Assessing Light Pollution Using POI and Luojia1-01 Night-Time Imagery From a Quantitative Perspective at City Scale

Fei Zhao, Chen Chu, Rui Liu, Zhiyan Peng, Qingyun Du, Zhiqiang Xie, Zhengbao Sun, Hongyun Zeng, and Jisheng Xia

***Abstract*—In previous studies using night-time light (NTL) image in analyzing light pollution, most of the researchers focused on national or regional scale analysis. While in this article we focus on the perception of light pollution's influence to the environment of human settlement. We propose an analysis method mainly utilizing NTL images and a city's point of interest (POI) data to assess the light pollution from the aspect of its impact on the environment of city residents. The method quickly provides light pollution analysis at a fine spatial scale. We also address the POI data in a novel aggregating algorithm to better construct the area of interest, which can conquer the limitation of spatial resolution of NTL data in some extent. By doing the assessment in two Chinese medium-size cities, light pollution sources, the pollution level for each residence are found and analyzed. Furthermore, several light pollution patterns are discovered and interpreted. The result of the experiment demonstrates our assessment method provides a fast way to analyze light pollution patterns and can show the detailed light pollution situation in a city.**

***Index Terms*—Night-time light (NTL), point of interest (POI), remote monitoring, urban light pollution.**

I. Introduction

Light pollution is caused by alteration of natural light levels in the night environment produced by the introduction of artificial light, a problem that is increasingly debated [1]. The impact of the light pollution on public health through either direct or indirect effects is of utmost concern, the potential adverse health outcomes include cancers, cardiovascular disease, obesity, adverse pregnancy outcomes, and metabolic diseases. Additionally, negative impacts result from the suppression of melatonin production and insomnia [2]–[4]. Therefore, research is strongly needed in the realm of analyzing the causes and status of night light pollution in cities.

In recent years, with the development of satellite based night-time light (NTL) images, researchers have started using satellite data to analyze the light pollution situation. The Defense Meteorological Satellite Program Operational Linescan System (DMSP/OLS) provides the longest time series of NTL images in the world. It was used to map the first world atlas of brightness in the artificial night sky as early as in 2001 [5]. DMSP/OLS data have been widely used to estimate night light pollution at the national and regional scale. By collecting images of China from 1992 to 2012, after the linear regression trend method and NTL indices method were applied to the images, researchers found that China's light pollution expanded significantly over the past 21 years. Furthermore, Northwest China followed by Southwest China is the fastest growth areas of light pollution. Shandong is one of the main province locations of light pollution [6]. DMSP/OLS was also shown to distinguish the light pollution changes in a specific area [7].

In 2011, the National Polar-Orbiting Partnership was launched with the visible infrared imaging radiometer suite (VIIRS). The day and night band (DNB) of VIIRS presents a significant improvement in resolution (740 m finer than the approximately 3000 m for DMSP/OLS), and it is shown to be more sensitive to lower light levels and does not saturate in urban areas [8]–[10]. With a finer resolution, it was employed to investigate light pollution. The connection between breast cancer incidence rate and artificial light-at-night intensities was modeled by VIIRS/DNB and DMSP/OLS data, and the model built by VIIRS/DNB better predicts the distribution than that of DMSP/OLS [11]. Astronaut photography from the International Space Station (ISS) is another fine spatial resolution NTL data source [12]. Due to its fine resolution and its multi-spectral band characteristics, it is used in assessing light pollution at the regional scale. By doing in-person NTL assessments in Montreal, ISS data has shown convergence with the assessment results of self-reported health proving the possibility of using high spatial resolution NTL data to assess light pollution in an intra-urban scale; and illustrated that spectral characteristics of artificial light is also a very important characteristic in causing light pollution [13]. It is also used to analyze the influence of light pollution on turtles [14], which is the perception of light pollution from a natural standpoint. However, the ISS NTL data

Manuscript received March 14, 2021; revised April 11, 2021; accepted July 10, 2021. Date of publication July 14, 2021; date of current version August 9, 2021. This work was supported in part by the National Natural Science Foundation of China under Grant 41961064 and in part by the Yunnan Department of Science and Technology Application of Basic Research Project under Grants 202001BB050030 and 202101AT070003. *(Corresponding author: Rui Liu.)*

Fei Zhao, Chen Chu, Rui Liu, Zhiyan Peng, Zhiqiang Xie, Zhengbao Sun, Hongyun Zeng, and Jisheng Xia are with the School of Earth Science, Yunnan University, Kunming 650091, China (e-mail: vwobai@163.com; chuchen2017@mail.ynu.edu.cn; ruiliu529@ynu.edu.cn; pengzy834@mail.yun.edu.cn; xzq_2010@126.com; zbsun@ynu.edu.cn; xjfzhy@163.com; xiajsh@ynu.edu.cn).

Qingyun Du is with the School of Resource and Environmental Science, Wuhan University, Wuhan 430079, China (e-mail: qydu@whu.edu.cn).

Digital Object Identifier 10.1109/JSTARS.2021.3097320

does not cover of the surface of earth completely. Therefore, it is difficult to implement it widely.

With the successfully launch of Luojia1-01, the sensor it carried provides NTL imagery with a spatial resolution of 130 m [15], [16]. NTL data of Luojia1-01 have been used in mapping urban extant and build-up areas [17], [18], estimating population [19], and detecting marine ships [20], [21]. In addition, mapping light pollution is another important research direction. Through investigating the artificial light pollution in China, researchers found that Luojia1-01 can detect a high dynamic range and capture the fine spatial detail of light pollution, and the averages of artificial light pollution of are different between various land use types [22]. Other research has concentrated on modeling the relationship between ambient illuminance, which refers to the light pollution, and satellite imagery of Luojia1-01. It noted that the area included large transportation hubs and large shopping areas, which exhibited high ambient illuminance [23]. The conclusion also showed that the Luojia1-01 imagery can distinguish the variation in NTL at the intra-urban scale.

To analyze sources of light pollution, a city's point of interest (POI) data are collected, usually from the internet. In recent years, POI data have been used to identify a city's commercial format [24], extract urban extent [25]–[28], and map population distribution [29], [30] and intra-urban housing prices [31]. Its location and attribute properties can help us better understand the characteristics of cities. However, the density of every POI category often varies greatly. In the previous study, researchers tried to aggregate POI to extract their similarity in attributes [32]. Thus, proper dealing with large amounts of POI, which have variable distribution, is of vital importance to the accuracy of the study.

In previous light pollution studies, research was usually performed at the national or regional scale, and little researches assessed intra-city light pollution. Based on ariel night photography, Hale *et al*. find the correlation between artificial light and different human activity and give suggestion to urban planning [33]. Also, by manually analyze, JL1-3B is also proved to be able to extract illumination characteristics inner city [34]. Cheng et al. used the imagery of JL1-3B to extract street light position [35]. However, JL1-3B is a commercial satellite, the cost of its imagery is relatively too high for a research and its imageries are usually too small to cover a whole city. Furthermore, few studies explored urban light pollution from the perception of its influence to residents. Normally, all light generate artificially is regarded as light pollution, although it may have no influence on humans. For instance, an airport or train station built in the suburbs is far from residential areas, thus, no direct influence is made. Therefore, from the perception of light's influence on mankind, this sort of light could be excluded from light pollution.

Thus, in this article, we clarify and define artificial light pollution from the aspect of its impact on human living environments, which captures the adverse influence from artificial light unnecessarily generated in residential areas. From this view, we proposed an assessment model to simulate the influence from one single point of light pollution source to residents. To better analyze the assessment result, we proposed three indices, which are generated from the characteristics of light pollution. Additionally, to make the model more accurate and be robust to POI noise, we propose a novel points aggregating algorithm, which performs well in extracting the area of interest (AOI) from POI in downtown. Finally, we apply our assessment model in two medium cities to determine their light pollution sources and pollution characteristics. The study area and data are introduced in Section II; the methodology is introduced in Section III, the result is in Section IV. Finally, Section V concludes the article.

II. Study Area and Data

A. Study Area

We selected two typical medium-sized cities as our study area shown in Fig. 1(a). The first city is Kunming, located in inland China, with a history dating back to 227 BC. Today it is one of the most important cities in Southwest China. Although the government has been trying to renovate its urban layout in recent years, it is still stereotypical in its urban center. The influence of this stereotype city plan on citizens life is well concerned in recent years. We try to reveal that from the perception of light pollution aspect.

The other city is Qingdao, built in 1891 AD, and originally planned by Germany. It is concerned as a city with relatively good urban planning in China, which is well known for its business, travel, and sea transportation. Since 2018, the local government has aimed to build its coastal light show to be a city highlight and to attract tourists. Although the artificial light in some costal scenery increased obviously since then, did it really cause light pollution to citizens is a very interesting topic to discuss.

The comparison between these two cities reveals the difference between their light pollution patterns, and also reveals the role city planning plays in controlling urban light pollution.

B. NTL Imagery

The study uses Luojia1-01 images as the NTL data. It has a spatial resolution of 130 m [16], [36]. The images are shown in . We selected cloud free images of each city during their peak season of the year; for Qingdao it is in summer during the prime tourism season, and Luojia1-01 image was collected in 2018, which is the beginning year for local government to build city's light show. And for Kunming it is near the time of the Spring Festival of 2019. Each city is located in the center of its image as shown in Fig. 1(a).

C. Google Earth Satellite Image and Open Street Map Data

According to the report of the Luojia1-01 designer and current application, the position accuracy ranges between 0.49 to 0.93 km [16], [22]. To accurately extract the DN value of POI from Luojia1-01 images, a geometrical correction is employed. The study uses high-resolution Google Earth satellite images and Open Street Map roads data [37]. By choosing ground control points manually, using road intersections and landmark locations, an L1-norm-regularized least squares method is employed to correct the images [38]. The accuracy after correction is given in Table I. And the comparison between before and after correction is shown in Fig. 2.

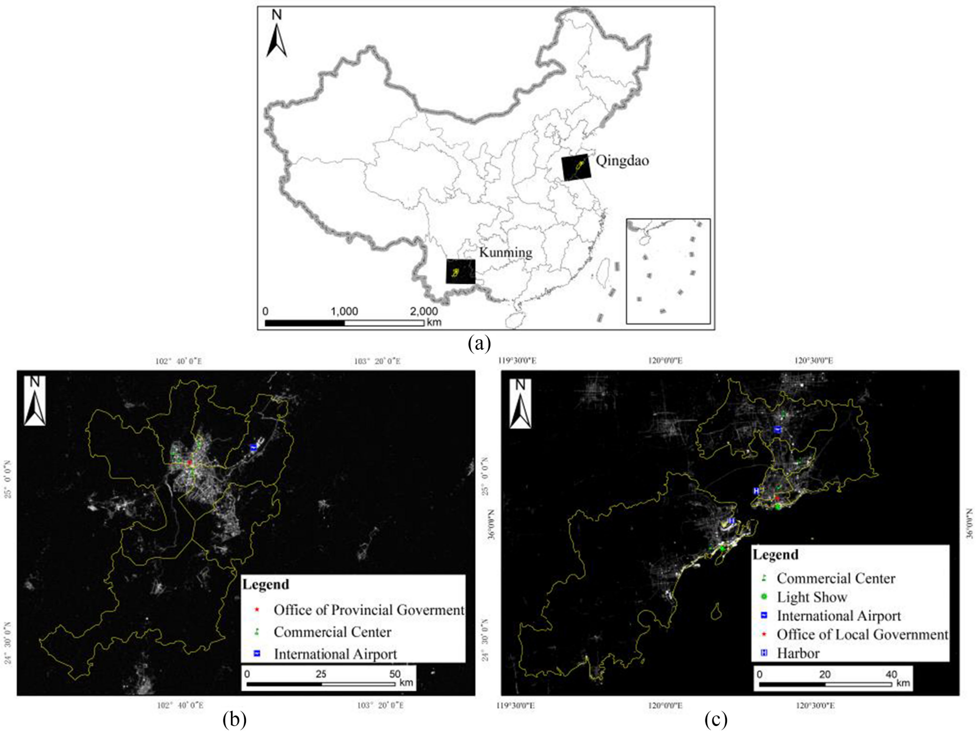


Fig. 1. Location and Luojia1-01 images of Kunming and Qingdao. (a) Location of two cites in China and in research images. (b) Luojia1-01 imagery of Kunming with some important landmarks' location. (c) Luojia1-01 imagery of Qingdao with some important landmarks' location.

TABLE I
DESCRIPTION OF LUOJIA1-01 DATA

Study area	Acquisition Date	Root mean square error
Kunming	*January 26, 2019*	*20.62 m*
Qingdao	*August 21, 2018*	*22.37 m*

TABLE II
EXAMPLE OF POI DATA COLLECTED

POI type	Point_X	Point_Y	Other Informatoin
Resident	*529744.232*	*4023397.179*	
Resident	*529599.0226*	*4023400.684*	
Tourist attraction	*530375.9516*	*4022647.147*	
Restaurant	*530226.046*	*4022578.743*	
……	……	……	……

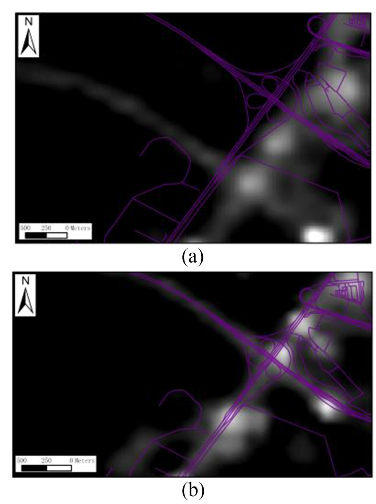


Fig. 2. Comparison of imagery georeferencing correction. (a) Imagery before correction. (b) Imagery after correction. The lines in figures are roads.

D. POI Data

In this article, we use POI to represent pollution sources and residents. Few samples of POI are shown in Table II. POI is retrieved from Amap [39] API, and it is originally cluster by it using type, these 15 categories of data are almost all of the main categories. Amap is one of the most reliable commercial map services providing companies in China. Generally, the position accuracy of these kind of POI data is ignored in other similar research [28] and after checking the position of POI manually, it is assured that there narrowly has any offset of POI. For each city, we collected resident POI and fifteen additional POI categories that are commonly seen in daily life. There are 105 324 POIs in total given in Table III.

Because restaurants and building materials markets are extremely densely distributed, and they are usually performed with a spatial cluster characteristic in real life; therefore, we employed our roads restricted aggregate algorithm to obtain AOIs. The numbers of AOI are shown in Table IV. So that the AOI illuminance extraction method can defeat the problem that NTL imagery resolution is hard to represent the illuminance that

TABLE III
NUMBER OF POIs IN KUNMING AND QINGDAO

POI type	Kunming	Qingdao
Resident	*5464*	*3892*
Entertainment venue	*1368*	*653*
Restaurant	*39730*	*15613*
Government building	*783*	*768*
Shopping mall	*283*	*253*
Hospital	*320*	*320*
Tourist attraction	*1667*	*933*
School	*1099*	*874*
Flyover	*205*	*48*
Factory	*716*	*881*
Building Materials market	*12597*	*15580*
Sports field	*384*	*131*
Agricultural facility	*246*	*237*
Train station	*32*	*16*
Toll station	*121*	*55*
Service area	*49*	*6*
Airport	*1*	*1*

TABLE IV
NUMBER OF AOIs AFTER AGGREGATING

AOI type	Kunming	Qingdao
Restaurant	*1299*	*302*
Building materials markets	*340*	*191*

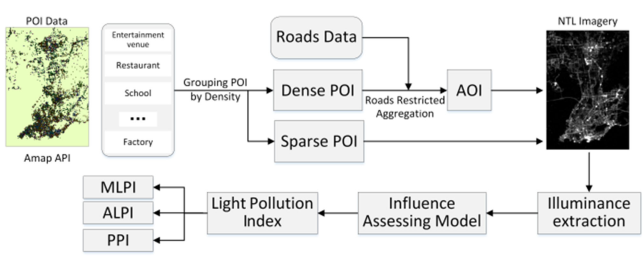


Fig. 3. Two-layer framework for obtaining the LPIs.

single POI generated and avoid to extracting light the generate by street lamp.

III. METHODOLOGY

As shown in Fig. 3, a two-layer framework has been designed for obtaining the light pollution indices (LPIs) of the study area. In the first layer POI data and NTL imagery are collected and processed. Then, in the second layer, LPIs are calculated from the model.

A. POI Data Processing

The POI represents the location of light pollution sources and serves as the starting point of light pollution influence assessment in the article. It is classified by its usage when it was collected from the digital map serving company on the internet. The categories include residences, restaurants, airports, and other types. The collected data were cleaned manually to ensure every POI is exactly in its corresponding category.

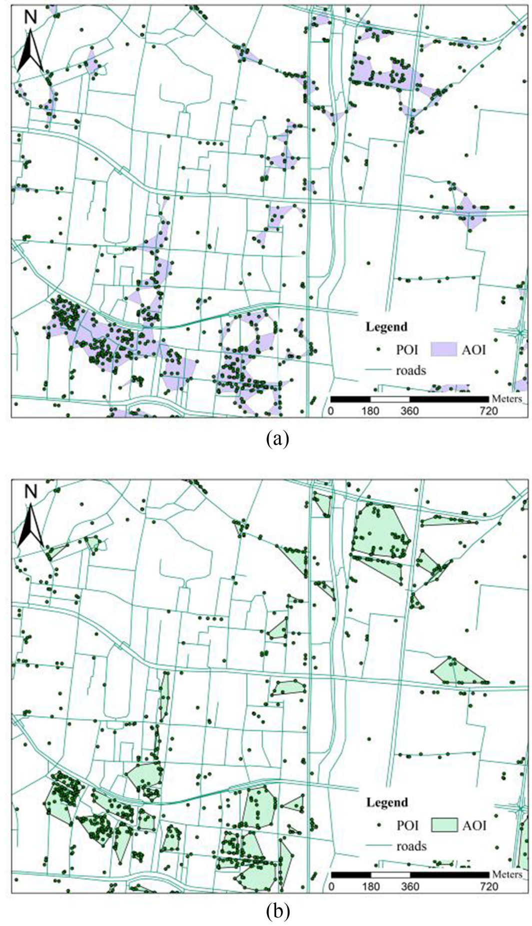


Fig. 4. Comparison of AOI assignment results. (a) Aggregate result of ArcGIS. (b) Aggregate result of the roads restricted aggregation algorithm.

1) Roads Restricted Aggregation: Due to the commercial usage of POI and data collecting model of the map serving company, business related POIs, such as restaurants, may be collected very completely (see Fig. 4). However, spatial resolution of Luojia1-01 imagery is 130 m, which does not have the ability to identify illuminance of every single POI. However, the digital number (DN) in one single pixel of the imagery often represents the summed influence from all the POIs in the pixel. Therefore, aggregating clustered POIs in the same category into AOI promised accurate illuminance extraction.

In the previous points aggregating algorithm, points are aggregated with distance as the only restriction. While in reality, AOI is usually restricted mainly by roads. Therefore, the roads restricted aggregation algorithm uses roads as the first limiting rule in aggregation to build restricting areas and then uses the density-based spatial clustering for application with noise (DBSCAN) [40] algorithm in the restricted area to cluster POIs. Finally, we construct AOIs from clustered POIs using the convex hull method, which is a very typical method for constructing AOIs [41], [42].

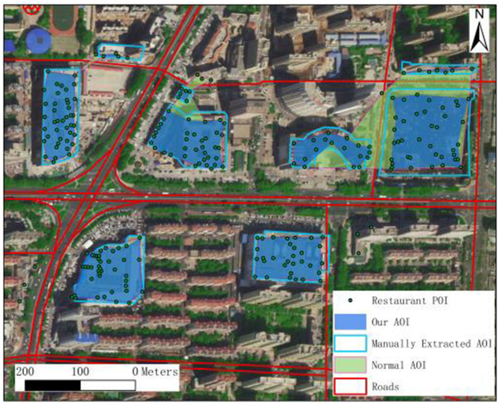


Fig. 5. AOI forming experiment result.

TABLE V
AOI EXPERIMENT RESULT

AOI Extract Method	Accuracy	Recall
Road Restrict Aggregate	*76.96%*	*98.85%*
Base Line Method	*78.01%*	*90.47%*

The DBSCAN method has been proved to be very efficient in detecting AOIs in urban areas [32]. There is no need to predetermine numbers of clusters. Moreover, it is robust to data noise; in this article, noise is caused by discrete POIs. The very dense discrete POIs usually represented places that cannot generated strong light, such as cafés, which are in restaurant category. Using DBSCAN can ensure that those POIs can be properly removed in the assessment.

The comparison between traditional aggregation algorithms and roads restricted AOI construction is shown in Fig. 4. Obviously, our algorithm can better cluster POIs and assign them into AOIs. The aggregation only applies to those categories of POI that are very dense and have shown obvious spatial clustered appearance. The main cause of error in forming AOI is insufficiently collecting of data. This error is minimized in this research by collecting the POI data grid by grid from Amap API.

To better present the improvement of our result, we manual extract a few restaurant AOIs for experiment (some are shown in Fig. 5.) The result shown in Table V illustrates that our aggregate algorithm has an obvious improvement on Recall value compare with the base line method of ArcMap. And the improvement is most obvious when there are two AOIs near each other. In our assessing model high Recall is more important than high Accuracy. Because higher Recall means the extraction of AOI is more representative for the corresponding area. It can avoid to extract the illuminance generated by the nearby roads. And the reason for low precision is that some of the POI data is lacked in the experiment area, as long as the POI data is sufficient the Accuracy can be increased.

2) Illuminance Extraction: The purpose of this step is to extract the illuminance POI generated. For those categories of POI that are distributed in space, POIs can directly extract illuminance by obtaining its corresponding pixel DN from NTL imagery. Furthermore, for those categories that have been formed as AOIs, which are restaurant and building materials markets in this experiment, the illuminance is extracted as the average value of pixels contained in the AOI. And for POI falls in other category of AOI, we remove the POI to assure the reasonable of the experiment. After extraction, every potential light pollution source has its corresponding illuminance, which is regarded as the light pollution it is responsible to.

B. Influence Assessing Model

As we want to determine the influence that every single light pollution source makes to residents, an influence simulate model is essential. However, preceding research has mainly focused on the influence that the whole city makes to the neighboring area [43]–[45].

What is worth mentioning is that residents in the assessment model are also regarded as POI for the data we collected is able to represent almost every building of it. In the result part, resident POI was converted into grid map with 100 m resolution. The aim of this step is just to better exhibit the experiment result and to find the common feature of light pollution. Actually, the experiment can get the light pollution severity and sources of every residents point.

In this article, we propose a simulated method based on kernel density estimation (KDE) [46]. In KDE, every single point has its kernel function to estimate its influence on nearby areas. Additionally, the influence rate decreases smoothly with distance, which is determined by a bandwidth parameter. There is also an attribute parameter; as this parameter increases, the influence rate increases at the point's location and extends further in distance. KDE has been used in many geographic applications [47], [48], for its great performance in following Tobler's first law of geography [49]. When estimating the influence that a light pollution source brings to its nearby area, we employed the kernel function as the influence simulating function and the DN value as the attribute value of the function. The light pollution influence assessment result can be calculated by the following formula:

$$I_j^i = \mathrm{DN} \times \frac{1}{(2\pi)^2 D} \times \exp\left(\frac{\boldsymbol{d}^2}{2D^2}\right) \tag{1}$$

where i is a resident, j is a light pollution source, and I_j^i is the LPI that j brings to i. DN is the DN that the light pollution source corresponds to on NTL imagery, D is the bandwidth parameter of kernel function, and d is the distance between i and j.

We extracted the cross-section DN value of an isolated POI from NTL imagery and plot its corresponding pollution indices curve with the 500 m bandwidth. The result is shown in Fig. 6.

As shown in Fig. 6, the influence indices decrease slower than POI illuminance because the influence indices is used to simulate the POI influence on the nearby area. The NTL imagery only shows the corresponding illuminance of the pixel location. Considering the light from one illuminated location

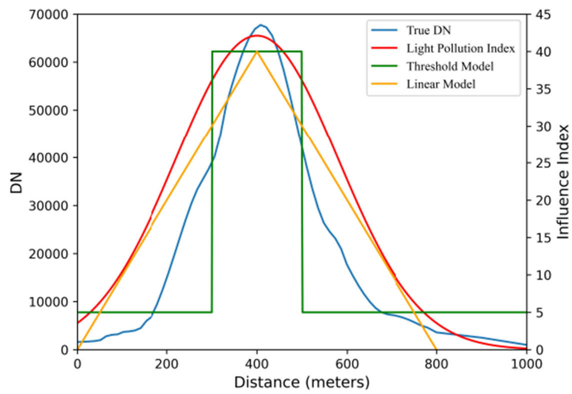


Fig. 6. Influence simulating result of an experiment POI with different model.

can influence nearby areas, slowing down the decreasing speed of the assessment indices is essential.

We have also tested other simulation models like it shown in Fig. 6. Compared with others, LPI is more interpretable with its parameters and its value decay smoother with distance. While Threshold model like influence index 2 and Linear model like influence index 3 is too sharp to simulate the decrease of influence of light pollution, LPI has great performance in the analyzing phase.

C. Light Pollution Indices

There are four main types of artificial light pollution include glare, light trespass, light cluster, and over illumination, which are raised by Global at Night [50] and Dark Sky Awareness [51], two international campaigns focused on artificial light pollution. To assess the impact from these four kinds of pollution, we propose two assessment indices as follow.

1) Maximum Light Pollution Indices (MLPIs): The MLPI aim to assess glare and light trespass situations, which are the strongest light pollution influences made to a resident. In most of news reports about light pollution, the main reason for residences to indicate light pollution is glare and trespass, which means there is a light source that generates extremely strong light and is close to the resident. In this situation, the resident is exposed in light pollution directly and intensively. Glare often cause visual discomfort and can decrease visibility [51]. To find the glare situation for residents, we use MLPI. It is calculated as follows:

$$I_{\mathrm{MAX}}^{i} = \mathrm{MAX}\left\{I_j^i\right\} \quad (j = 1, 2, 3, \ldots\ldots, \text{all POI}), \tag{2}$$

where I_{MAX}^{i} is the MLPI of resident *i*. It is the maximum value of all the light pollution the resident is suffering and is used to assess seriously polluted areas. Meanwhile, the causes of MLPI are also recorded to assess which kind of pollution sources tend to cause serious light pollution.

2) Accumulated Light Pollution Indices (ALPIs): The ALPI aim to assess light clusters and over illumination. These two aspects concentrate on the total light pollution a resident suffered. Besides glare, light cluster pollution is another hot spot. This kind of pollution comes from the summed influence of multi-pollution sources and their accumulation leads to bright light and confusion problems to a resident. The ALPI can be calculated from the following:

$$I_{\mathrm{type}}^{i} = \sum_{j=0}^{n} I_j^i \quad (j = 1, 2, 3, \ldots\ldots, \text{all POI}) \tag{3}$$

where I_{type}^{i} is the ALPI of the *type* category of POI to resident *i*. By calculating the ALPI of various POI and selecting the maximum value, we can find the main pollution source for residents in an area, which is the light cluster in the area.

TABLE VI
REFERENCE PLACES AND THEIR DN VALUE

Land using type	DN
General roads	30000–45000
Well-lit roads	50000–60000

D. Pollution Source Assessment

To better explore sources of light pollution, this article, in addition to mapping the geographical distribution, also tries to analyze the distribution statistically. Considering that the amount of POI varies greatly with category, we proposed a potential polluting index (PPI), which aims to measure the potential of pollution sources to cause light pollution

$$r_{\mathrm{POI}} = \frac{n_{\mathrm{resident}}}{n_{\mathrm{POI}}} \tag{4}$$

where r_{POI} is the pollution rate of *POI* category, $n_{\mathrm{residence}}$ is the number of residents polluted by POI, and n_{POI} is the number of POI. The POI type with little quantity that pollutes many residents has a higher PPI than one with greater quantity but polluting the same number of residents. Therefore, a category with bigger PPI is more likely to be a light pollution source.

IV. Result

A. NTL Reference Selection

The DN value of Luojia1-01 imagery is too abstract to analyze. Therefore, we select some typical POI types and some landmarks to measure their DN values, which can provide a reference of ground illuminance during assessment. This part is only used to help us learn more about the abstract NTL data as a reference.

As given in Table VI, the DN value varies greatly with different places. After referring to the light management law issued by the Shanghai government recently [52] and information from international organizations [50], [51], we set the direct polluting threshold as 60 for our LPI proposed in Section III-B. That approximately equals to the light pollution a pollution source with 80000 DN, such as a flyover, contributes to residents within 100 m. Additionally, we set the moderate pollution threshold as 30, which approximately refers to a pollution source with 60000 DN, such as a well illuminated road, at a 500 m distance.

B. Maximum Light Pollution Indices Analysis

In the analysis of MLPI, because the indices mainly measure the glare and light trespass pollution, we only gather statistics

TABLE VII
MLPI Assessment of Study Areas

	Kunming			Qingdao		
Pollution sources	Polluted residents	Average LPI	PPI	Polluted residents	Average LPI	PPI
Entertainment Venue	841	93.5	0.615	328	149.9	0.502
Restaurant	379	80.0	0.291	92	99.3	0.305
Government Building	370	77.6	0.473	335	172.7	0.436
Shopping mall	205	100.6	0.724	170	135.1	0.672
Hospital	191	78.0	0.597	48	82.5	0.150
Tourist Attraction	162	76.4	0.097	101	203.9	0.108
School	156	86.9	0.142	42	181.0	0.048
Flyover	114	90.5	0.556	3	65.7	0.063
Factory	71	83.5	0.099	17	78.2	0.019
Building Materials Market	61	81.1	0.179	73	182.5	0.382
Sports Field	60	81.3	0.156	24	96.4	0.183
Agricultural Facility	5	0.0	0.020	0	0	0
Train Station	2	76.0	0.063	0	0	0
Toll Station	1	64.5	0.008	1	86.0	0.018
Service Area	1	64.0	0.020	0	0	0
total	2619			1234		

of pollution above the direct pollution threshold. Additionally, we use the PPI proposed in Section II-E to analyze the potential a pollution source has in causing direct pollution.

As given in Table VII, in Kunming, 2619 residential areas are likely to be directly polluted, which accounts for 48.2% of all residents, while the number in Qingdao is 1234, or 31.2% of all residents. Therefore, light pollution is more common in Kunming. However, Qingdao's average LPI is higher than that of Kunming, which means the light pollution problem in Qingdao is more severe.

From the view of pollution sources, entertainment venues are the most common pollution sources in Kunming; furthermore, it ranks second in the average LPI and PPI. Therefore, to some extent, entertainment venues are the major pollution sources in Kunming. Furthermore, although shopping malls do not pollute many residents, its average pollution indices and PPI are the highest, which means it is very likely to pollute residents with strong light. For Qingdao, government buildings are the main pollution sources as it has polluted largest number of residents and its average LPI is very high. Tourist attractions in Qingdao have the highest average LPI, and that is because the light show pollutes some coastal residents; however, due to the low building number, the number of influenced residents is not very large. It is worth noting that the shopping mall in Qingdao also has the largest PPI; thus, we believe shopping malls are some of the most common sources of intensive light pollution.

Overall, there is great similarity in two cities' light pollution sources and POIs like entertainment venues, restaurants, government buildings, and shopping malls, which rank ahead of both city and agricultural facilities, train stations, and toll stations; service areas only pollute a small number of residents.

Spatially, in Figs. 7 and 8, the study transfers the POI into raster to show the rule of spatial distribution more clearly. For areas that are not plotted in maps, it is because its land use type is not residential, meaning from the perception of light pollution's effect to human being, the area whether illuminated or not does not influence residents. Therefore, it can also be regarded as a non-pollution area. However, for better performance, we did not plot that area.

Obviously, the most heavily polluted areas of both cities are near their commercial centers and government buildings. For Kunming, it is around the office of the provincial government. This is because the city's center area is a residential area built around government building at the very beginning, while with the development of the city, it generally becomes a commercial center. Additionally, these commercial centers with strong light generated at night pollute the original residential area. Furthermore, highlighting the old city planning, now the local government has made efforts to move government offices to the suburbs. Considering this can reduce the number of light pollution sources, we believe it will reduce the severe light pollution situation in downtown Kunming.

For Qingdao, its heaviest polluted area is in its coastal area. The sources of light pollution are mainly the entertainment venues and tourist attractions. The light pollution situation is better than Kunming, considering most of the area is in low polluted level.

Furthermore, airports and harbors in cities did not cause serious pollution problems, because their location is usually far from residents.

C. Accumulated Light Pollution Indices Analysis

Two other pollution types are light clusters and over illumination. By using ALPI we try to determine the major pollution sources and their influence area of both cities. The study calculates the ALPI of all categories of pollution sources for every resident. By extracting the maximum of these values and their respective POI type, we mapped the distribution of major light pollution sources in Figs. 9 and 10.

From Figs. 9 and 10, entertainment venues are the major sources of light cluster pollution in both cities. They occupy approximately one quarter of the polluted area in both cities and are mainly distributed in the city center.

For Kunming another large pollution area in downtown is pollution from tourist attraction areas, caused by a famous park in city center. The park has substantial decorative illumination leading to an over illumination problem. Furthermore, outside the city center is a range of restaurant polluted areas, which leads to the restaurant pollution becoming the most common source for light cluster pollution.

In Qingdao, its coastal area is mainly polluted by entertainment venues and tourist attractions. This is also from the city's decorative illumination, which is the coastal light show in Qingdao. Additionally, government building polluted areas are widely distributed. However, in inland areas, many residents are free from light pollution.

D. Polluting Risk

After calculating the pollution indices every pollution source makes to residents, we divided it into two types. The first type was severe polluting sources; polluting sources in this type had

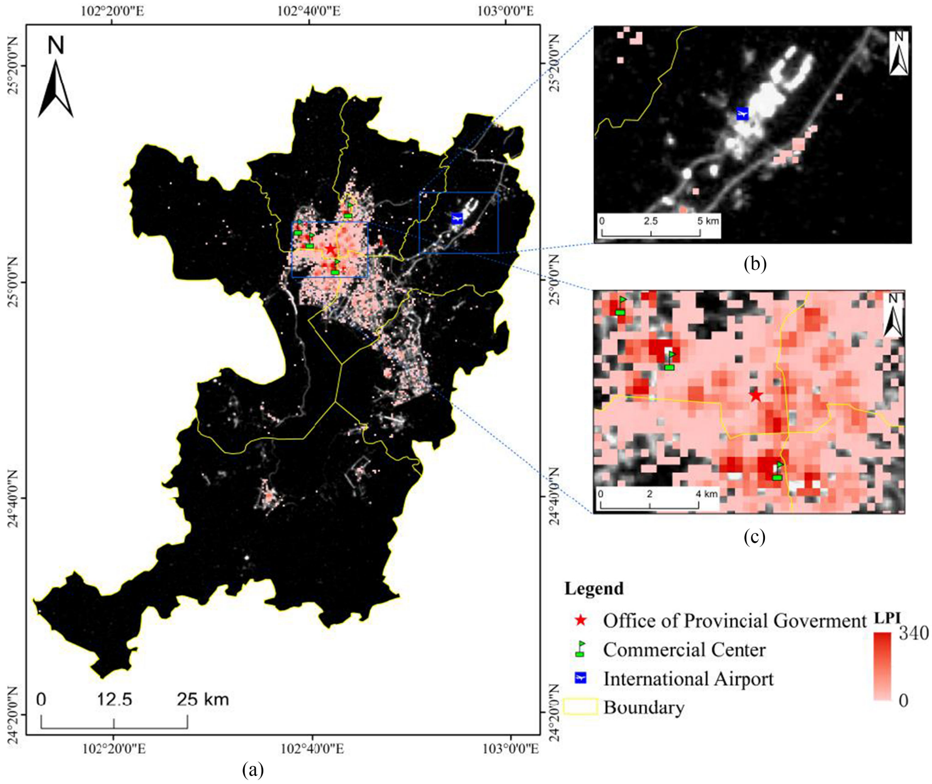


Fig. 7. Spatial distribution of LPI in Kunming. (a) Overall view of LPI in Kunming. (b) LPI near the airport. (c) LPI in downtown Kunming.

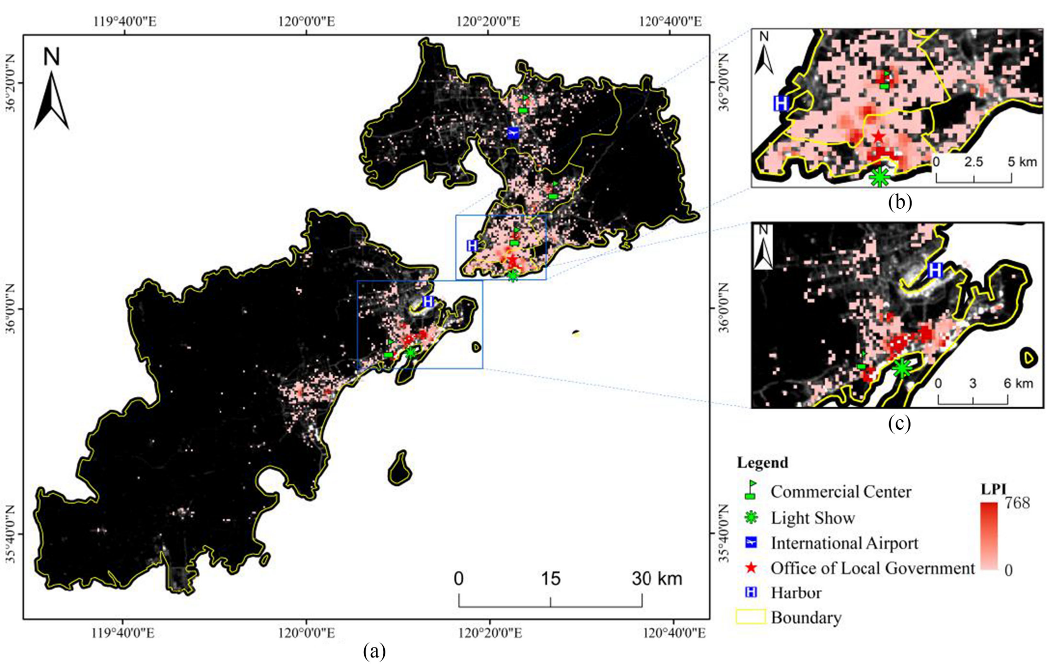
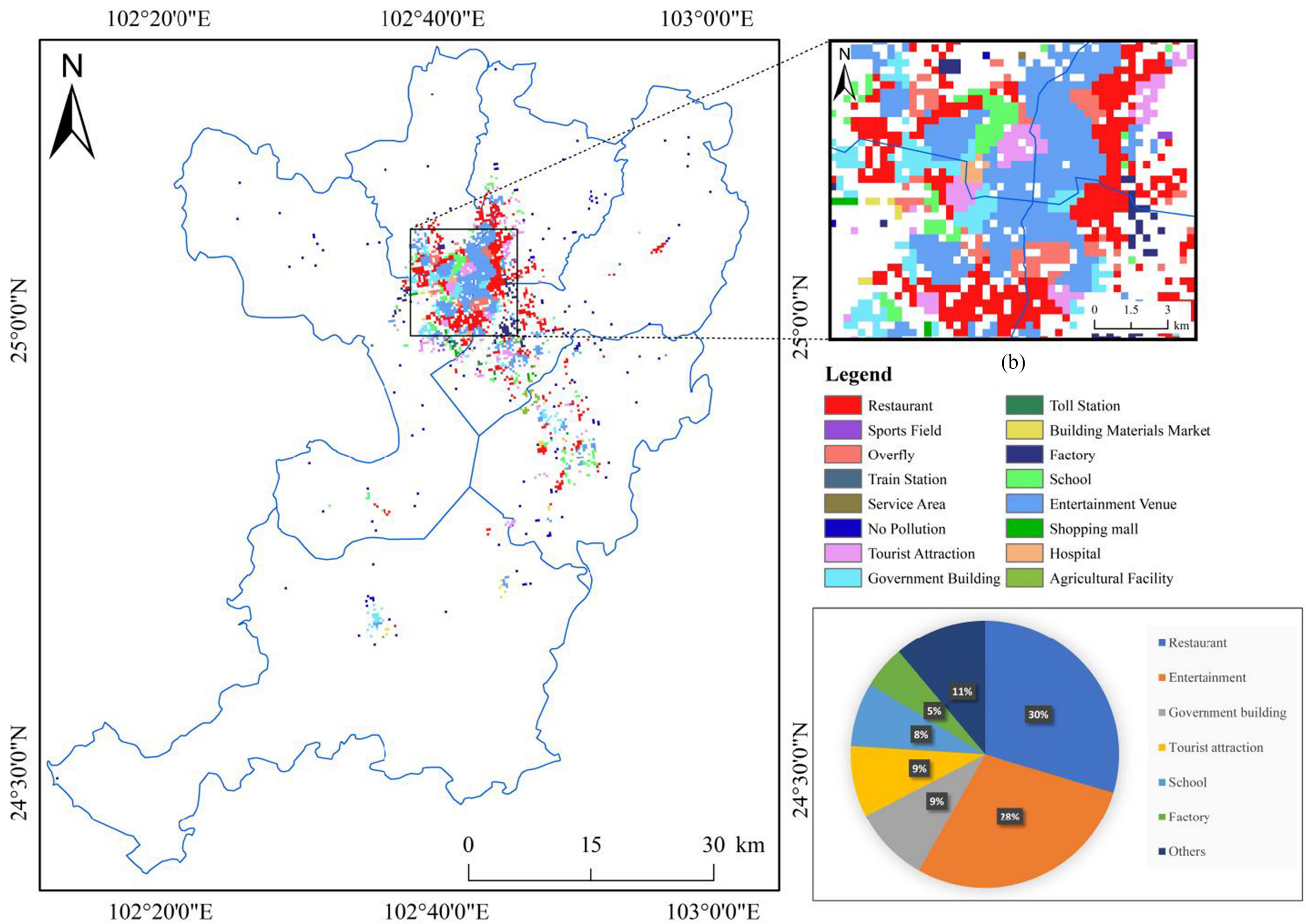


Fig. 8. Spatial distribution of LPI in Qingdao. (a) Overall view of LPI in Qingdao. (b) LPI in downtown Qingdao. (c) LPI near the harbor.

their maximum pollution indices greater than the direct polluting threshold, which is set as 60 in the part A of this section. The second type was moderate pollution sources, where the threshold was moderate pollution threshold. Statistics of the two types are given in Table VI.

For Table VIII, for most POI categories, only a few cause light pollution to residential areas. The shopping mall in Qingdao has the highest polluted proportion, but the sum is not greater than 7%. Considering it also has the highest PPI in MLPI, shopping malls should be regarded as a high potential land use type

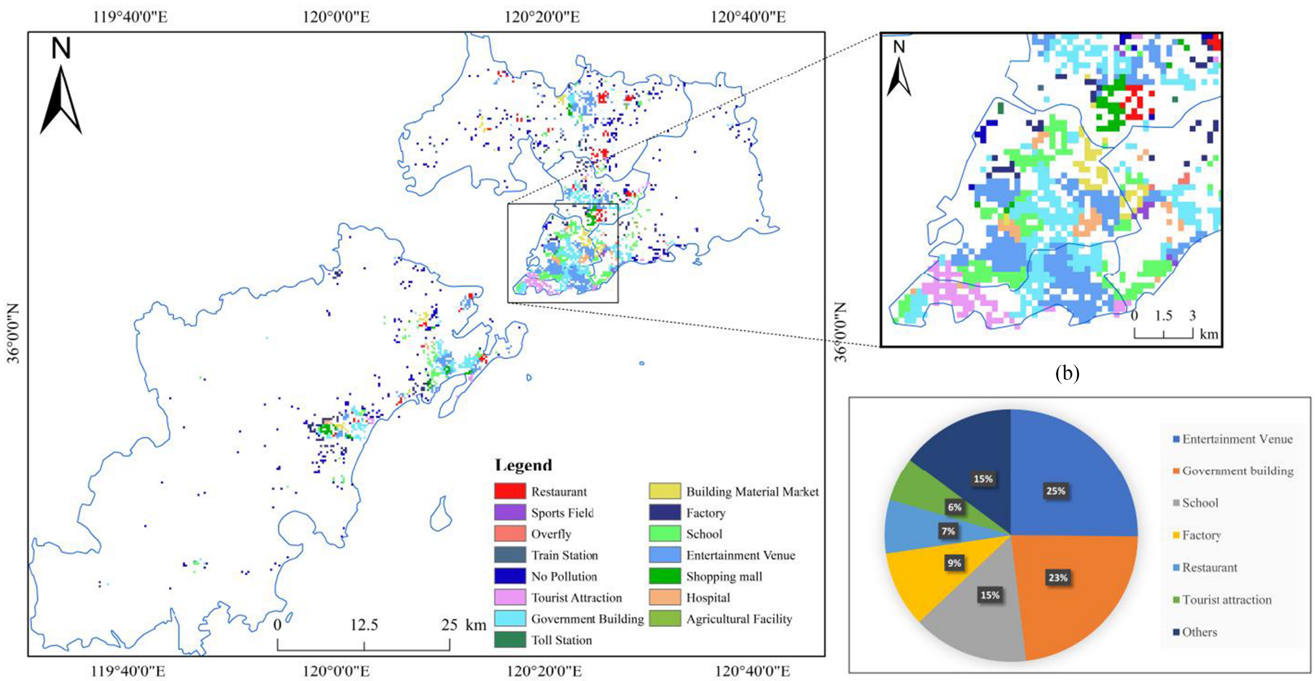


(a) (c)

Fig. 9. Influence area distribution of major pollution sources analyzed by ALPI in Kunming. (a) Overall view of influence area of pollution sources in Kunming. (b) Distribution in downtown Kunming. (c) Pie chart of the percentage of area each pollution source occupies in all polluted areas of Kunming.

TABLE VIII
PPI Assessment of Study Areas

	Kunming		Qingdao	
Pollution sources	Polluted residents	Average LPI	Polluted residents	Average LPI
Entertainment venue	1.97%	75.14%	2.45%	3.22%
Restaurant	0.85%	10.24%	0.66%	2.98%
Government building	0.77%	16.22%	0.65%	4.30%
Tourist attraction	0.42%	6.30%	0.86%	1.93%
School	0.27%	6.28%	0.23%	0.92%
Overfly	11.22%	12.68%	0.00%	0.00%
Factory	0.28%	6.01%	0.00%	0.00%
Hospital	0.31%	16.88%	1.25%	4.38%
Agricultural facility	0.00%	1.63%	0.00%	0.00%
Building materials market	0.29%	9.71%	0.00%	0.52%
Shopping mall	3.53%	14.84%	4.35%	2.37%
Toll station	8.26%	8.26%	0.00%	0.00%
Sports field	1.04%	6.77%	2.29%	0.76%
Service area	0.00%	2.04%	0.00%	0.00%
Train station	3.13%	0.00%	0.00%	0.00%



(a) (c)

Fig. 10. Influence area distribution of major pollution source analyzed by ALPI in Qingdao (a) Overall view of influence area of pollution sources in Kunming;. (b) Distribution in downtown Qingdao, (c) Pie chart of the percentage of area each pollution source occupies in all polluted area of Qingdao.

causing light pollution in Qingdao. In Kunming, most of the entertainment venues cause moderate pollution in a high proportion compared with other categories in Kunming and Qingdao. Furthermore, the overfly has the second largest proportion, even it is much smaller than the entertainment venue. Comparing the situation of the two cities, the light pollution control in Qingdao is much better than that in Kunming. However, Kunming is working on controlling its pollution sources, such as entertainment venues.

E. Pollution Patterns in Cities

As the paper has discussed previously, there are several light pollution patterns have shown obviously in two cities. The similarity and differences are believed to be caused by electricity habits of citizens and spatial distribution of urban area.

The different patterns include the light show in Qingdao, which generates very severe pollution to its neighbor residents while this situation does not exist in Kunming. Additionally, a famous park in Kunming's downtown area causes pollution to nearby areas. These differences are caused by local specialization. Considering every city has its special events or places that generate light pollution to its local region, through LPI assessment severity of light pollution caused by these places can be found.

The spatial distribution of urban area also leads to some different pollution patterns. Because of the historical city planning and lack of management of Kunming, light pollution in Kunming is much more common and severe than that in Qingdao. This can be seen from a great proportion of entertainment venues and overflies have caused light pollution to their nearby residences. While the proportion of that in Qingdao is extremely tiny.

Furthermore, the difference of these patterns may reflect the living and electricity habits of citizens in two cities. Qingdao is a northern city of China and is known for its low active sequence of night life. While oppositely, Kunming is known for its tourism and entertainment industry. These various living habits are believed to cause the great different value of average LPI of entertainment venue in Section IV-D.

The similar patterns are believed to be the typical pattern of most Chinese cities. The major pollution sources of two cities are common, includes entertainment venues and government buildings. Because entertainment venues are usually active in night and generate strong light. And government buildings' illumination usually represents the prosperity of a district, so it usually is over-illuminated.

On the other hand, the illumination in places like harbors and airports are necessary. However, because they are usually built far from residents, they scarcely contribute direct light pollution to residential areas. Therefore, this kind of artificial light can be regarded in proper use from the aspect of mankind. While in previous studies these well illuminated places usually are regarded as light pollution sources.

V. Discussion

Overall, this article establishes a light pollution assessment method based on NTL images and POI data. The method can rapidly analyze light pollution at the city scale without field work and map the severity and sources of light pollution spatially. The core of this article assesses light pollution to understand its influence on residents, which has been infrequently discussed by previous studies. Generally, studies focus on analyzing light pollution changes at the national or global scale without considering characteristics of light pollution [5], [6]. Otherwise, researchers have analyzed light pollution by combining NTL data with field work [23]. However, citizens' recognition of light pollution is usually formed by the influence brought by pollution sources near their homes. We developed our assessment method and indices considering this factor.

We apply our method to two Chinese cites. The assessment results show obvious differences between cites analyzed in the article. Meanwhile, there are also many similarities, which are believed to be typical characteristics of light pollution in most Chinese cities. Furthermore, because POI data and Luojia1-01 data is easy to acquire and our methodology is relatively easy to be understood, we believe that our method can be easily transferred to any other city.

For the accuracy of our assessment, considering our aim is to reveal the difference of the light pollution that different resident POI received. The differences include pollution sources and pollution severity. As the result shown in the article, the differences vary greatly and have shown an obvious spatial and statistic pattern, which is in the line with our normal cognition. It is reasonable to believe that this close with cognition is a kind of validate to our experiment. Therefore, the method of our study can perform a relatively accurate assessing of light pollution in a fine scale.

The other problem is road light dispersions. Its influence has been minimized by picking highest resolution imagery presently and proposing a roads restricted aggregate algorithm to exclude roads from assessing in this research. But, it still is a problem need to be totally solved in our future work.

Luojia1-01 data is easy to access through website deliver center [53]. Its data contains most of the regions on earth. So, assessment can be done in any regions of the world.

VI. Conclusion

In this article, we define light pollution from the view of its influence on residential areas and we propose a method using NTL imagery and POI data to assess this influence. An influence assessment model is proposed to quantify light pollution influence. With this model, three assessment indices are employed to make the results analyzable.

The pollution resources classification is based on POI categories. To increase the accuracy of illuminance extraction, we propose a novel points aggregate algorithm, which aims to better construct AOI from dense POI categories in urban areas. The algorithm is compared with base line method to show its performance.

Subsequently, we apply our methodology to two cities in China to detect their pollution sources and spatial distribution of light pollution types. The findings are as follows.

1) The similarities between two experiment cities are believed to be the typical patterns of most Chinese cities. Such as the pollution caused by overilluminated of government buildings.
2) Illumination generated by airports and harbors are usually properly used. For they are built far from residents and can hardly influence citizens in a direct way.
3) The difference of pollution patterns between two cities are caused by different local specialization, spatial distribution of urban functional area and living habit of citizens.

In future work, it would be interesting to bring in the digital surface model of urban area to analyze light pollution taking building shadows in to consideration. Moreover, using NTL image with multispectral to analyze light pollution of POI in each spectral would also be interesting. Because light with different wave length decrease differently with distance and different types of light also lead to different feeling to human being.

Acknowledgment

The authors would like to thank anonymous reviewers and the editors for their constructive comments and suggestions. The authors would like to thank the Hubei Data and Application Center of the High-Resolution Earth Observation System for providing Luojia1-01 data.

References

[1] F. Falchi *et al.*, "Limiting the impact of light pollution on human health, environment and stellar visibility," *J. Environ. Manage.*, vol. 92, no. 10, pp. 2714–2722, 2011.
[2] R. M. Lunn, D. E. Blask, and A. N. Coogan, "Health consequences of electric lighting practices in the modern world: A report on the national toxicology program's workshop on shift work at night, artificial light at night, and circadian disruption," *Sci. Total Environ.*, vol. 607/608, pp. 1073–1084, 2017.
[3] F. Hölker *et al.*, "The dark side of light: A transdisciplinary research agenda for light pollution policy," *Ecol. Soc.*, vol. 15, no. 4, pp. 634–634, 2010.
[4] K. J. Gaston *et al.*, "The ecological impacts of nighttime light pollution: A mechanistic appraisal," *Biol. Rev.*, vol. 88, no. 4, pp. 912–927, 2013.
[5] P. Cinzano, F. Falchi, and C. D. Elvidge, "The first world atlas of the artificial night sky brightness," *Monthly Notices Roy. Astronomical Soc.*, vol. 328, no. 3, pp. 689–707, 2001.
[6] J. Wei *et al.*, "Assessing light pollution in china based on nighttime light imagery," *Remote Sens.*, vol. 9, no. 2, p. 135, 2017.
[7] W. Xiang and M. Tan, "Changes in light pollution and the causing factors in china's protected areas, 1992–2012," *Remote Sens.*, vol. 9, no. 10, p. 1026, 2017.
[8] C. D. Elvidge *et al.*, "Why VIIRS data are superior to DMSP for mapping nighttime lights," *Proc. Asia Pac. Adv. Netw.*, vol. 35, pp. 62–69, 2013.
[9] C. D. Elvidge *et al.*, "VIIRS night-time lights," *Int. J. Remote Sens.*, vol. 38, pp. 1–20, 2017.
[10] L. B. Liao *et al.*, "Suomi NPP VIIRS day-night band on-orbit performance," *J. Geophys. Res. Atmos.*, vol. 118, no. 22, pp. 12705–12718, 2013.
[11] N. A. Rybnikova and B. A. Portnov, "Outdoor light and breast cancer incidence: A comparative analysis of DMSP and VIIRS-DNB satellite data," *Int. J. Remote Sens.*, vol. 38, pp. 5952–5961, 2017.
[12] W. L. Stefanov *et al.*, *Astronaut Photography: Handheld Camera Imagery from Low Earth Orbit, Handbook of Satellite Applications*. New York, NY, USA: Springer, 2013.
[13] C. Côté-Lussier, A. Knudby, and T. A. Barnett, "A novel low-cost method for assessing intra-urban variation in night time light and applications to public health," *Social Sci. Med.*, vol. 248, 2020, Art. no. 112820.
[14] T. Mazor *et al.*, "Can satellite-based night lights be used for conservation? The case of nesting sea turtles in the mediterranean," *Biol. Conserv.*, vol. 159, pp. 63–72, 2013.
[15] X. Li *et al.*, "A preliminary investigation of luojia-1 night-time light imagery," *Remote Sens. Lett.*, vol. 10, no. 6, pp. 526–535, 2019.
[16] L. Deren *et al.*, "Design and processing night light remote sensing of LJ-1 01 satellite," *J. Remote Sens.*, vol. 23, no. 06, pp. 1011–1022, 2019.
[17] X. Li *et al.*, "Mapping urban extent using luojia 1-01 nighttime light imagery," *Sensors*, vol. 18, 2018. Art. no. 3665.

[18] L. Quanyi *et al.*, "Extracting built-up areas using luojia 1-01 nighttime light imageries in Wuhan, China," *Geomatics Inf. Sci. Wuhan Univ.*, vol. 12, pp. 1–18, 2019.
[19] L. Wang, H. Fan, and Y. Wang, "Improving population mapping using luojia 1-01 nighttime light image and location-based social media data," *Sci. Total Environ.*, vol. 730, 2020, Art. no. 139148.
[20] Z. Xiaoge, "Extracting geological structure information by multi-principal component analysis [J]," *J. Remote Sens.*, vol. 04, pp. 299–303, Apr. 2000.
[21] X. Li, L. Zhao, D. Li, and H. Xu, "Mapping urban extent using luojia 1-01 nighttime light imagery," *Sensors*, vol. 18, 2018, Art. no. 3665.
[22] J. Wei *et al.*, "Potentiality of using luojia 1-01 nighttime light imagery to investigate artificial light pollution," *Sensors*, vol. 18, no. 9, 2018, Art. no. 2900.
[23] J. Li *et al.*, "Investigation of nighttime light pollution in nanjing, China by mapping illuminance from field observations and luojia1-01 imagery," *Sustainability*, vol. 12, no. 2, p. 681, 2020.
[24] Y. Hu and Y. Han, "Identification of urban functional areas based on POI data: A case study of the guangzhou economic and technological development zone," *Sustainability*, vol. 11, no. 5, 2019, Art. no. 1385.
[25] W. Chen, L. Liu, and Y. Liang, "Retail center recognition and spatial aggregating feature analysis of retail formats in Guangzhou based on POI data," *Geographical Res.*, vol. 35, no. 4, pp. 703–716, 2016.
[26] L. Ze *et al.*, "Identifying the spatial range of urban agglomerations in china based on night light remote sensing and POI data," *Geographical Res.*, vol. 39, no. 1, pp. 92–102, 2020.
[27] Z. Honghan *et al.*, "Urban built-up area extraction method based on nighttime light images and point of interest data," *Geographical Geo-Inf. Sci.*, vol. 35, no. 02, pp. 25–32, 2019.
[28] Z. Liang, Z. Qi, and Y. Fan, "Identification of urban agglomeration boundary based on POI and NPP/VIIRS night light data," *Prog. Geography*, vol. 38, no. 06, pp. 840–850, 2019.
[29] X. Yang *et al.*, "Population mapping with multisensor remote sensing images and point-of-interest data," *Remote Sens.*, vol. 11, p. 574, 2019.
[30] W. Luyao, F. Hong, and W. Yankun, "Improving population mapping using luojia 1-01 nighttime light image and location-based social media data," *Sci. Total Environ.*, vol. 730, 2020, Art. no. 139148.
[31] X. Yixiong *et al.*, "Exploring determinants of housing prices in beijing: An enhanced hedonic regression with open access POI data," *Int. J. Geo-Inf.*, vol. 6, no. 11, p. 358, 2017.
[32] Y. Hu *et al.*, "Extracting and understanding urban areas of interest using geotagged photos," *Comput. Environ. Urban Syst.*, vol. 54, pp. 240–254, 2015.
[33] J. D. Hale *et al.*, "Mapping lightscapes: Spatial patterning of artificial lighting in an urban landscape," *Plos One*, vol. 8, no. 5, 2013, Art. no. e61460.
[34] Q. Zheng *et al.*, "A new source of multi-spectral high spatial resolution night-time light imagery—JL1-3B," *Remote Sens. Environ.*, vol. 215, pp. 300–312, 2018.
[35] B. Cheng *et al.*, "Automated extraction of street lights from JL1-3B nighttime light data and assessment of their solar energy potential," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 13, pp. 675–684, 2020.
[36] "Data access for Luojia1-01," Accessed: Jul. 29, 2021. [Online]. Available: http://www.lmars.whu.edu.cn/gcss/index.php/sjzy/285.html
[37] "Open street map," Accessed: Jul. 29, 2021. [Online]. Available: https://www.openstreetmap.org
[38] S. Yavari *et al.*, "Accuracy improvement of high resolution satellite image georeferencing using an optimized line-based rational function model," *Int. J. Remote Sens.*, vol. 39, no. 6, pp. 1655–1670, 2018.
[39] "Amap developer," Accessed: May 20, 2020. [Online]. Available: https:/lbs.amap.com/
[40] M. Ester, "A density-based algorithm for discovering clusters in large spatial databases with noise," in *Proc. Int. Conf. Knowl. Discovery Data Mining*, 1996, pp. 226–231.
[41] C. B. Barber, D. P. Dobkin, and H. Huhdanpaa, "The quickhull algorithm for convex hulls," *ACM Trans. Math. Softw.*, vol. 22, no. 4, pp. 469–483, 1993.
[42] B. Yu *et al.*, "Object-based spatial cluster analysis of urban landscape pattern using nighttime light satellite images: A case study of china," *Int. J. Geographical Inf. Sci.*, vol. 28, no. 11/12, pp. 2328–2355, 2014.
[43] P. Cinzano, "The propagation of light pollution in diffusely urbanised areas," *Memorie della Soc. Astronomia Italian*, vol. 71, no. 1, pp. 93–112, 2000.
[44] A. J. Cabello and C. F. Kirschbaum, "Modeling of urban light pollution: Seasonal and environmental influence," *J. Illum. Eng. Soc.*, vol. 30, no. 2, pp. 142–151, 2001.
[45] M. F. Walker, "The California site survey," *Pub. Astronomical Soc. Pac.*, vol. 82, no. 487, pp. 672–698, 1970.
[46] S. J. Sheather and M. C. Jones, "A reliable data-based bandwidth selection method for kernel density estimation," *J. Roy. Statist. Soc.. Ser. Methodolog.*, vol. 53, no. 3, pp. 683–690, 1991.
[47] W. Yu and T. Ai, "The visualization and analysis of POI features under network space supported by kernel density estimation," *Acta Geodaetica Et Cartographica Sinica*, vol. 44, no. 1, pp. 82–90, 2015.
[48] Z. Xie and J. Yan, "Kernel density estimation of traffic accidents in a network space," *Comput. Environ. Urban Syst.*, vol. 32, no. 5, pp. 396–406, 2008.
[49] A. Okabe, T. Satoh, and K. Sugihara, "A kernel density estimation method for networks, its computational method and a GIS-based tool," *Int. J. Geographical Inf. Sci.*, vol. 23, no. 1, pp. 7–32, 2009.
[50] "Globe at night," Accessed: Jul. 29, 2021. [Online]. Available: https://www.globeatnight.org/
[51] "Dark skies awareness," Accessed: Jul. 29, 2021. [Online]. Available: http://www.darkskiesawareness.org/
[52] "Administrative measures of China municipality on landscape lighting," Accessed: Jul. 29, 2021. [Online]. Available: http://www.mohurd.gov.cn/fgjs/jsbgz/201006/t20100612_201310.html
[53] "Luojial-01 data distribution center," Accessed: Jul. 29, 2021. [Online]. Available: http://59.175.109.173:8888/app/login_en.html

Fei Zhao received a Ph.D. in cartography and geographic information engineering from Wuhan University, Wuhan, China, in 2012. He is currently a Lecturer at Yunnan University. His main research interests include cartography and spatial analysis.

Chen Chu received the B.S. degree in geographic information science from Yunnan University, Kunming, China, in 2021. He is currently working toward the M.S. degree in cartography and geography information system with the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, China.

His research interests include spatiotemporal data mining.

Rui Liu was born in Yunnan Province, China, in 1981. She received the Ph.D. degree in environment science from Fudan University, Shanghai, China, in 2019.

She is currently with the School of Earth Science, Yunnan University, Kunming, China. Her research interests include ground-to-space measurements of trace gases in the atmosphere.

Zhiyan Peng received the B.S. degree in geographic information science from Northeast Normal University, Changchun, China, in 2019. She is currently working toward the M.S. degree in remote sensing and geographic information with Yunnan University, Kunming, China. Her research interests include remote sensing application and cartography.

Qingyun Du is a professor of cartography and GIS with the School of Resource and Environmental Science, Wuhan University, Wuhan, China. He received his Ph.D. degree in cartography and geographic information engineering from Wuhan University. His research interests include linguistic conceptual modal of geographical information, automatic cartographic generalization, electronic mapping and spatial visualization.

Zhiqiang Xie received a Ph.D. in cartography and geographic information system from Wuhan University, Wuhan, China, in 2015. He is currently a Professor at Yunnan University. His main research interests include the theory and method of cartography.

Zhengbao Sun was born in 1985. He received the M.S. degree in physical geography from the Chinese Academy of Science, in 2012. His research interests include massive spatial data analysis.

Hongyun Zeng received the Ph.D. degree in ecology from Yunnan University, Kunming, China, in 2011.

His research interests include geospatial data mining and geospatial big data analysis

Jisheng Xia received the Ph.D. degree in cartography and geographic information system from Yunnan University, Kunming, China, in 2010. He is currently a Professor with Yunnan University, Kunming, China. His main research interests include GIS applications and basin ecological environment informatization.