A Study on the Severity of Global Light Pollution Based on Comprehensive Evaluation

Jinping Kuang [#, *], Lijun Ren [#], Qian Wu [#]

School of Economics and Management, Beijing University of Chemical Technology, Beijing 100029, China

* Corresponding Author Email: kuangjinping2023@163.com

[#]These authors contributed equally.

Abstract. The widespread use of artificial light at night has improved the quality of human life, but it has also brought about a global light pollution problem with profound and complex ecological, human and economic impacts. To measure the severity of light pollution, a new light pollution risk index was developed in this paper. Three main aspects of light pollution impacts were considered: economic level (EL_1), ecological level (EL_2) and social level (SL), and six tertiary levels were identified under the secondary evaluation indicators. Then, the light pollution risk indices of these four areas were derived from the model using the Tuvaijuituq Marine Reserve in Canada (protected area), Homer City in USA (rural area), Pinggu District in Beijing (suburban area), and Manhattan City in USA (urban area), and the results were compared with the Bortle dark sky scale to test the accuracy of the model and further demonstrate the generality and validity of the LPRI index.

Keywords: Comprehensive Evaluation, Light Pollution Risk Index, Bortle Dark Sky Scale.

1. Introduction

The widespread use of artificial lighting at night has improved the quality of human life and is positively associated with security, wealth and modernization. However, while artificial light lights up the world, it also dims the starlight, with some negative consequences. The rapid increase in global artificial lighting over the last six decades has revolutionized the starlight of the night sky, both in terms of quantity (6% increase per year, range: 0-20%) and quality (i.e., color spectrum); it has even triggered serious light pollution problems, which are reported to cause environmental changes by altering the circadian rhythms of organisms such as birds, and to the environment, human health, and ecology, with negative effects.

Considering that the current global light pollution is gradually deteriorating, it is urgent to raise the awareness of the environment for this reason. However, neither the access to light data such as VIRSS nor the Bolt dark sky light classification can be used as a broad quantitative indicator of light pollution risk levels around the world. In order to utilize the data available to people to effectively identify the level of light pollution impacts around the globe, this thesis expected to develop a light pollution risk evaluation model with broad applicability to improve people's awareness of light pollution.

The existing literature has studied the light pollution problem mainly through threshold, experimental and machine learning methods. The effects of light pollution on organisms such as mice [1-2] and dung beetles [3] and on human diseases such as breast cancer [4], colorectal cancer [5], and thyroid cancer [6] are described by delineating light pollution risk thresholds. Experimental measurements are designed to obtain the interference light limit criteria [7] and the distribution of light pollution in cities [8]. Real-time light pollution assessment and path selection can be achieved by extracting curtain walls through deep learning identification [9], and ship signal light identification model can be constructed by neural network to manage maritime light pollution [10].

In contrast to the approach of the existing literature, this paper determined the relationship between environmental, economic, and social influences on light pollution risk levels based on available literature and data, respectively, and define a new Light Pollution Risk Index: LPRI, which

scientifically explains the light pollution risk levels at any location in the world with wide applicability.

Then, this paper applyed the model to four widely different locations to measure their respective light pollution risk levels. First, this paper identified Tuvaijuituq Marine Reserve, Canada (protected area), Homer City, USA (rural area), Pinggu District, Beijing (suburban area), and Manhattan City, USA (urban area) as the study subjects based on authoritative definitions with high credibility. After continuous optimization and improvement of our model, the light pollution risk levels of the above four regions were calculated. At the same time, this paper compared the results with the Bortle Dark-Sky Scale and found that the results were accurate, further demonstrating the generalizability and scientific validity of LPRI index.

2. Index model of global light pollution risk level

2.1. Overview

In order to better assess the complex effects that light pollution everywhere may have on human and non-human aspects, such as human sleep levels, ecological quality, etc., this section combines several relevant indicators to create a comprehensive measure of light pollution impact levels: the Light Pollution Risk Indication (LPRI). As shown in Figure 1, the LPRI reveals which events and factors are affecting the level of light pollution in each region and exacerbating the damage to our living environment. According to our design, the higher the LPRI score an area receives, the higher the level of light pollution it currently suffers from, and at the same time, the worse the negative impact of light pollution on the local area. Three secondary indicators with an upper limit of 100 are introduced in the model, namely, ecosystem level (EL1), economic level (EL2), and social level (SL).

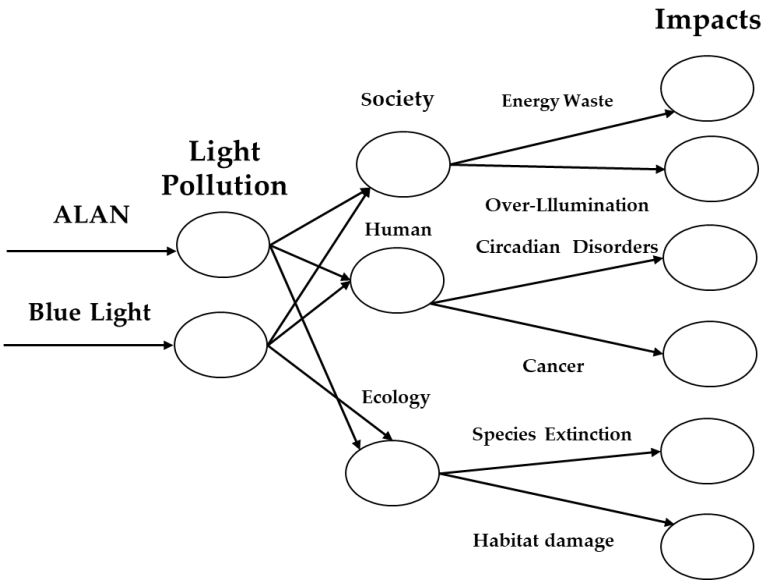


Figure 1. Risk impact pathways of common light pollution on cities, ecology, and humans

LPRI is the average of these three indicators which highest value is 100, and is expressed as:

$$LPRI = \frac{EL_1+EL_2+SL}{3} \quad (1)$$

Although factors related to light pollution were not included in our indicator system, drawing on a large body of literature, this paper argued that the state of environmental, social, and economic factors in a locality can reflect the level of light pollution, as well as the complex impact of light pollution locally.

The basic parameters mentioned in this model are as follows, as shown in Table 1.

Table 1. Values of relevant parameters in the LPRI index model

Parameter	Value
α_1	0.2393
α_2	0.0976
ω_1	0.849
ω_2	0.799
ω_3	0.3174
β_0	9.565
β_1	2.852
β_2	-2.387
γ	0.798%

2.2. Economy, Ecology, Society Levels

2.2.1 Economy Level

In economic terms, from a macro perspective, light pollution affects local economic development through gross domestic product (GDP) and regional population density. According to Keynes' law: demand creates supply. The more densely populated a place is, the stronger the demand is, the more developed the industry is, the higher the GDP is, and the more serious the corresponding light pollution level is; on the other hand, the excessive use of artificial light and the abnormal intrusion of light waves will also affect the local population size and industrial layout. For this reason, the economic level (EL1) is expressed by the following equation.

$$EL_1 = \alpha_1 GDP + \alpha_2 Number \tag{2}$$

Where GDP denotes the gross regional product and Number denotes the regional population. α_1, α_2 denote the coefficients describing the effects of GDP and population size light pollution, respectively.

2.2.2 Ecology Level

The impact of light pollution may be related to the local ecological condition. Usually, the higher the level of light pollution, the worse the local ecological environment suffers, while energy consumption tends to reflect the light use status and light pollution level of a place from the side. Whereas carbon emissions and energy consumption cut across the entire ecosystem, with both humans and non-humans as resource owners and carbon dioxide emitters, the above factors were considered to express the environmental quality of the region. Here EL_2 was defined as the combined score of carbon emission and energy consumption levels, expressed as.

$$EL_2 = \omega_1 \log C + \omega_2 \log Power \tag{3}$$

where C denotes the amount of CO_2 emitted from the luminaire and Power denotes the amount of electricity consumed by the luminaire. ω_1, ω_2 denote the coefficients describing the amount of CO_2 escaping from the luminaire and the amount of electricity consumed, respectively.

2.2.3 Society Level

On the social side, the effects of light pollution were divided on the social level into positive and negative components. Light pollution causes physiological and psychological burdens on people by directly affecting their sleep quality, which in turn indirectly causes them to become ill. At the same time, light at night brings a lot of convenience to people's production and manufacturing, and positively improves the quality of life in the region.

$$SL = Dependence - Improvement \tag{4}$$

Where Dependence indicates how much people depend on nighttime lights, i.e., the lights necessary to develop manufacturing.

$$Dependence = f_{de}(g_{de}(GDPRate)) \quad (5)$$

GDP Rate is the regional GDP growth rate. The national manufacturing level was expressed by the Fourier approximation equation, which is

$$g_{de}^{-1}(x) = \beta_0 + \beta_1 \cos \omega x + \beta_2 \sin \omega x \quad (6)$$

$f_{de}(x)$ converts the manufacturing level to the degree of light pollution.

Improvement indicates the degree of improvement in people's quality of life after improving light pollution, as expressed by sleep quality.

$$Improvement = \gamma Sleep \quad (7)$$

Where γ indicates the extent to which light pollution affects sleep quality.

3. Applications of light pollution in locations

3.1. Case Studies: Four different locations

In this section, data from four areas that meet the definition and are representative of the area was raised, namely the Tuvaijuituq Marine Reserve in Canada (protected area), Homer, Alaska, USA (rural area), Pinggu District in Beijing, China (suburban area), and Manhattan, USA (urban area), and bring their data into LPRI to measure their light pollution levels.

The majority of the world's protected area locations based on publicly available data on the World Database of Protected Areas (WDPA) and it is one of the data source. And the Tuvaijuituq Marine Reserve in Canada, located in the Arctic, is the first local marine reserve to be designated for interim protection by ministerial order under the Law of the Sea. Under the order, no new or additional human activities are allowed to occur in the area for five years, while the Inuit Association of Chiquiketani, the Government of Nunavut and the Government of Canada, in collaboration with Inuit and northern partners, are also exploring the feasibility of long-term protection for the area. In summary, the Tuvaijuituq Marine Reserve benefits from local government and legal support and was protected from a variety of human activities for extended periods of time, which fits the definition of a protected area in the title. For this reason, the Tuvaijuituq Marine Reserve in Canada was selected as one of the study areas.

The U.S. Department of Agriculture Economic Research Service developed zip code level Frontier and Remote Area (FRA) codes for related studies to be conducted. FRA areas are defined in relation to the time it takes to reach the edge of a nearby urban area (UA) by car, and this set of codes provides four FRA definition levels, with FRA levels one through four gradually indicating the more remote the area, and FRA level IV being used to describe an area is small in population and remote in location. Because rural areas have lower population levels and are more remote, access to different types of goods and services is difficult, and FRA Level IV residents have extreme difficulty accessing either basic necessities or advanced services, so FRA Level IV code Region is closer to Rural. Therefore, the extremely remote city with very small population: Homer was discovered, Alaska (USA) as the study object representing rural areas.

Suburbs usually refer to the outer and peripheral areas of urban centers. Most countries do not have a clear distinction between urban and suburban areas, while China has a clearer delineation between the central and suburban boundaries of cities, making it easy to distinguish where the suburbs are located. As one of the suburbs of Beijing, Pinggu District is at the junction of Beijing, Tianjin, and Hebei, with well-connected roads and obvious location transportation advantages, and the commuting time to downtown Beijing is less than one hour; meanwhile, the population density is 481 people/km2, which is slightly lower than the average population density of Beijing. In summary, Pinggu District in Beijing, China, basically meets the definition of suburban area in the title, and it was designated as a representative of suburban communities.

An urban area was defined as a permanent, densely populated place with administratively defined boundaries and extensive systems of housing, transportation, sanitation, utilities, land use, goods production, and communications, whose members are primarily engaged in non-agricultural work. Manhattan, located in the heart of New York City, USA, is the smallest of the five boroughs of New York City and the most densely populated, with a population density of 28, 154 people/km2 that far exceeds the global average of 60.7 people/km2. Manhattan was described as the economic and cultural center of the entire United States, housing the headquarters of most of the Fortune 500 companies, a large number of high schools and universities, and one of the most expensive areas in the world. Based on the administrative divisions of the United States and the associated characteristics of Manhattan, which was used as a representative of urban communities.

In summary, the above four different regions have typical characteristics of protected areas, rural areas, suburban areas, and urban areas, respectively. Applying the above regional data to the LPRI model not only allows us to accurately measure local light pollution levels, but also demonstrates the broadness of our model.

3.2. Results

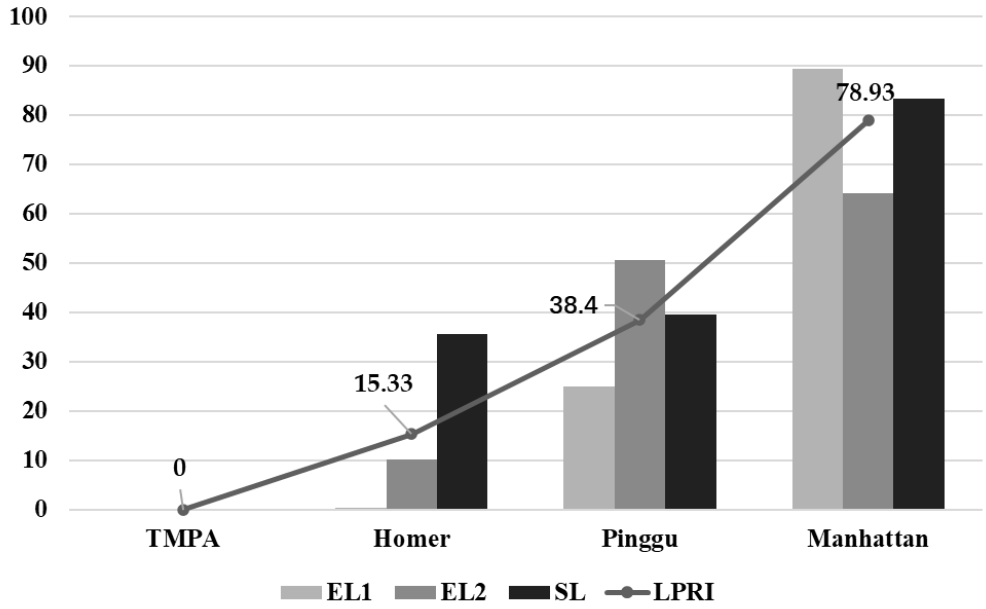


Figure 2. Numerical comparisons of the light pollution indexes of the four typical locations

As shown in Figure 2, the LPRI scores of MPA, Homer, Pinggu, and Manhattan are 0, 15.33, 38.4 and 78.93, respectively, indicating that different regions suffer from different levels of light pollution risk due to their variability. In general, urban areas have the most severe level of light pollution risk, followed by suburban and rural areas, while protected areas have the lowest level of light pollution risk. This may be mainly due to the fact that large cities have the largest population and the most developed nighttime economy, with excessive lighting at night and the highest level of light pollution, as well as the most drastic level of comprehensive negative impacts; in contrast, more remote areas have a lower level of light pollution risk due to their small population and lower market potential, but instead have less light use at night.

In order to verify the authenticity of the results, the light pollution levels of the above four regions were analyzed by combining the more common Bortle Dark-Sky Scale, and the results were shown in Figure 3.

As shown below, the MPA corresponds to Class 1, almost no light pollution, Homer corresponds to Class 4, Pinggu corresponds to Class5, and Manhattan corresponds to Class8-9, proving that the local pollution was extremely serious, which was almost the same as our LPRI score, which proves the accuracy of the model and calculation results from the side.

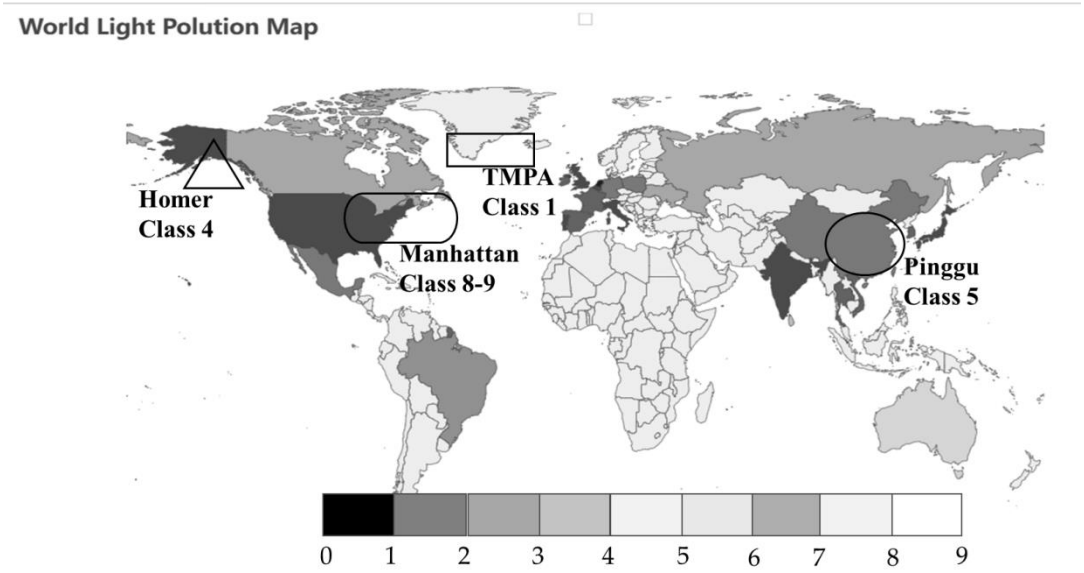


Figure 3. Pollution levels of four locations under the Boldt dark sky classification

4. Conclusions

While people stay up all night, the balance of the galaxy has been broken. The widespread use of artificial light at night has improved the quality of human life, but it has also brought about a global light pollution problem with profound and complex impacts on the ecology, human beings and economy.

In order to make more people understand the level of light pollution risk they are facing, after rigorous data cleaning and testing of multiple models, models based on Light Pollution Risk Index (LPRI) were developed to quantify the impacts of light pollution. Firstly, 3 main respects of light pollution impacts were considered: Economic Level (EL_1), Ecological Level (EL_2) and Social Level (SL), respectively. Secondly, considering the generalizability and applicability of the model, 6 three-level evaluation indicators were identified among complex factors with relevant parameters obtained from authoritative literature.

Then, the LPRI model was applied to 4 different locations. Based on the scientific definitions on the official website, Tuvaijuituq Marine Protected Area (TMPA), Homer, Pinggu, and Manhattan were assumed as study subjects, and obtained LPRI values of 0.00, 15.33, 38.40, and 78.93, respectively. In addition, the LPRI model was considered valid compared with Bortle Dark-Sky Scale.

References

[1] Walker W H, Borniger J C, Gaudier-diaz M M, et al. Acute exposure to low-level light at night is sufficient to induce neurological changes and depressive-like behavior [J]. Molecular Psychiatry, 2020, 25(5): 1080-1093.

[2] Ma Qianwen, Tan Yong. Effect of light pollution on MicroRNA in rat ovaries and the sequential intervention effect of nourishing Yin and tonifying Yang formula [J]. World Science and Technology - Modernization of Chinese Medicine, 2019, 21(11): 2499-2507.

[3] Foster J J, Tocco C, Smolka J, et al. Light pollution forces a change in dung beetle orientation behavior [J]. Current Biology, 2021, 31(17): 3935.

[4] Lamphar H, Kocifaj M, Limon-romero J, et al. Light pollution as a factor in breast and prostate cancer [J]. Science of the Total Environment, 2022, 806: 150918.

[5] Garcia-saenz A, De Miguel a S, Espinosa A, et al. Association Between Outdoor Light-at-night Exposure and Colorectal Cancer in Spain [J]. Epidemiology, 2020, 31(5): 718-727.

[6] Zhang D, Jones R R, James P, et al. Associations between artificial light at night and risk for thyroid cancer: A large US cohort study [J]. Cancer, 2021, 127(9): 1448-1458.

[7] Hao Ying, Zhang Peng, Gao Feng et al. Analysis of light pollution management policies and interference light limitation standards for LED advertising screens [J]. China Environmental Monitoring, 2022, 38(03): 199-206.

[8] Li Jiayi, Xu Yongming, Cui Weiping et al. Nighttime light pollution monitoring in Nanjing based on Liaojia-1 nighttime light remote sensing data [J]. Remote Sensing of Natural Resources, 2022, 34(02): 289-295.

[9] Ying Shen, Tang Mal, Zhang Xin Yue et al. Light pollution analysis of glass curtain walls in three-dimensional cities [J]. Journal of Wuhan University (Information Science Edition), 2021, 46(05): 610-619.

[10] Liu Na. Application of BP neural network in the management of maritime light pollution [J]. Ship Science and Technology, 2016, 38(18): 163-165.