the factor continues to increase, and the change of the characteristic root is not obvious, so the principal components of the best factor are 2.

3. By analyzing the factor load coefficient and heat map, the importance of the hidden variables in each factor can be analyzed, and the factor formula can be obtained by analyzing the component matrix. Based on the factor load plot, the multifactor dimension is reduced to a double factor. The above table is a table of factor loading factors, which can analyze the importance of hidden variables in each principal component.

Table of factor load coefficient after rotation

	Factor load coefficient after rotation		Common degree (common factor variance)
	Factor 1	Factor 2	
Index 2	0.774	0.596	0.955
Index 17	0.725	0.654	0.953
Index 3	0.681	0.689	0.938
Index 1	0.543	0.827	0.979
Index 6	0.737	0.634	0.945
Index 4	0.627	0.745	0.949
Index 18	0.792	0.572	0.955
Index 5	0.686	0.689	0.946
Index 7	0.699	0.685	0.957
Index 12	0.758	0.607	0.943
Index 11	0.732	0.65	0.958
Index 13	0.698	0.682	0.953
Index 9	0.781	0.593	0.962
Index 8	0.702	0.679	0.954
Index 15	0.673	0.711	0.959
Index 10	0.737	0.636	0.947
Index 14	0.708	0.679	0.962
Index 16	0.694	0.682	0.948

Figure 14: Table of factor load factors

Assuming that n factors are determined above, the factor loading coefficients of a, b, c, and d in factor i are large, so factor i can be determined as a component (can be summarized and renamed). From this we can get the factors of the principal component. The above figure

Figure 15: Factor load matrix heat map

shows the load matrix heat map, which can analyze the importance of hidden variables in each principal component. From this, we determine the weights of each factor in the principal component, and then obtain the component matrix table.

5. By analyzing the component matrix, the factor component formula and weight are obtained. The above table is a component matrix table, which is intended to illustrate the factor

Name	Composition matrix table Component	
	Component 1	Component 2
Index 2	0.045	4.998
Index 17	0.043	5.481
Index 3	0.04	5.776
Index 1	0.032	6.933
Index 6	0.043	5.318
Index 4	0.037	6.247
Index 18	0.046	4.794
Index 5	0.04	5.775
Index 7	0.041	5.745
Index 12	0.044	5.086
Index 11	0.043	5.449
Index 13	0.041	5.722
Index 9	0.046	4.976
Index 8	0.041	5.696
Index 15	0.039	5.963
Index 10	0.043	5.333
Index 14	0.042	5.691
Index 16	0.041	5.722

Figure 16: Composition matrix table

score coefficient (principal component load) contained in each component, which is used to calculate the component score and obtain the principal component formula.

Formula of comprehensive evaluation model of light pollution: From the above you can get:

F1 = 0.04543 x index2 + 0.0425 x index17 + 0.0399 x index3 + 0.03188 x index1 + 0.04323 x index6 + 0.03679 x index4 + 0.04649 x index18 + 0.0402 x index5 + 0.04098 x index7 + 0.04447 x index12 + 0.04295 x index11 + 0.0409 x index13 + 0.0458 x index9 + 0.0411 x index8 + 0.03949 x index15 + 0.04321 x index10 + 0.04155 x index14 + 0.04072 x index16

F2 = 4.9979 x index2 + 5.4811 x index17 + 5.7762 x index3 + 6.9325 x index1 + 5.3176 x index6 + 6.24705 x index4 + 4.7935 x index18 + 5.7748 x index5 + 5.7445 x index7 + 5.0863 x index12 + 5.4494 x index11 + 5.7217 x index13 + 4.9756 x index9 + 5.6958 x index8 + 5.9629 x index15 + 5.3329 x index10 + 5.6905 x index14 + 5.7218 x index16

Figure 17: The data on which the model runs

$$F = \frac{0.505}{0.954} \times F1 + \frac{0.449}{0.954} \times F2 \tag{1}$$

The above table is the principal component weight analysis based on load coefficient and other

Name	Interpretation rate of rotation rear error (%)	Interpretation rate of cumulative variance after rotation (%)	Weight (%)
Factor 1	50.48	50.48	52.941
Factor 2	44.871	95.351	47.059

Figure 18: Factor weight analysis

information of factor analysis, and its calculation formula is: variance explanation rate/cumulative variance explanation rate after rotation.

Intelligent Analytics:

The weight calculation results of factor analysis show that the weight of factor 1 is 52.941% and the weight of factor 2 is 47.059%, and the maximum weight of the index is factor 1 (52.941%) and the minimum value is factor 2 (47.059%).

6. Output the comprehensive score of the light pollution factor analysis method in each region.

We obtain the comprehensive score of light pollution in each region according to the factor analysis method, and it needs to be pointed out here that the larger the comprehensive score of light pollution, the more serious the light pollution. Combining the comprehensive score of light pollution (modeled) and the actual light radiation value of each place (from the light pollution map and dark map of the world light pollution produced by satellite), we roughly divide the degree of light pollution in various places into four levels: Based on the above

Comprehensive score	Light pollution degree
>50	Serious
0~50	Medium
-50~0	Low
-70~-50	Slight
<-70	Null

Figure 19: Different levels of light pollution

evaluation criteria, we have arrived at the following table: See the appendix for details

6 Model II Light Pollution Evaluation Models for Four Different regions

For question two, we obtained multiple sets of data, each array including 18 light pollution indicators of protected land location, a rural community, a suburban community, and an urban community, and scored it with the comprehensive light pollution evaluation model in question 1. We visualize the content obtained from the evaluation and plot the chord diagram as follows: It

Regional type	The degree of light pollution	Comprehensive score	Index 1	Index 2	Index 3	Index 4	Index 5	Index 6	Index 7	Index 8	Index 9	Index 10	Index 11	Index 12	Index 13	Index 14	Index 15	Index 16	Index 17	Index 18
Urban community1	serious	75.44	0.922	0.934	0.816	0.863	0.966	0.928	0.894	0.996	0.898	0.92	0.784	0.905	0.922	0.996	1.009	0.997	0.957	0.975
Urban community2	serious	75.14	0.945	0.881	0.984	0.953	1	0.973	0.863	0.936	0.962	0.826	0.971	0.759	0.891	0.951	0.902	0.952	0.846	1.023
Urban community3	serious	75.02	0.946	1.01	0.947	0.978	0.979	0.965	0.926	0.799	0.963	0.872	0.902	0.869	0.945	0.816	0.937	0.807	1.056	0.905
Urban community4	serious	74.88	0.966	0.933	1.011	0.839	0.945	0.971	0.866	0.98	1.008	0.982	0.893	0.893	0.908	0.89	0.928	0.843	0.822	0.936
Urban community5	serious	65.22	0.857	1.068	0.762	0.867	0.923	0.756	0.849	0.845	0.808	0.927	0.862	0.78	0.905	0.906	0.878	0.825	0.81	0.926
Suburban community1	medium	8.78	0.529	0.5	0.423	0.511	0.604	0.516	0.456	0.49	0.619	0.489	0.463	0.467	0.574	0.58	0.496	0.561	0.506	0.494
Suburban community2	medium	8.10	0.464	0.463	0.525	0.416	0.283	0.56	0.511	0.474	0.607	0.544	0.475	0.584	0.594	0.566	0.548	0.564	0.446	0.624
Suburban community3	medium	7.88	0.546	0.601	0.495	0.571	0.512	0.46	0.511	0.447	0.461	0.481	0.431	0.631	0.546	0.436	0.533	0.54	0.339	0.646
Suburban community4	medium	7.53	0.519	0.456	0.476	0.443	0.45	0.413	0.473	0.486	0.504	0.535	0.547	0.471	0.429	0.489	0.632	0.565	0.679	0.555
Suburban community5	medium	6.80	0.588	0.47	0.285	0.614	0.441	0.496	0.441	0.51	0.514	0.508	0.539	0.435	0.528	0.532	0.523	0.623	0.538	0.416
Rural community 1	low	-24.35	0.338	0.275	0.386	0.265	0.312	0.287	0.352	0.195	0.347	0.269	0.359	0.269	0.343	0.259	0.352	0.315	0.378	0.29
Rural community 2	low	-25.85	0.331	0.217	0.277	0.371	0.326	0.321	0.391	0.268	0.302	0.268	0.276	0.221	0.322	0.297	0.282	0.414	0.319	0.183
Rural community 3	low	-25.94	0.303	0.174	0.39	0.283	0.35	0.285	0.283	0.264	0.391	0.216	0.262	0.224	0.307	0.357	0.382	0.167	0.365	0.426
Rural community 4	low	-25.99	0.302	0.287	0.441	0.22	0.291	0.232	0.473	0.251	0.215	0.296	0.298	0.355	0.233	0.321	0.26	0.281	0.292	0.375
Rural community 5	low	-26.43	0.274	0.331	0.322	0.445	0.263	0.247	0.243	0.312	0.321	0.381	0.202	0.192	0.212	0.265	0.308	0.339	0.331	0.376
Protected land 1	slight	-50.77	0.156	0.014	0.142	0.138	0.165	0.071	0.221	0.173	0.189	0.094	0.23	0.142	0.155	0.214	0.082	0.04	0.166	0.18
protected land 2	slight	-51.81	0.18	0.219	0.272	0.234	0.179	0.044	0.059	0.013	0.122	0.229	0.084	0.133	0.039	0.003	0.232	0.1	0.221	0.18
protected land 3	slight	-52.63	0.141	0.054	0.144	0.188	0.24	0.079	0.099	0.165	0.065	0.087	0.29	0.279	0.088	0.077	0.064	0.132	0.182	0.056
protected land 4	slight	-52.84	0.15	0.095	0.062	0.267	0.013	0.087	0.123	0.113	0.109	0.241	0.24	0.255	0.109	0.135	0.095	0.063	0.139	0.127
protected land 5	slight	-53.58	0.078	0.027	0.204	0.014	0.156	0.155	0.063	0.155	0.118	0.133	0.154	0.009	0.261	0.027	0.167	0.195	0.165	0.179

Figure 20: Data obtained using Model 1

can be seen from the figure and table that for the degree of light pollution, all urban communities are evaluated as serious, suburban communities are evaluated as medium, rural areas are all evaluated as low, and protected land locations are rated as slight. It can be realistic, but also proves the broad adaptability and reliability of the model.

Figure 21: Chord plot obtained after data visualization

7 Model III A Recommendation Model Based on Gradient Boosting Descition Tree

Since the main factors affecting light pollution in different regions are different, in order to propose more targeted interventions, we further construct a gradient boosting tree (GBDT) regression model to find out the main factors affecting the degree of light pollution in each region.

Gradient-boosted regression trees are another ensemble method that distinguishes from random forests, characterized by correction and reinforcement, by merging multiple decision trees to build a more powerful model. We used SPSS software to construct a gradient boosting tree (GBDT) regression model with 18 indexes as independent variables and the comprehensive score of light pollution evaluation as the dependent variable, and analyzed the indicators affecting the degree of light pollution in four regions.

Procteced land location

As can be seen from the bar chart, the main factors affecting the degree of light pollution in protected land locations are Index 17 (Biodiversity), Index 8 (Sky Brightness Discription) and Index 16 (Intensity limitation of residential interference light). In this regard, we can propose the following three targeted interventions:

1. Improve the quality of biological base layer, mainly to increase the area and proportion of

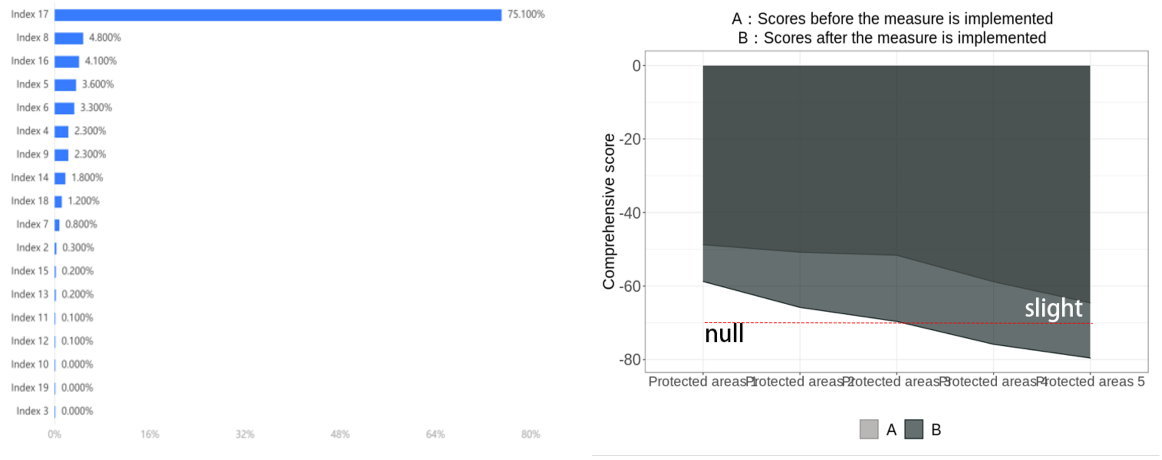


Figure 22: Procteced land location

ecological land, increase the area of green space, strengthen the connectivity of habitat patches and ecological network connection, and increase the coverage area of trees, shrubs and ground cover. The use of the policy will reduce the impact of this indicator by 18.8938%.

2. Reduce human activities in protected land locations, and formulate corresponding regulations to control the use of lights by humans in protected land locations. The use of the policy change will reduce the impact of this indicator by 8.2548%.

3. Improve the development level of protected land locations, achieve green development, and improve scientific management of protected land locations. The use of policy changes will reduce the impact of this indicator by 2.1564%.

The implementation of the above three measures can reduce the light pollution score by 16.8465%.

Rural community

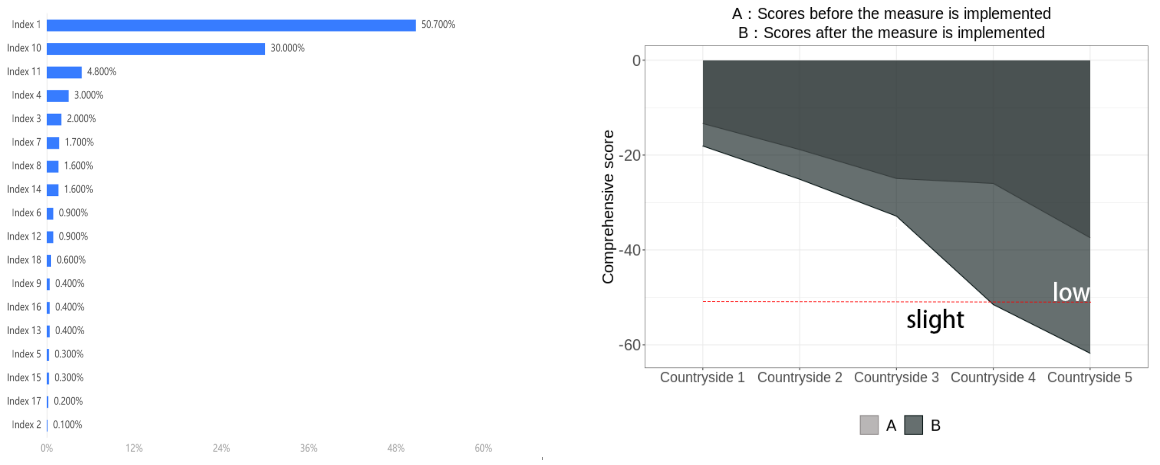


Figure 23: Rural community

As can be seen from the bar chart, the main factors affecting the degree of light pollution in rural communities are Index 1 (Overall lighting ratio), Index 10 (Installation form), Index 11 (Population) and Index 4 (Light out time) Index 1 (overall lighting ratio), Index 10 (installation form), Indicators 11 (population) and 4 (lights out).

In this regard, we can propose the following three targeted interventions:

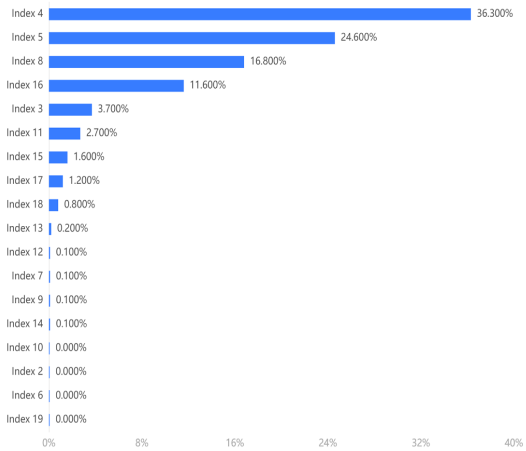
1. Control the lighting in rural areas, improve the overall lighting ratio, improve the waste utilization rate of light resources, and reduce the use of excess light resources The use change policy will reduce the impact of this indicator by 15.8761%.

2. Improve the installation form of light sources in rural areas, reduce the proportion of upper illumination, and formulate corresponding policies and regulations to standardize the installation form of light sources. The use of the policy will reduce the impact of this indicator by 9.1945%.

3. Adjust the population structure of rural areas, control regional population density, and educate and guide rural residents to control the lights out time. The use of the policy will reduce the impact of this indicator by 12.9987%.

The implementation of the above three measures can reduce the light pollution score by 18.4468%.

Suburban community



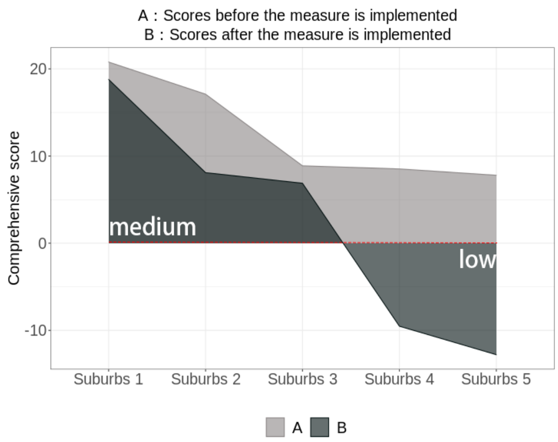


Figure 24: Suburban community

According to the bar chart, the main factors affecting the degree of light pollution in suburban communities are Index 4 (Light out time), Index 5 (Geography and Climate), Index 8 (Sky brightness distribution) and Index 16 (Regional development level)

In this regard, we can propose the following three targeted interventions:

1. Educate and guide residents in suburban communities to control the lights out time, and regularly publicize the harm and prevention of light pollution, so that residents can enhance their awareness of light pollution prevention and control, and adjust the lights out time from the small things around them. The use of the policy will reduce the impact of this indicator by 12.9987%.

2. Improve the local environment and reduce the occurrence of extreme weather in suburban communities in order to control the local climate. Using the policy change will reduce the impact of this indicator by 8.1297%.

3. Control the development trend of the region in the suburb communities, encourage a green economy, fully develop the local economy without sacrificing the environment, and reduce the risk of light pollution. The use of the policy change will reduce the impact of this indicator by 2.8556%.

4. The implementation of the above three measures can reduce the light pollution score by 23.2254%.

Urban community

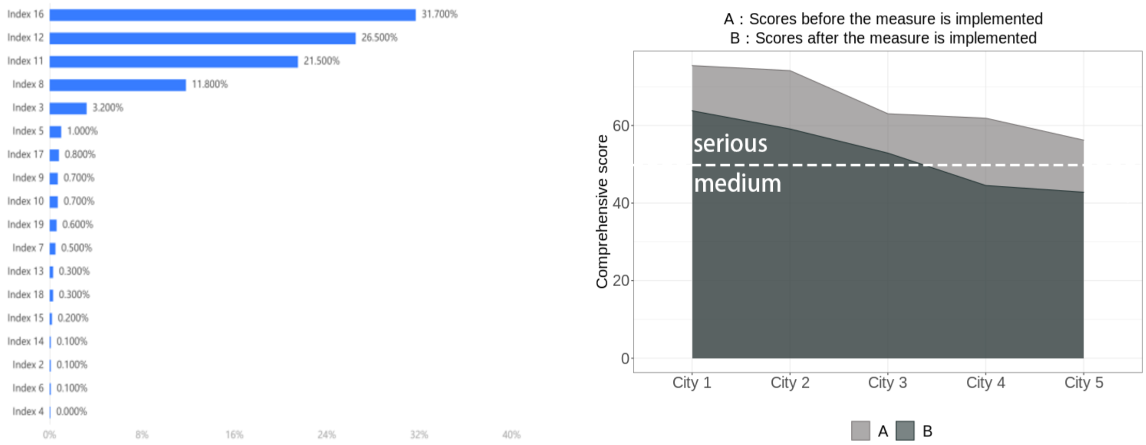


Figure 25: Urban community

As can be seen from the bar chart, the main factors affecting the degree of light pollution in urban communities are Index 16 (Regional development level), Index 12 (Intensity limitation of residential interference light), Index 11 (Population) and Index 8 (Sky brightness). distribution)

In this regard, we can propose the following three targeted interventions:

1. Control the development trend of the area in urban communities, encourage green economy, fully develop the local economy without sacrificing the environment, and reduce the risk of light pollution. The use of the policy change will reduce the impact of this indicator by 18.3697%.

2. Formulate corresponding regulations to restrict the use of residential light sources, reduce the occurrence of unreasonable and easy to cause light pollution, and the use change policy will reduce the impact of this indicator by 9.5599%.

3. Adjust the demographic structure of urban communities, control regional population density, minimize large-scale gatherings of people, in order to reduce the excessive use of light resources, and the use of reform policies will reduce the impact of this indicator by 1.1254%.

8 Sensitivity Analysis

According to sensitivity analysis, this model is sensitive to population, regional development level and biodiversity. With the increase of population, the light pollution level increases gradually, and the more population, the more sensitive the light pollution level is, but the sensitivity is low when the fluctuation range is small. The level of light pollution decreases with the increase of biodiversity, and changes greatly when the fluctuation range is small, so the government will achieve good results by controlling biodiversity to reduce light pollution.

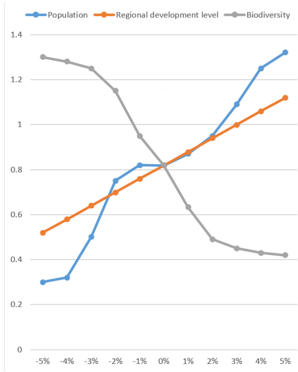


Figure 26: Chord plot obtained after data visualization

The level of light pollution will increase with the growth of regional development level, which changes approximately linearly and is relatively stable.

9 Evaluate of the Mode

9.1 Strengths

1: The establishment of the light pollution evaluation model integrates a large number of indicators and global data, and the evaluation system has strong universality.

2.In the establishment of the light pollution evaluation model, the factor analysis method was selected over the entropy weight TOPSIS method after comparison, which avoided the "concentration" and "tail dragging" phenomena in the score distribution of the entropy weight TOPSIS model and made the evaluation system more scientifically reasonable.

3.Innovative use of Gradient Boosting Decision Tree to solve the main influencing factors of various regions, using multiple decision tree regressions to make the solution of the main influencing factors more accurate.

9.2 Weaknesses

1.The scoring and estimation of some indicators were based on actual conditions, which introduced certain errors into the results.

2.When using Earth Radio Information obtained from satellites, factors such as cloud cover and altitude were not taken into account.

9.3 Model Improvement

1.Obtain more comprehensive and objective data and adopt more authoritative methods for quantification.

2.Further increase the light pollution evaluation indicators and include factors such as cloud cover and altitude in the model scope.

10 Conclusions

1.We used light pollution maps to capture images of global light pollution levels, and after obtaining data using ArcGIS, we converted the values to DN values for the main areas. We also collected extensive light pollution index data from around the world, which we processed and used to build our model.

2.After completing the data collection and processing work, we used both the entropy weight TOPSIS method and the factor analysis method to comprehensively evaluate the level of light pollution in various regions. Through visual analysis of the evaluation results, we selected the factor analysis method, which had a better evaluation effect, to establish our final evaluation model. This avoided the problem of score "concentration" and "tail dragging" in the entropy weight TOPSIS model, making the evaluation results of our model more scientifically reasonable.

3.We evaluated the degree of light pollution in four different types of areas according to the model we built and used visualizations such as chord graphs to display the results. The results showed that the light pollution level of all urban communities was rated as serious, all suburban communities were rated as medium, all rural communities were rated as low, and all protected land was rated as slight. This is consistent with the actual situation and also demonstrates the accuracy of our evaluation model.

4.Since the main factors affecting light pollution in different areas are different, we innovatively constructed a gradient boosting tree (GBDT) regression model to find the main factors affecting the light pollution scores of the four types of areas through multiple decision tree regressions. Based on these main factors, we proposed three interventions for each type of area. After the implementation of these measures, the light pollution degree of protected land decreased by 18.4468%, the light pollution degree of rural communities decreased by 18.4468%, the light pollution degree of suburban communities decreased by 23.2254%, and the light pollution degree of urban communities decreased by 21.5569%.

5.Based on the model we built and the main factors affecting urban light pollution, we created a promotional poster for light pollution prevention and control in urban areas.

6.At the end of our paper, we conducted a sensitivity analysis of the factor parameters obtained from the factor analysis method in our model, demonstrating the stability of our model. Based on the changes in sensitivity, we also proposed further rational suggestions for addressing light pollution.

References

[1] Gao Huixuan. Applied multivariate statistical analysis[M].Beijing:Peking University Press,2005.

[2] Franz Ho¨ lker1, Christian Wolter1, Elizabeth K. Perkin1,2 and Klement Tockner1,2. LettersLight pollution as a biodiversity threat. Leibniz-Institute of Freshwater Ecology and Inland Fisheries, Mu¨ ggelseedamm 310, 12587 Berlin, Germany

[3] https://data.un.org/

[4] Mizon.Light Pollution Responses and Remedies.Springer Science+Business Media New York 2012

[5] https://www.gbif.org/

[6] Bashiri*, Che Rosmani Che Hassan.Light Pollution and Its Effect on the Environment.Received Nov 2013; Published March 2014

[7] Falchi a, Pierantonio Cinzano a, Christopher D. Elvidge b, David M. Keith c, Abraham Haim d.Limiting the impact of light pollution on human health, environment and stellar visibility.https://doi.org/10.1016/j.jenvman.2011.06.029

[8] https://www.lightpollutionmap.info/

[9] Platform Serving for Statistics Professional 2021. SPSSPRO. (Version 1.0.11)[Online Application Software]. Retrieved from https://www.spsspro.com.

[10] J. Gaston, Jonathan Bennie, Thomas W. Davies, John Hopkins.The ecological impacts of nighttime light pollution: a mechanistic appraisal.First published: 08 April 2013

[11] Falchi, F.; Cinzano, P.; Duriscoe, D.; Kyba, C. C. M.; Elvidge, C. D.; Baugh, K.; Portnov, B. A.; Rybnikova, N. A.; Furgoni, R. (2016). The new world atlas of artificial night sky brightness. Science Advances, 2(6), e1600377–e1600377. doi:10.1126/sciadv.1600377

11 Appendix

Rank	The degree of light pollution	Compreh- -ensive score	Index 1	Index 2	Index 3	Index 4	Index 5	Index 6	Index 7	Index 8	Index 9	Index 10	Index 11	Index 12	Index 13	Index 14	Index 15	Index 16	Index 17	Index 18
1	serious	75.56	0.934	0.863	0.975	0.922	0.966	0.816	0.928	0.957	1.009	0.997	0.784	0.996	0.905	0.894	0.922	0.996	0.92	0.898
2	serious	75.14	0.881	0.953	1.023	0.945	1	0.984	0.973	0.846	0.902	0.952	0.971	0.951	0.759	0.863	0.891	0.936	0.826	0.962
3	serious	75.03	1.01	0.978	0.905	0.946	0.979	0.947	0.965	1.056	0.937	0.807	0.902	0.816	0.869	0.926	0.945	0.799	0.872	0.963
4	serious	74.89	0.933	0.839	0.936	0.966	0.945	1.011	0.971	0.822	0.928	0.843	0.893	0.89	0.893	0.866	0.908	0.98	0.982	1.008
5	serious	73.40	1.009	0.889	0.961	0.873	0.913	0.923	0.862	0.777	0.93	0.824	0.87	0.973	0.914	1.062	0.976	1.002	0.868	0.828
6	serious	73.37	0.85	0.918	0.924	0.758	0.992	0.917	1	0.944	0.992	0.864	0.859	0.923	0.911	0.968	0.957	0.887	0.953	0.836
7	serious	72.85	0.925	0.99	0.822	0.956	0.917	0.927	0.857	0.946	0.99	0.913	0.861	0.901	0.805	0.905	0.934	0.843	0.986	0.849
8	serious	72.38	0.863	1.061	0.92	0.845	0.778	0.919	0.983	0.857	0.862	0.971	0.932	0.959	0.976	0.821	0.841	1.046	0.807	0.87
9	serious	72.36	0.803	0.902	0.837	0.816	0.897	1.04	0.866	0.895	0.99	0.882	0.975	0.935	0.847	0.935	0.974	0.93	0.843	0.939
10	serious	71.23	0.843	0.927	0.916	0.887	0.728	0.875	0.752	0.922	0.993	0.839	0.959	0.952	0.969	0.89	0.795	1.018	0.959	0.956
11	serious	70.08	0.901	0.831	0.85	0.932	0.857	0.928	0.909	0.939	1.008	0.762	0.928	0.878	0.926	0.959	0.909	0.866	0.774	0.907
12	serious	68.81	1.009	0.726	0.991	0.617	0.906	0.834	0.987	1.006	0.774	0.971	0.982	0.901	0.93	0.911	0.921	0.712	0.873	1.015
13	serious	68.74	0.935	0.935	0.927	0.924	0.926	0.822	0.791	0.913	0.863	0.827	0.768	0.905	0.953	0.958	0.997	0.83	0.887	0.744
14	serious	68.01	0.825	1.004	0.881	0.801	0.94	0.894	0.838	0.861	0.781	0.876	0.859	0.931	0.915	0.844	0.936	0.9	0.759	1
15	serious	65.22	1.068	0.867	0.926	0.857	0.923	0.762	0.756	0.81	0.878	0.825	0.862	0.906	0.78	0.849	0.905	0.845	0.927	0.808
16	medium	8.79	0.5	0.511	0.494	0.529	0.604	0.423	0.516	0.506	0.496	0.561	0.463	0.58	0.467	0.456	0.574	0.49	0.489	0.619
17	medium	8.10	0.463	0.416	0.624	0.464	0.283	0.525	0.56	0.446	0.548	0.564	0.475	0.566	0.584	0.511	0.594	0.474	0.544	0.607
18	medium	7.88	0.601	0.571	0.646	0.546	0.512	0.495	0.46	0.339	0.533	0.54	0.431	0.436	0.631	0.511	0.546	0.447	0.481	0.461
19	medium	7.53	0.456	0.443	0.555	0.519	0.45	0.476	0.413	0.679	0.632	0.565	0.547	0.489	0.471	0.473	0.429	0.486	0.535	0.504
20	medium	6.80	0.47	0.614	0.416	0.588	0.441	0.285	0.496	0.538	0.523	0.623	0.539	0.532	0.435	0.441	0.528	0.51	0.508	0.514
21	medium	6.66	0.481	0.501	0.517	0.5	0.583	0.528	0.576	0.472	0.542	0.453	0.443	0.55	0.404	0.612	0.449	0.489	0.515	0.411
22	medium	6.27	0.5	0.378	0.581	0.453	0.537	0.507	0.492	0.441	0.47	0.522	0.523	0.548	0.541	0.385	0.55	0.506	0.592	0.512
23	medium	5.43	0.492	0.589	0.554	0.389	0.474	0.38	0.682	0.465	0.526	0.422	0.425	0.612	0.429	0.498	0.498	0.386	0.546	0.58
24	medium	5.38	0.47	0.494	0.377	0.491	0.635	0.464	0.552	0.494	0.431	0.46	0.473	0.53	0.5	0.448	0.585	0.516	0.457	0.513
25	medium	5.26	0.684	0.416	0.515	0.455	0.507	0.521	0.583	0.542	0.419	0.526	0.501	0.481	0.451	0.403	0.376	0.53	0.478	0.555
26	medium	4.49	0.525	0.477	0.446	0.583	0.423	0.427	0.535	0.467	0.559	0.419	0.477	0.591	0.53	0.477	0.5	0.51	0.312	0.533
27	medium	3.66	0.488	0.515	0.636	0.336	0.554	0.494	0.481	0.433	0.502	0.477	0.47	0.414	0.55	0.423	0.526	0.487	0.448	0.528
28	medium	3.22	0.367	0.548	0.451	0.658	0.401	0.519	0.535	0.328	0.513	0.492	0.449	0.506	0.403	0.512	0.497	0.492	0.518	0.388
29	medium	2.65	0.571	0.392	0.529	0.56	0.46	0.408	0.48	0.449	0.556	0.434	0.553	0.414	0.453	0.545	0.366	0.512	0.416	0.504
30	medium	-0.14	0.466	0.494	0.422	0.47	0.53	0.483	0.413	0.46	0.548	0.53	0.359	0.443	0.427	0.455	0.411	0.413	0.467	0.473
31	low	-17.64	0.434	0.295	0.196	0.266	0.362	0.402	0.304	0.427	0.285	0.29	0.391	0.376	0.483	0.45	0.379	0.368	0.208	0.467
32	low	-23.50	0.288	0.274	0.371	0.264	0.385	0.321	0.145	0.342	0.3	0.289	0.339	0.331	0.335	0.349	0.353	0.334	0.331	0.359
33	low	-23.79	0.331	0.231	0.441	0.265	0.33	0.297	0.41	0.303	0.297	0.35	0.28	0.361	0.289	0.228	0.197	0.373	0.382	0.347
34	low	-24.36	0.275	0.265	0.29	0.338	0.312	0.386	0.287	0.378	0.352	0.315	0.359	0.259	0.269	0.352	0.343	0.195	0.269	0.347
35	low	-25.85	0.217	0.371	0.183	0.331	0.326	0.277	0.321	0.319	0.282	0.414	0.276	0.297	0.221	0.391	0.322	0.268	0.268	0.302
36	low	-25.94	0.174	0.283	0.426	0.303	0.35	0.39	0.285	0.365	0.382	0.167	0.262	0.357	0.224	0.283	0.307	0.264	0.216	0.391
37	low	-26.00	0.287	0.22	0.375	0.302	0.291	0.441	0.232	0.292	0.26	0.281	0.298	0.321	0.355	0.473	0.233	0.251	0.296	0.215
38	low	-26.43	0.331	0.445	0.376	0.274	0.263	0.322	0.247	0.331	0.308	0.339	0.202	0.265	0.192	0.243	0.212	0.312	0.381	0.321
39	low	-26.62	0.249	0.311	0.399	0.322	0.312	0.125	0.223	0.318	0.339	0.323	0.29	0.32	0.243	0.328	0.396	0.362	0.248	0.225
40	low	-27.08	0.284	0.331	0.319	0.257	0.289	0.34	0.225	0.265	0.088	0.307	0.362	0.207	0.382	0.286	0.433	0.272	0.346	0.323
41	low	-27.16	0.312	0.376	0.347	0.163	0.298	0.405	0.224	0.237	0.36	0.261	0.3	0.198	0.309	0.268	0.298	0.286	0.313	0.363
42	low	-28.50	0.257	0.207	0.423	0.304	0.274	0.24	0.228	0.263	0.319	0.237	0.341	0.301	0.315	0.332	0.209	0.269	0.306	0.338
43	low	-29.59	0.355	0.258	0.292	0.127	0.217	0.359	0.308	0.344	0.251	0.127	0.276	0.261	0.429	0.284	0.279	0.276	0.308	0.344
44	low	-29.85	0.29	0.349	0.292	0.149	0.321	0.283	0.306	0.233	0.286	0.335	0.299	0.386	0.282	0.268	0.129	0.205	0.319	0.283
45	low	-31.53	0.41	0.205	0.218	0.196	0.225	0.194	0.231	0.285	0.293	0.139	0.253	0.345	0.285	0.364	0.286	0.33	0.266	0.331
46	slight	-46.66	0.227	0.282	0.238	0.092	0.235	0.062	0.181	0.088	0.109	0.049	0.175	0.236	0.131	0.181	0.205	0.203	0.31	0.152
47	slight	-48.14	0.195	0.157	0.164	0.176	0.203	0.176	0.321	0.229	0.214	0.184	0.178	0.184	0.117	0.123	0.09	0.093	0.066	0.098
48	slight	-48.87	0.087	0.241	0.089	0.335	0.129	0.229	0.053	0.142	0.1	0.253	0.161	0.23	0.193	0.086	0.108	0.132	0.117	0.12
49	slight	-49.56	0.193	0.129	0.302	0.041	0.011	0.063	0.21	0.212	0.191	0.241	0.225	0.107	0.168	0.125	0.022	0.256	0.257	0.101
50	slight	-50.20	0.008	0.176	0.212	0.144	0.127	0.219	0.117	0.111	0.198	0.12	0.189	0.233	0.277	0.106	0.122	0.204	0.128	0.019
51	slight	-50.29	0.073	0.215	0.184	0.138	0.139	0.05	0.288	0.129	0.202	0.113	0.144	0.02	0.021	0.204	0.181	0.198	0.204	0.221
52	slight	-50.68	0.11	0.224	0.329	0.012	0.119	0.013	0.073	0.096	0.155	0.222	0.242	0.206	0.173	0.117	0.116	0.143	0.142	0.233
53	slight	-50.96	0.162	0.208	0.228	0.059	0.169	0.094	0.131	0.15	0.125	0.126	0.035	0.139	0.199	0.083	0.174	0.143	0.265	0.202
54	slight	-51.58	0.184	0.102	0.101	0.179	0.23	0.127	0.14	0.174	0.101	0.117	0.119	0.1	0.23	0.121	0.199	0.082	0.092	0.2
55	slight	-51.78	-0.014	0.138	0.18	0.156	0.165	0.142	0.071	0.166	0.082	0.04	0.23	0.214	0.142	0.221	0.155	0.173	0.094	0.189
56	slight	-51.81	0.219	0.234	0.18	0.18	0.179	0.272	0.044	0.221	0.232	0.1	0.084	0.003	0.133	0.059	0.039	0.013	0.229	0.122
57	slight	-52.64	0.054	0.188	0.056	0.141	0.24	0.144	0.079	0.182	0.064	0.132	0.29	0.077	0.279	0.099	0.088	0.165	0.087	0.065
58	slight	-52.85	0.095	0.267	0.127	0.15	0.013	0.062	0.087	0.139	0.095	0.063	0.24	0.135	0.255	0.123	0.109	0.113	0.241	0.109
59	slight	-54.59	0.027	0.014	0.179	0.078	0.156	0.204	0.155	0.165	0.167	0.195	0.154	0.027	0.009	0.063	0.261	0.155	0.133	0.118
60	slight	-54.62	0.052	0.176	0.165	0.003	-0.008	0.108	0.118	0.135	0.226	0.134	0.065	0.135	0.202	0.189	0.029	0.274	0.058	0.205

Figure 27: Comprehensive evaluation index by region