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Revealing the Spatiotemporal Patterns of Anthropogenic Light at Night within Ecological Conservation Redline Using Series Satellite Nighttime Imageries (2000–2020)

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Abstract: With the rapid urbanization process, the construction of lighting facilities is increasing, whereas artificial light at nighttime (ALAN) negatively affects organisms in protected areas and threatens ecosystems. Therefore, a deep research of ALAN within protected areas is significant for better preserving biodiversity by scientific ALAN management. Taking the ecological conservation redline (ECR) in Zhejiang Province as a case study, we consistently applied remotely sensed ALAN data from 2000 to 2020 for exploring spatiotemporal changing characteristics of ALAN. More importantly, both human living and ecological safety were considered to classify ALAN status in 2019 in order to propose rational suggestions for management. The results showed ALAN intensified and expanded, increasing from $3.05 \times 10^{12}$ nW·sr$^{-1}$ to $5.24 \times 10^{13}$ nW·sr$^{-1}$ at an average growth rate of $2.35 \times 10^{12}$ nW·sr$^{-1}$·year$^{-1}$. Hotspot analysis and bivariate spatial clustering identified the aggregation situation of ALAN and the population. They showed that statistically significant ALAN hotspots accounted for only 20.40% of the study area while providing 51.82% of the total ALAN. Based on the mismatches between human demand and ALAN supply, two crucial areas were identified where regulation is needed most, and targeted policy recommendations were put forward. The study results can contribute to the effective regulation of ALAN in protected areas.

Keywords: artificial light at nighttime (ALAN); light pollution; hotspot analysis; supply and demand; lighting regulation; ecological conservation redline

1. Introduction

Ecosystems are vital for human survival and development since they provide tremendous ecological services, including biodiversity maintenance, water conservation, and climate change mitigation [1–4]. However, with the rapid development of the economy, the process of urbanization has led to enormous irreversible consequences to ecosystems, such as environmental pollution and a decrease in biodiversity [3,5,6]. To maintain ecosystem services and conduct sustainable development, protected areas have been designed by governments worldwide [7,8]. China drew up ecological conservation redlines (ECR) nationwide, designating 25 percent of its land area as crucial for ecosystem services, ecological sensitivity, and biodiversity health [2]. Although the past few years have witnessed a profound increase in the scale and number of protected areas, there are still deficiencies in
management to enhance the validity of protected areas [8]. Uncontrolled light pollution, resource exploration, and other human footprints pose potential threats to ecological security in protected areas [9,10]. While the harmful effects of artificial light at nighttime (ALAN) are becoming clear, the attention given to light pollution in protected areas is increasing [11]. Researchers have amplified various effects of ALAN, finding that ALAN has biological consequences on fauna [12,13], such as birds [14–16], turtles [12,17,18], and insects [19]. For instance, Grenis and Murphy found that ALAN contributes to the loss of insect biomass by affecting the traits of plants [19]. Since ecosystems are holistic, their balance is likely to be broken once some vital species are significantly affected [18]. Therefore, it is imperative to determine the trend and source of ALAN within protected areas to implement sustainable development strategies better.

Because of the distribution and scale of protected areas, it is not cost-efficient to carry out field research on ALAN or human settlement [20]; thus, few studies have been performed on estimating and analyzing these factors [9]. However, ALAN remotely sensed by satellite sensors has been confirmed to have great potential in monitoring urbanization [21–23], modeling demographic and socioeconomic variables [24–26], and observing the ecological environment [18,27,28], which provides a unique perspective to study the ALAN status within ECR. Before the Suomi National Polar-orbiting Partnership (NPP) satellite was launched in 2011, the Defense Meteorological Satellite Program/Operational Linescan System (DMSP/OLS) was the only source to obtain remotely sensed ALAN data. Due to the service life discrepancy between the two sensors, DMSP/OLS can offer ALAN data from 1993 to 2012, whereas VIIRS can provide ALAN data only after 2012. The two products are both excellent proxies when assessing the changing traits of ALAN at various spatial scales [29]; hence, long time series analysis is possible if the two products can be appropriately composited. However, both sensors’ performance discrepancies and inherent drawbacks resulted in severe inconsistency between DMSP/OLS and NPP-VIIRS ALAN data [30]. Therefore, studies based on long-term time series ALAN data from 1993 to now are difficult to achieve, whereas these analyses are significant for ALAN dynamic monitoring and evaluation. In 2021, Chen published a global continuous ALAN data product by calibrating DMSP/OLS and NPP-VIIRS ALAN data, which offered an opportunity to conduct studies through the entire historical period and better discover the patterns of ALAN spatiotemporal change [31]. Beyond that, with the development of new space borne sensors for quantifying light at night, nighttime data supporting ALAN researches has become abundant [32]. For example, remote sensing of night lights from the International Space Station (ISS) such as night-time astronauts’ photographs provided moderate spatial resolution (often between 5 and 200 m) images [33], and additional night-time sensors on the ISS might also be able to obtain some light pollution measurements [32]. In 2019, NASA released Black Marble nighttime lights product suite (VNP46A1) with a spatial resolution of 500 m [34], and researchers have been able to estimate a 30 m product for changes on neighborhood scales based on its composite and ancillary data layers [35]. Furthermore, the Israeli EROS-B satellite launched in 2006 was the first commercial satellite with high spatial resolution nighttime capabilities (at 0.7 m) [36], and the Chinese J1L-3B (Jilin-1) satellite launched in 2017 was the first commercial satellite to offer multispectral (red, green, and blue) nighttime lights images (at 0.92 m) [37]. The data mentioned make it possible to carry out research in finer detail, but is still unviable for an extended time series exploration of light pollution.

The spatiotemporal trend and distribution of light pollution throughout protected areas based on ALAN data have been the focus of several studies [9,38,39]. Based on NPP-VIIRS ALAN data, P. Xu et al. found that lighted pixels within protected areas in mainland China had comprehensive coverage and increased significantly from 2012 to 2017 [9]. Jiang et al.’s study indicated that mineral exploitation, tourism development, distance to urban areas and residents’ migration were significant factors influencing light pollution changes in protected areas in China [38]. The existing studies were more concerned about the negative impacts of ALAN on the environment while neglecting the basic needs of ALAN for
humans in the region, which led to a dilemma when giving specific suggestions on ALAN regulation. Compared with other pollution sources, ALAN has a double-edged trait: on the one hand, it brings convenience for human activities at night, whereas on the other hand, excessive ALAN tends to increase energy consumption and carbon emissions and even leads to environmental damage. Therefore, it is necessary to comprehensively consider the distribution pattern of ALAN and the population living in protected areas to put forward scientific ALAN management strategies. Furthermore, few studies have focused on ECR in China, whereas ECR has become the kernel of ecological safety regulation. Zhejiang Province is advanced in both the economy and ecological function in China [40]; therefore, we chose the area within the ECR of Zhejiang Province as a study area to offer a prospective reference to other regions that also face the dilemma of balancing economic development and environmental protection.

This study focused on the spatiotemporal trend and distribution patterns of ALAN within ECR in Zhejiang Province from 2000 to 2020, aiming to identify the critical areas from the perspective of human demand and ALAN supply and provide regulation recommendations. This study constructed four ALAN indexes to analyze the primary trend of light pollution and visualized spatial and temporal changes in light pollution by using a standard deviational ellipse model based on a long-term time-series ALAN remote sensing product. Furthermore, the Getis-Ord Gi* statistic was calculated to identify the ALAN hotspots, whereas bivariate clustering analysis was performed between the population and ALAN to classify the whole study area. By comprehensively considering these results, two crucial areas were identified where light pollution risk was the highest, and the relationship between ALAN supply and human demand had the lowest match. Finally, advices were given to better regulate light pollution within the study area.

2. Materials and Methods

2.1. Study Area

Zhejiang Province has been at the forefront of China’s economic development, and its GDP reached RMB 64,754.01 hundred million in 2020 (China Statistical Yearbook of 2021). In addition, Zhejiang Province is rich in ecological resources due to its diverse topographical features and meteorological resources [40]. The most valuable ecological resources have been conserved by delineating ECR for sustainable development. The area within ECR in Zhejiang Province sustains four ecological functions, i.e., water resource conservation, biodiversity conservation, soil conservation, and other ecological functions, which cover 248,000 km², accounting for 23.82% of the land area of Zhejiang Province (Figure 1), according to the NO. 30 document released in 2018 by the People’s Government of Zhejiang Province. On the one hand, the delineation of ECR comprehensively considered ecosystem services, ecological sensitivity, and biodiversity [3], which coordinated the great significance of ecological security and sustainable development. On the other hand, the construction of ECR encourages the public and government agencies to pay more attention to ecological protection during the rapid process of urbanization. Therefore, ECR in Zhejiang Province were chosen as the study area to analyze the spatiotemporal patterns of ALAN to develop regulation suggestions.

2.2. Data Sources

The data sources include extended time-series (2000–2020) NPP-VIIRS-like ALAN data, population data (PD), and ECR data. The detailed information of these data is as follows:

1. Extended time-series (2000–2020) NPP-VIIRS-like ALAN data

The ALAN data from 2000 to 2018 were derived from the product released by Chen et al. in 2020 [31], and the detail of it is referred to in the Supplementary Materials. It is recognized that the performance discrepancies and inherent drawbacks of both sensors resulted in severe inconsistencies between DMSP/OLS and NPP-VIIRS ALAN data [30], whereas Chen’s product makes it possible to make full use of both ALAN data together through a cross-sensor calibration. To expand the time span of our study, we
produced the composited NPP-VIIRS ALAN data for the years 2019 and 2020, referring to the method of Chen’s product. The monthly composite NPP-VIIRS ALAN data used in this study were downloaded from the National Oceanic and Atmospheric Administration (NOAA) (https://eogdata.mines.edu/nighttime_light/) (accessed on 6 June 2021).

2. Population data.

The PD of 2019 with a spatial resolution of 100 m was obtained from the WorldPop website (www.worldpop.org) (accessed on 7 June 2021). The product was mapped by using top-down modeling methods to disaggregate a few datasets, including a global administrative unit-based census and projection counts dataset and a set of geospatial datasets, to grid cell-based population counts [41–43].

3. ECR data.

The ECR data was derived from the No. 30 document released in 2018 by the People’s Government of Zhejiang Province. Four main stages delineated the ECR: (1) Adopting the model assessment methods issued by the National Development and Reform Commission and Ministry of Environmental Protection of China to evaluate the importance of water conservation, biodiversity conservation, the ecological function of soil and water conservation, the sensitivity of soil and water loss, and superimposing the evaluation results with the extremely sensitive and fragile ecological environment to obtain the critical area of ecological protection. (2) Amending the result obtained above by verifying whether it has covered all kinds of restricted and natural protected areas. (3) Coordinating other spatial planning and deducting small independent patches for ecological integrity and continuity. (4) Delineating ECR referred to high-resolution remote sensing image data and land use/land cover (LULC) data.

![Figure 1. (a) Location of Zhejiang Province; (b) The land area within ECR in Zhejiang.](image)

This study used a unified projected coordinate system named WGS_84_UTM_Zone_51N, and all the spatial data were resampled to 500 m to guarantee that all the spatial images could be overlaid accurately.

2.3. Methods

The methodologies implemented in this study are shown in Figure 2. First, the required ALAN and PD data were collected and resampled to the same resolution. Second, four ALAN indexes were constructed (Section 3.1), and the standard deviational ellipse (SDE) model was used (Section 3.2) to describe the spatial and temporal characteristics of ALAN. Third, the Getis-Ord Gi* statistic was calculated to identify the ALAN hotspots (Section 3.3). Bivariate clustering analysis was performed between the population and ALAN to classify...
the study area into four clusters. After overlaying the results of the hotspots and clusters, two crucial areas were delineated (Section 3.4). Finally, lighting regulations were put forward based on the results of those methodologies.

**Figure 2.** The flowchart of the methodology.

### 2.3.1. Nighttime Light Index Construction

Analyzing the changing trends of ALAN intensity and luminous areas can help us understand the status of ALAN at different stages of development. In this study, the total nighttime light (TNL), the proportion of luminous area (PLA), the mean nighttime light (MNL), and the slope index (SI) were defined as indicators to assess the ALAN characteristics within ECR of Zhejiang Province.

TNL is used to describe the temporal change in ALAN, which reflects the trend of light pollution within ECR. TNL is calculated as follows:

\[ TNL = \sum_{i=1}^{n} (ANL_i/Area_i) \]  

where \( ANL_i \) represents the radiance of ALAN in the \( i \)th pixel, \( Area_i \) represents the area of the \( i \)th pixel, and \( n \) denotes the number of lit pixels, which is defined as pixels with radiance larger than 1 nW·cm\(^{-2}\)·sr\(^{-1}\).

PLA is constructed to reflect the changing trend of the ALAN extent, which is calculated as follows:

\[ PLA = \frac{Area_i}{Area_i} \]  

where \( Area_i \) refers to the area of lit pixels, and \( Area_i \) refers to the size of all pixels within the study area.

To dispense with the influence related to the administrative area discrepancy among cities, we constructed the MNL as a standardized index to describe the variation tendency of ALAN of each city, which is calculated as follows:

\[ MNL_i = \frac{TNL_i}{Area_i} \]  

where \( TNL_i \) and \( Area_i \) represent the TNL and \( Area_i \) of the \( i \)th city, respectively.

To intuitively compare the characteristics of the ALAN change rate at the local level, SI is defined to demonstrate the rate of ALAN variation of each pixel in the whole period. SI is calculated as follows:

\[ SI = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \]  

where \( x_i \) denotes the \( i \)th year number, \( \bar{x} \) indicates the mean of all year numbers, \( y_i \) represents the radiance of ALAN in the pixel of the \( i \)th year, and \( \bar{y} \) represents the mean radiance of ALAN in the pixel from 2000 to 2020.
2.3.2. Standard Deviational Ellipse

The SDE model was used to describe the spatial characteristics and changing orientation of ALAN. SDE has served as a utility GIS tool to analyze the spatial distribution traits and the spatiotemporal evolution processes of a target object [44]. There are some attributes of SDE, including the x and y coordinates of the mean center, standard distance of the major axis and minor axis, and the orientation of SDE. The model chooses the mean center as the origin to calculate the standard deviation of the x and y coordinates, thus defining the axis of the ellipse [45]. The attributes were calculated as follows:

\[
SDE_x = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{n}}
\]

\[
SDE_y = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \bar{y})^2}{n}}
\]

\[
\tan \theta = \frac{(\sum_{i=1}^{n} \tilde{x}_i^2 - \sum_{i=1}^{n} \tilde{y}_i^2) + \sqrt{(\sum_{i=1}^{n} \tilde{x}_i^2 - \sum_{i=1}^{n} \tilde{y}_i^2)^2 + 4(\sum_{i=1}^{n} \tilde{x}_i \tilde{y}_i)^2}}{2 \sum_{i=1}^{n} \tilde{x}_i \tilde{y}_i}
\]

where \(SDE_x\) and \(SDE_y\) represent the lengths of the x and y axes, respectively; \(x_i\) and \(y_i\) are the coordinates of the \(i\)th lit pixel, \([\bar{x}, \bar{y}]\) is the mean center of the spatial element, \(n\) is the total number of lit pixels, and \(\tan \theta\) is the rotation angle.

2.3.3. Hotspot Analysis

A hotspot is a specific location or area where incidents are concentrated within a prescribed limit; thus, it can identify high-value features surrounded by high-value features [45]. Hotspot analysis is one of the most frequently used spatial autocorrelation statistics at a local level, and hotspot analysis (Getis-Ord \(G^*_i\)), a tool in ArcGIS, was used to recognize the aggregation of high-value and low-value features by calculating the z score \((G^*_i)\), \(p\) value and confidence level of each part. The formula is calculated as follows:

\[
G^*_i = \frac{\sum_{j=1}^{n} w_{ij} x_j - \bar{X} \sum_{j=1}^{n} w_{ij}}{S \sqrt{\sum_{j=1}^{n} w_{ij}^2 - (\sum_{j=1}^{n} w_{ij})^2}}
\]

\[
\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n}, S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2}
\]

where \(x_j\) is the radiance of ALAN in the \(j\)th pixel, \(w_{ij}\) is the spatial weight value of 1 or 0 depending on the distance between pixels \(i\) and \(j\), and \(n\) is the total number of pixels in one image.

In this way, high z scores and small \(p\) values pixels were defined as hotspots, whereas low z scores and small \(p\) values pixels were classified as cold spots. Hotspot analysis contributes to exploring regions with high ALAN intensity aggregation characteristics.

2.3.4. Delineation of Crucial Areas

Considering the double-edged trait of ALAN, we explored the overall spatial aggregation of PD and ALAN to discover the reasonability of the ALAN supply considering human demand and divided the areas within ECR into four clusters: cluster with high PD and high ALAN (C1), cluster with high PD and low ALAN (C2), cluster with low PD and low ALAN (C3), and cluster with low PD and high ALAN (C4). Since ALAN and PD are from disparate dimensions and cannot be compared directly, these two variables were
separately taken in the form of the logarithm and normalized by the z score formula and calculated as follows [46]:

$$Z_{Ni} = \frac{N_i - EN_i}{\sqrt{VN_i}}$$

(10)

$$Z_{Pi} = \frac{P_i - EP_i}{\sqrt{VP_i}}$$

(11)

where $N_i$ and $P_i$ are the logarithm values of ALAN and PD; $EN_i$ and $EP_i$ are the mean values of $N_i$ and $P_i$; and $VN_i$ and $VP_i$ are the variance levels of $N_i$ and $P_i$.

After the calculations mentioned above, the pixels within the ECR were grouped into four clusters: C1 includes pixels with a positive $Z_{Ni}$ and positive $Z_{Pi}$; C2 includes pixels with a negative $Z_{Ni}$ and positive $Z_{Pi}$; C3 includes pixels with a negative $Z_{Ni}$ and negative $Z_{Pi}$; and C4 includes pixels with a positive $Z_{Ni}$ and negative $Z_{Pi}$. Furthermore, we overlaid the results of bivariate clustering with ALAN hotspots to delineate two crucial areas where light pollution risk was the highest and where light supply and human demand had the lowest match. The statistically significant hotspots in C1 were defined as CA1 and the statistically significant hotspots in C4 were defined as CA2.

3. Results

3.1. Intensification and Expansion of ALAN

As shown in Figure 3, the TNL within the ECR of Zhejiang Province increased significantly during the study period, from $3.05 \times 10^{12}$ nW·sr$^{-1}$ to $5.24 \times 10^{13}$ nW·sr$^{-1}$ at an average growth rate of $2.35 \times 10^{12}$ nW·sr$^{-1}$·year$^{-1}$. Furthermore, the PLA had a similar trend as the TNL, showing a growing trend during the study period. The results above indicated that the ALAN within the ECR intensified and expanded from 2000 to 2020.

Figure 3. TNL and PLA within the ECR of Zhejiang Province from 2000 to 2020.

The MNL was constructed to compare the ALAN change rate between different cities. As shown in Figure 4, the MNL of each city increased over the 21 years overall. Among the 11 cities, Jiaxing had the largest mean MNL of $2.21$ nW·sr$^{-1}$·cm$^{-2}$ and the fastest growth rate of $0.26$ nW·sr$^{-1}$·cm$^{-2}$·year$^{-1}$. In contrast, in Lishui and Quzhou, the MNL each year was relatively low and increased slowly, related to their economic development level. In detail, according to the Zhejiang Statistics Yearbook of these years, the economic development level of those cities was relatively backward.

The expansion rate of each pixel symbolized by SI was calculated and connected to its coordinate for mapping to represent the spatial characteristics of the expansion rate. As shown in Figure 5, the spatial distribution of SI had significant aggregation features, and the values of SI varied in different regions. The statistic determined that 99.96% of the pixels in the study area had a positive SI, with a mean value of 0.026, a maximum value
of 2.774, a minimum value of −0.369, and a standard deviation of 0.055, which indicated that most regions experienced a consistent increase during this period. Figure 5 also shows that areas with a high SI were mainly distributed in some specific types of areas within the ECR, such as scenic spots and forest parks, for example, the West Lake Scenic Area in Hangzhou, and the National Forest Park in Jinhua, which are more likely to be disturbed by human activities.
3.2. Distribution and Spatiotemporal Pattern of ALAN

In this study, Hangzhou, Jiaxing, Jinhua, and Huzhou were chosen to perform the SDE analysis since these four cities had the largest lit area during the study period. Considering that the variation between adjacent years was slight, we chose the SDEs of 2000, 2005, 2010, 2015, and 2020 for further analysis and comparison. The spatial patterns and the center locus of SDEs are shown in Figure 6.

![Figure 6. SDEs of ALAN in four cities: (a) Huzhou; (b) Hangzhou; (c) Jinhua; (d) Jiaxing.](image)

The centers of the SDEs of most cities showed significant regional migration trends except for those in Jiaxing. The SDEs in Hangzhou were in a “northeast-southwest” pattern after 2005, with ratios between major axes and minor axes larger than 2.5, showing that ALAN had clear directionality. In Huzhou, the rotation increase rotated the SDEs clockwise from 2000 to 2015. The direction was elongated to the southeast and northwest, which indicated that the ALAN expansion in those directions was faster. In Jinhua, the major axes of SDEs decreased. In contrast, the minor axes increased gradually, reducing directionality, indicating that human activities have become more common in these areas.

The scope expansion of SDEs in Hangzhou and Huzhou was the most obvious among all the cities, indicating more severe light pollution. Furthermore, we noticed that the discrepancy between SDEs in 2015 and 2020 was not as obvious as that between the other two adjacent years, which may be related to the proposal of China’s ecological civilization construction policy in 2012. We concluded that effective environmental protection measures could slow the speed of ALAN expansion to some extent.
3.3. Hotspots and Cold Spots of ALAN

The hotspots and cold spots with different confidence levels are shown in Figure 7. In general, features with confidence above 95% were deemed statistically significant [47]. In this study, statistically significant hotspots were mainly distributed in coastal areas, central areas, and northern areas, as shown in Figure 7, which accounted for only 20.40% of the whole study area but provided 51.82% of the total ALAN. However, the cold spots with confidence above 95%, concentrated in the western part of the study area, comprised 63.67% of the area while providing only 32.37% of the total ALAN (Table 1). Furthermore, the mean ALAN in Hotspots—99%—was 4.96 times that in Coldspots—99%. The results indicated that small areas of hotspots provided most of the ALAN, so these areas should be the focus of regulation regarding light pollution prevention. The results also showed that as long as the key areas are well controlled, the light pollution within the whole region can be effectively alleviated.

![Figure 7. Hotspots and cold spots of the study area in 2019.](image)

| Area Ratio (%) | Annual ALAN Ratio (%) | Mean ALAN | Standard Deviation |
|----------------|------------------------|-----------|--------------------|
| Cold spots-99% | 63.67                  | 32.37     | 0.25               | 0.17               |
| Cold spots-95% | 0                      | 0         | -                  | -                  |
| Cold spots-90% | 0                      | 0         | -                  | -                  |
| Not significant| 10.13                  | 10.27     | 0.49               | 0.55               |
| Hotspots-90%  | 1.89                   | 1.81      | 0.47               | 0.59               |
| Hotspots-95%  | 3.90                   | 3.73      | 0.46               | 0.64               |
| Hotspots-99%  | 20.40                  | 51.82     | 1.24               | 2.36               |

3.4. Delineation of Crucial ALAN Regulation Areas

Bivariate clustering was conducted to detect the relation between the ALAN supply and human demand within the study area. The ecological damage caused by light pollution...
can be minimized whereas the ALAN needs of residents are satisfied by scientific regulations. As shown in Figure 8, the distribution of the four clusters within ECR was related to different regions’ geographic features and development levels. C1, with a high ALAN and high PD, was mainly concentrated in cities where the economy is more advanced, such as Hangzhou and Jiaxing, as well as in coastal cities, including Zhoushan, Ningbo, and Wenzhou. C4 has a small population, but the ALAN there was even higher than that in C2, where the population is more significant, which implied some mismatches between lighting facilities and human needs. C2 and C3 were scattered in the south and west of Zhejiang Province, where the economy is relatively more backward according to the Zhejiang Statistics Yearbook.

Figure 8. Bivariate clustering result of the study area in 2019.

Compared to C2 and C3, where the ALAN was relatively low, and the relation between the ALAN supply and human demand was reasonable, C1 and C4 had a higher risk of light pollution, so regulation measures to improve light efficiency are necessary. As proven by many studies [37,48–50], the spatial patterns of hotspots can effectively guide targeted priority policymaking. Therefore, we overlaid the statistically significant hotspots with C1 and C4 and delineated two crucial areas to put forward more scientific regulation suggestions.

CA1 accounted for 17.25% of the whole study area and mainly aggregated around some developed metropolitan areas of Zhejiang, such as Hangzhou and Ningbo. At the same time, some were distributed on the coastal side of cities, such as in southern Wenzhou and Taizhou (Figure 9). CA1 had the highest risk level of light pollution, but the number of residents there makes it unrealistic to remove the ALAN source simply. Before light pollution causes irreversible damage to ecological security, measures should be adopted to solve the dilemma comprehensively. CA2 accounted for 3.01% of the study area, scattered in the middle and west of Zhejiang Province. CA2 was also at risk of light pollution, but the population is relatively low so the improvement methods can focus on the allocation and type of luminaires.
4. Discussion

4.1. Factors Leading to the Increase and Mismatch of ALAN

According to the ALAN index analysis results, the ALAN within the ECR of Zhejiang Province intensified and expanded overall from 2000 to 2020. Additionally, most regions experienced a lifting trend of ALAN intensity at the pixel level. These conclusions revealed that light pollution within ECR is worsening, and measures must be adopted before irreversible damage occurs. The results of SDE analysis and hotspot analysis implied that most areas with high ALAN were distributed in scenic spots, forest parks, or wetland parks around urban regions. There are two main reasons to explain this phenomenon: (1) Urbanization developed rapidly in Zhejiang Province during the study period, increasing the demand for ALAN to meet people’s needs for working and recreation at night. As a result, lighting facilities intensified, and the cities lost the black sky at night. Many studies have proven that light has a diffusion effect [51,52]; thus, the ALAN increase in urban areas indirectly leads to light pollution deterioration within ECR around urban areas. (2) More attention has been given to constructing protected areas in China in recent years. The number of protected areas within the ECR has been endowed with receiving tourists [38]. To make the scenes more ornamental and ensure the safety of tourists at night, numerous public lighting facilities were installed, which directly contributed to the intensification of light pollution.

Furthermore, the bivariate clustering of ALAN and PD results discovered some mismatches between the light supply and human demand in C4. The diffused light from C1 and adjacent cities was one of the reasons, whereas the luminaries within C4 were another crucial reason. We discovered that tourism is allowed within the ECR, such as in forest parks, wetland parks, and scenic spots, so luminaires were installed to meet the demands of large numbers of tourists rather than a few residents. However, when there are no visitors in the dead of night, it is still common for street lamps to stay on all night. The waste of energy and the potential ecological threat of leaving lights on all night within the ECR urgently need to be avoided.
4.2. Policy Suggestions on Lighting Regulation

According to the delineation results, we proposed targeted regulation suggestions, especially for two crucial areas, to optimize the supply of luminaires to conserve ecological safety within the ECR.

1. Optimize the placement of luminaires. Future construction of luminaires should comprehensively consider human demands and the current situation of ALAN [46]. According to the delineation results, in C3 and C4, where human settlements are scarce, useless light should be removed from the ECR, and no stable light source should be placed in the area off the beaten path. In C1 and C2, where lighting is necessary for human living, the aim should be zero growth of total installed luminaires.

2. Perfect the traits of luminaires. The lamp shape and orientation could be changed to reduce the light projected directly at or above the horizontal plane [53]. Light interception equipment should be added to guarantee that only areas within the targeted zone are illuminated to avoid the waste of downward light flux. It is noteworthy that the diffusion effect of light expands the reach of excess light, so strictly limiting the scope of light is necessary [53]. The use of short wavelength ‘blue’ light should be reduced as much as possible, since it is recognized that it has more negative impacts on living organisms [54].

3. Restrict the intensity and time of lighting. The light intensity in C1 and C2 should be reduced to the minimum required level based on standard values (CJJ 45e2015) [46] because it is worthwhile to put the ecosystem first after weighing the damage of ALAN to the ecosystems against the residents’ needs within the ECR. An intelligent lighting system could be operated to reduce light waste when the areas are not in use.

4. Strengthen evaluation and management. Establish a scientific evaluation mechanism of the light environment and issue evaluation standards. Laws and regulations on light pollution prevention and control should be proposed, and regulations should be obeyed when planning and designing lighting facilities. Areas with a high risk of light pollution, such as CA1 and CA2, should be strictly controlled and regulated in time.

4.3. Strengths and Limitations

This study used multiple scientific methods to obtain a comprehensive view of ALAN within the ECR of Zhejiang Province. It delineated two crucial regulation areas based on the ALAN supply and human demand to protect areas within ECR from light pollution. The ALAN data from 2000 to 2020 used in this study are long and consistent; thus, the spatiotemporal trend of light pollution was more reflective of the actual situation than that in previous studies focused on the period after or before 2012 [9,38]. Moreover, the study area we chose contained protected areas and included areas of critical ecological functions and places where the ecosystem is extremely fragile. Therefore, the study area is less fragmented than merely protected areas and is relatively more meaningful and practical to policy formulation and control.

However, there are still some shortcomings to overcome in this paper: (1) The ALAN data used in this study has limitations in some respects. Firstly, compared to those of the nighttime imagery of Luojia-01, EROS-B, Jilin-1 et.al, the resolution and radiometric quantization of ALAN data used in this study were less advanced, thus limiting the precision of the results of local studies. Furthermore, both DMSP/OLS and NPP-VIIRS ALAN data is unable to detect blue light from LEDs which is acknowledged to scatter more and have passive effects on astronomical observations and ecosystems [55], whereas ground-based measurements can fill the insufficiency of lacking sensitivity to blue light [56]. Moreover, considering the light perceived by creatures is mostly horizontal light but the light measured from space is mostly vertical upward light, ground-based methods should be contained to measure nighttime brightness for further ecological studies [56]. (2) The PD data used in this study were mapped by top-down modeling methods using a few relevant datasets; thus, they reflect the population distribution at only a relatively coarse spatial resolution and cannot represent the accurate population size at a specific time. Some
studies have acquired local PD based on big data derived from social media applications, representing dynamic human activities at a finer resolution [46]. We will further detect the main driving forces of light pollution within protected areas based on multisource remote sensing data as well as big data captured from the internet, aiming to arrange the luminaires better and reduce light pollution to the greatest extent based on satisfying the primary demand for nighttime light for humans.

5. Conclusions

To analyze the spatiotemporal change patterns within the ECR of Zhejiang Province from 2000 to 2020, four nighttime light indexes were constructed, and SDEs were calculated. Considering the economic fluctuation caused by Coronavirus in 2020, the data of year 2020 is less representative. In this paper, we chose year 2019 to carry out hotspot analysis and bivariate spatial clustering, in order to obtain a comprehensive view of light pollution within the study area from the perspectives of humans and the ecological environment. As a result, two crucial regulation areas were identified for possible effective regulatory measures. The conclusions of this study are summarized as follows:

1. The ALAN indexes showed that from 2000 to 2020, ALAN within the ECR of Zhejiang Province intensified and expanded overall. At the city level, ALAN was more intense and grew faster in more developed cities, such as Hangzhou and Jiaxing; at the pixel level, areas with ERA scenic spots or forest parks experienced a more obvious upward trend in ALAN intensity.

2. The SDE analysis results of four major cities indicated that the scope of light pollution has generally been extended. Most cities showed a significant regional migration trend since regional development differences led to more severe influence in some specific areas.

3. From the results of the hotspot analysis of 2020, we were informed that areas identified as hotspots accounted for only 20.40% of the whole area while they also contributed more than half of the total ALAN, which suggested that the regulation of priority areas is vital to the ecological balance of the whole region.

4. The bivariate clustering classified the study area into four clusters, thus identifying the areas with high ecological risk as C1, where ALAN and PD were both at high levels, and discovering some mismatches of the ALAN supply and human demand as in C4, where PD was low but ALAN was relatively high. After overlaying the results with hotspots, two crucial areas were delineated for targeted regulation.

China has paid increasing attention to ecological and environmental protection in recent years. However, it is still in its infancy to notice the ecological harm of light pollution in protected areas. Moreover, since residents and tourists are allowed within the ECR, both human demand and ALAN’s harm to ecosystems should be considered in the management process. Therefore, the crucial areas outlined in this paper are meaningful for formulating future control measures. Future research can use multisource data to detect light pollution factors in protected areas, including big data.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/rs14143461/s1, File S1: Details of the extended time-series (2000–2020) NPP-VIIRS-like ALAN data.

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