

# Article Multi-Level Relationships between Satellite-Derived Nighttime Lighting Signals and Social Media–Derived Human Population Dynamics

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Abstract: Satellite-based measurements of the artificial nighttime light brightness (NTL) have been extensively used for studying urbanization and socioeconomic dynamics in a temporally consistent and spatially explicit manner. The increasing availability of geo-located big data detailing human population dynamics provides a good opportunity to explore the association between anthropogenic nocturnal luminosity and corresponding human activities, especially at fine time/space scales. In this study, we used Visible Infrared Imaging Radiometer Suite (VIIRS) day/night band (DNB)-derived nighttime light images and the gridded number of location requests (NLR) from China's largest social media platform to investigate the quantitative relationship between nighttime light radiances and human population dynamics across China at four levels: the provincial, city, county, and pixel levels. Our results show that the linear relationship between the NTL and NLR might vary with the observation level and magnitude. The dispersion between the two variables likely increases with the observation scale, especially at the pixel level. The effect of spatial autocorrelation and other socioeconomic factors on the relationship should be taken into account for nighttime light-based measurements of human activities. Furthermore, the bivariate relationship between the NTL and NLR was employed to generate a partition of human settlements based on the combined features of nighttime lights and human population dynamics. Cross-regional comparisons of the partitioned results indicate a diverse co-distribution of the NTL and NLR across various types of human settlements, which could be related to the city size/form and urbanization level. Our findings may provide new insights into the multi-level responses of nighttime light signals to human activity and the potential application of nighttime light data in association with geo-located big data for investigating the spatial patterns of human settlement.

**Keywords:** VIIRS nighttime light; social media uses; human activity; multi-level relationships; spatial autocorrelation; spatial consistency

# 1. Introduction

It is well documented that anthropogenic nocturnal lighting data are informative and indicative measures of various human activities at the local, regional, and national scales over both time and space [1–5]. In comparison with other sources of remotely sensed data, the most notable advantage of satellite-derived nighttime light data is that it can provide us with the spatiotemporal dynamics of the regional degree of demographic and socioeconomic activities [6–11]. Related studies are typically



based on the quantitative correlations of the observed magnitudes of nighttime light radiances with several statistical and census indices, such as the gross domestic product, population size, extent of urban built-up areas, and energy consumption [12–18]. Therefore, satellite-derived artificial lighting data are widely regarded as a proxy measure of human activity in a spatially explicit and temporally consistent manner [3,11,19].

Previous studies have usually focused on the regional-scale quantitative relationship between the annual composite of nocturnal luminosity and yearly statistical data. Such investigations generally quantified the mean response of the anthropogenic nighttime brightness to inter-regional variations and inter-annual changes in demographic and socioeconomic variables (e.g., human population size, gross domestic product, electric power consumption, urban built-up areas) over space and time (typically using monotonic functions such as linear, log-linear, and power-law models). In fact, remotely sensed nighttime light data currently derived from the Visible Infrared Imaging Radiometer Suite (VIIRS) instrument with the day/night band (DNB), which is located on board the Suomi National Polar-Orbiting Partnership (Suomi-NPP) satellite that generates monthly composite products, can provide timely and spatially explicit information regarding artificial lighting signals at night [20–25]. VIIRS DNB data thus potentially enable us to investigate the dynamics of human settlement at a fine spatiotemporal scale [26–39], especially when daily products with cloud-free and ambient factor-corrected brightness become available in the near future [40]. However, how nighttime light brightness signals timely respond to corresponding demographic and socioeconomic activities, particularly at the pixel level, remains less well understood, largely because of the lack of large-scale synchronous observations of human activities.

The currently increasing availability of crowd-sourced big data detailing the temporal and spatial records of individual metadata, which are typically derived from taxi, bill tract, mobile phone, and social media uses, enables us to obtain an estimate of the spatiotemporal patterns of human population dynamics [41–43]. Therefore, an investigation into the quantitative relationship between two types of sensed data is essentially important for the following issues: (i) to further clarify the quantitative responses of artificial nighttime lighting signals to corresponding human activities, particularly at fine spatiotemporal scales, and (ii) to further improve our understanding of the spatial patterns of human settlement based on the combination of remotely sensed signals of artificial nighttime lights and socially sensed data of human activity.

The primary objective of the present study is to investigate the quantitative relationship between VIIRS DNB–derived composite signals of anthropogenic nighttime lights and synchronous observations of human activities derived from geo-located social media applications on a monthly time scale across China at four different levels: the provincial, the city, the county, and the pixel levels. In addition to widely used ordinary least squares regression, quantile regression, geographically weighted regression, and the spatial autoregressive model are applied to further investigate this quantitative relationship at different levels. A partition algorithm based on the association of pixel-level VIIRS DNB signals with social media–derived measurements of human activity is proposed to characterize the spatial pattern of human settlement from a joint perspective of satellite-sensed anthropogenic nocturnal lights and social media-based human activity.

#### 2. Materials and Methods

# 2.1. VIIRS Nighttime Light Data

Satellite-derived nighttime light images are provided by National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Information (NCEI) (we downloaded the data from the website at https://ngdc.noaa.gov/eog/viirs/index.html). To reduce the impacts of cloud cover on the monthly composites, two monthly cloud-free composites of VIIRS DNB nighttime brightness data collected in February and March 2018 are used in this study. We used the maximum value composite (MVC) to generate a nighttime light image covering China based on two monthly composites

of VIIRS DNB data. As shown in Figure 1, this composited image is produced in 15 arc-second geographic grids (~500 m at the equator) in the WGS84 reference system representing cloud-free average values of the anthropogenic nighttime light brightness (NTL, in nW cm<sup>-2</sup> sr<sup>-1</sup> hereafter).



**Figure 1.** Spatial distributions of Visible Infrared Imaging Radiometer Suite (VIIRS) day/night band (DNB)–derived nighttime light radiances (upper, the two-month composite of February and March 2018) and the number of location requests derived from Tencent's social media platform (lower, the monthly composite of February 2018) across China. Blue lines represent province-level boundaries.

# 2.2. Tencent's Location-Aware Data

Tencent's big data location map (available at https://heat.qq.com/) provides grid cell-level (with a spatial resolution of  $0.01 \times 0.01$  decimal degrees, ~1 km by 1 km at 25°N) records of the number of location requests (termed as NLR hereafter) sent by local social media users with diverse purposes,

such as navigating, location sharing, and searching for nearby people, regarding location-based applications. We collected a dataset from Tencent's online location map spanning the period from 1 February to 28 February 2018. As shown in Figure 1, this dataset consists of the locally aggregated volume counting the total NLR for every grid cell over 28 days across China.

To reduce noise in the original Tencent data, those pixels with a daily average NLR less than 10 were excluded from our study (through comparison with remote lands). A total of 1,870,364 pixels covering nearly 1.92 million km<sup>2</sup> of land area were selected for subsequent analyses. The original composite of VIIRS DNB images was resampled into  $0.01 \times 0.01$  decimal degree by the nearest neighbor method in order to match the resolution of Tencent's gridded data. To eliminate the effects of area distortion in the WGS84 reference system, we used the area-weighted nighttime light brightness (calculated as the product of NTL and the corresponding pixel area, which is approximately estimated through the ellipsoid trapezoid area) to quantify the degree of anthropogenic nocturnal radiance. Based on the VIIRS DNB and Tencent images, we obtained regional-level estimates of both the NTL and the NLR for 31 provinces and municipalities, 340 cities, and 2852 counties in China by overlaying the administrative unit map onto the VIIRS DNB and Tencent data.

#### 2.3. Statistical Analysis

Ordinary least squares (OLS) regression and quantile regression are used to statistically fit the global quantitative relationship between VIIRS DNB-derived nighttime light signals and the corresponding Tencent-derived observations of human activity; the former technique is directed at the conditional mean responses of the variables, while the latter yields estimates of the conditional median and other quantiles (including 0.05, 0.25, 0.50, 0.75, and 0.95) of the variables. Quantile regression enables us to obtain a more comprehensive view of the complicated relationships between the two observed variables through measures of the central tendency and statistical dispersion. We perform both of the abovementioned regression analyses at four different levels: the provincial, the city, the county, and the pixel levels. Furthermore, geographically weighted regression (GWR) is used to investigate the local quantitative relationship between the two observed variables to provide separate assessments of the spatial heterogeneity of their association at the provincial, city, and county levels. Moran's *I* statistics is employed to measure the degree of spatial autocorrelation of variables. The spatial simultaneous autoregressive (SAR) lag model is used to deal with a global-scale linear regression model incorporating the spatial autocorrelation structure.

# 3. Results and Discussion

# 3.1. Quantitative Relationship between Tencent's Data and Human Population Dynamics

The relationship between Tencent's data and the degree of actual human activity can be exemplified in the ancient town of Qingyan, a tourist attraction in Guizhou Province covering ~90 km<sup>2</sup>. As illustrated in Figure 2, observed changes in the daily number of location requests can totally explain ~80% of the variances in the number of tourists over time. Hence, Tencent's data-derived NLR is indicative of the degree of human population dynamics, and it can be regarded as a direct measure of human activity.

#### 3.2. Quantitative Relationship between the VIIRS DNB and Tencent Data

In general, there are significant linear (Figure 3a) and log-linear (Figure 3b,c) relationships between the regional sum of the area-weighted NTL data derived from VIIRS DNB images and the total pixel-level NLR acquired by social media platforms. The OLS regression results state that the nighttime light radiance can totally explain nearly 68%, 78%, and 75% of the inter-regional variances in the NLR at the provincial, city and county levels, respectively. These findings imply that satellite-derived observations of artificial lighting signals at night can quantitatively indicate the regional dynamics of the human population at short time scales at the three different levels consistently. Similar results have been widely observed by numerous previous studies investigating the response of NTL to socioeconomic variables [1,4,6,9,19,26,27]. Such proxy measurements, however, appear to be limited at the pixel level (see Figure 3d), in which the NTL can explain only 33% of the nationwide variation in the NLR, probably because of the increased spatial heterogeneities in the distributions of both artificial nighttime lighting sources and human activities at a fine spatial scale [30].



**Figure 2.** The relationship between the number of location requests derived from Tencent's big data map and the number of tourists (both were normalized using the standard score) in the ancient town of Qingyan (located in Guiyang City, Guizhou Province, China) over the 61-day period in 2017.



**Figure 3.** Quantitative relationship between the area-weighted nighttime light radiances and the number of location requests estimated by ordinary least square (OLS) and quantile regression at four different levels: (**a**) the provincial level (linear scale, samples = 31); (**b**) the city level (log-linear scale, samples = 340); (**c**) the county level (log-linear scale, samples = 2852); and (**d**) the pixel level (log-linear scale, samples = 1,870,364). All quantile regressions show statistical significance with P < 0.001.

In comparison with OLS, quantile regression analysis provides us with a more comprehensive view of the relationship between NTL and NLR through measures of central tendency and statistical dispersion [30]. As represented in Figure 3, it should be noted that there are visible dispersions of the linear (Figure 3a) and log-linear (Figure 3b–d) responses with changes in the magnitudes of both variables with respect to the NTL and NLR among the administrative units and pixels. At the provincial level (Figure 3a), the disparity between the area-weighted NTL and the regional NLR magnitude (according to the linear response) is conspicuously distinct from the lower quantiles to the higher quantiles with gradually increasing fitted slopes (from 3.49 to 9.43). At the city and the county levels, the fitted slopes show decreases from 1.12 to 0.91 and from 1.05 to 0.80, respectively, both of which occur commonly from the lower quantiles to the higher quantiles according to the log-linear response. Different relationships of the conditional quantiles with various fitted slopes between NTL and NLR indicate that regions exhibiting similar nighttime lighting brightness could have distinctly different magnitudes of human activity. For instance, although Guangdong and Jiangsu have similar area-weighted NTL ( $3.91 \times 10^5$  vs.  $3.90 \times 10^5$  nW cm<sup>-2</sup> sr<sup>-1</sup> km<sup>2</sup>, see Figure 3a), these two provinces show a notable difference in NLR ( $21.74 \times 10^8$  vs.  $14.08 \times 10^8$ ). This result suggests that the relationship between NTL and NLR could regionally vary due to differences in the sizes and forms of human settlements and the distribution of human population.

On the one hand, the abovementioned findings confirm the typical utility of VIIRS DNB data for measurements of the regional-level degree of human activity with monotonic positive responses. On the other hand, it should be noted that there could exist shifts in the quantitative relationship between the two measured variables that might reflect the inter-regional difference in the response of artificial nighttime lighting signals to the corresponding human activity.

# 3.3. The Spatial Autocorrelation of the NTL and NLR

The quantile regression results clearly reveal the visible impacts of changes in the degree of regional-level human activity in terms of social media applications on the conditional distribution of anthropogenic nocturnal luminosity. Such impacts can be partly attributed to the spatial variations in the distributions of both observed variables. In particular, as represented in Figure 4, there should exist a spatial autocorrelation (i.e., regions spatially close to each other appear to have observed values that are more similar than those farther apart) in both variables at a given observation level. For NTL, Moran's *I* test statistic indicates that there are positive spatial autocorrelations gradually increasing from the provincial level (Figure 4a, *I* = 0.04 and *P*-value = 0.34) to the city level (Figure 4c, *I* = 0.20 and *P*-value < 0.01) to the county level (Figure 4e, *I* = 0.26 and *P*-value < 0.01). A similar pattern appears to occur in the NLR at the city level (Figure 4d, *I* = 0.21 and *P*-value < 0.01) and the county level (Figure 4f, *I* = 0.26 and *P*-value < 0.01) and the county level (Figure 4f, *I* = 0.26 and *P*-value < 0.01), although not at the provincial level (Figure 4b, *I* = -0.06 and *P*-value = 0.74).

In practices, the presence of spatial dependence between the two measured variables should be taken into account in investigations of the quantitative relationship between NTL and the corresponding degree of the NLR. The widely used linear and log-linear regression models at the regional level (see Figure 3a–c) would be mis-specified if the effect of this spatial dependence is overlooked. In this study, Moran's *I* test statistic for the OLS regression residuals shows statistically significant spatial positive autocorrelation results, especially at the city level (I = 0.36 and *P*-value < 0.01) and the county level (I = 0.35 and *P*-value < 0.01), suggesting that the magnitude of the response of NTL to the NLR might be overestimated in regional-level OLS regression analysis.



**Figure 4.** Spatial distributions of regional area-weighted nighttime light radiances (**left**, **a**, **c** and **e**) and the number of location requests (**right**, **b**, **d** and **f**) at the provincial (**upper**, **a** and **b**), the city (**middle**, **c** and **d**), and the county (**lower**, **e** and **f**) levels across China.

Furthermore, the global effect of the spatial autocorrelation of two variables can be represented by an SAR lag model. In this spatial regression model, the component of inter-regional variations in the NLR caused by the spatial autocorrelation is distinguished from the corresponding NTL signals by introducing an autoregressive item in the OLS regression as

$$NLR = \rho W \times NLR + Intercept + slope \times NTL + \varepsilon$$
(1)

where  $W \times NLR$  is the autoregressive item (i.e., the spatial lag) with geographical weight matrix W (based on regions with contiguous boundaries),  $\rho$  is the autoregressive coefficient, and  $\varepsilon$  is the residential error. Consequently, our results show that the fitted slope of NTL with respect to the NLR as a linear (for the provincial level) or log-linear (for both the city and the county levels) response estimated by the SAR lag model is conspicuously and consistently smaller than that estimated by OLS from the provincial level (4.79 with *P*-value < 0.01 vs. 5.07 with *P*-value < 0.01) to the city level (0.87 with P-value < 0.01 vs. 1.00 with P-value < 0.01) to the county level (0.66 with P-value < 0.01)vs. 1.39 with P-value < 0.01). Moreover, the SAR lag model-based regression results suggest that the spatial dependence of the variables could account for a respectable proportion of inter-regional changes in the observed degree of human activity, which is estimated to increase from the provincial level (~4.6%, calculated here as the ratio of the autoregressive coefficient and the sum of the autoregressive coefficient and the fitted coefficient of nighttime lights) to the city level (~23.7%) to the county level (~37.7%). These results suggest that the quantitative relationship between the volume of nighttime light signals and the degree of human activity over regions can be overestimated, especially at a fine spatial scale, if the effect of the spatial autocorrelation of variables is not considered in a global OLS regression model.

# 3.4. Spatial Patterns in the Relationships between NTL and the NLR

The abovementioned regression results provide us with a global view regarding the regional-level quantitative relationship between nighttime light signals and the volume of location requests in social media applications. Next, we used geographically weighted regression (GWR) to further quantify the local relationships between these two variables at three different levels. For a given target region *g*, GWR is calculated as

$$NLR(g) = Intercept(g) + slope(g) \times \sum W \times NTL + \varepsilon(g)$$
(2)

where *W* is distance-based weight matrix in which bandwidth for an optimal kernel is estimated using the corrected Akaike Information Criterion, and  $\varepsilon(g)$  is the residential error. In contrast to OLS, quantile regression and SAR lag models with globally constant coefficients, GWR allows us to obtain local estimates of these relationships with spatially varying coefficients.

As shown in Figure 5a,b, the fitted coefficients of the slope and intercept commonly show slight spatial variations at the provincial level with respective ranges of 5.06-5.07 and  $7.96 \times 10^5-8.02 \times 10^5$ , which are not significantly different from those produced by OLS regression (see Figure 3a). At the city level, however, the fitted coefficients show spatially visible fluctuations ranging from 0.72 to 1.34 for the slope (Figure 5c) and from -0.63 to 1.89 for the intercept (Figure 5d). The GRW-based results suggest that nighttime light signals can totally explain ~91% (according to the coefficient of determination,  $R^2$ ) of the inter-regional variations in human activity; this result is notably higher than that in the global OLS-based estimate (see Figure 3b, here  $R^2$  is estimated to be ~78%). In general, western regions in China appear to have a higher fitted slope and a lower intercept (both with respect to a log-linear regression) than eastern regions. Relatively visible spatial variations in the fitted coefficients appear to occur at the county level (as shown in Figure 5e,f). The fitted slope and intercept are estimated to range respectively from 0.54 to 1.30 and from -0.36 to 2.28. Relatively larger fitted slopes are typically found in western, northeastern and parts of southeastern China, while the fitted intercept shows an opposite spatial pattern. All these results jointly indicate a spatial disparity in the quantitative

relationship between regional nighttime light signals and the corresponding degree of location requests; the variation gradually increases with the observation level from the provincial level to the county level, primarily due to the enhanced spatial independence of both variables.



**Figure 5.** Spatial distributions of the estimated slope (**left, a, c** and **e**) and intercept (**right, b, d** and **f**) for the local relationship between the nighttime light radiance and the number of location requests by geographically weighted regression (GWR) at the provincial (**upper, a** and **b**), the city (**middle, c** and **d**), and the county (**lower, e** and **f**) levels across China.

Additionally, It should be mentioned that although the observed degree of human activity in association with the effect of spatial autocorrelation can explain most major variations in nighttime lighting signals, other underlying driving factors, for example, cultural differences on street lighting [44] and its dynamics [45], inter-regional differences in demography [46], and various lighting technology uses [47], can also contribute the regional disparity in the relationship between NTL and NLR at different observation levels. Thus, the quantitative response of nighttime lights to corresponding human activity might differ regionally with various demographic, socioeconomic, cultural, and technical factors, especially across a vast region like China.

# 3.5. Pixel-Level Partition Based on the Bivariate Relationship

Generally speaking, the spatial pattern of NTL is mainly determined by the distribution of artificial lighting sources at night over human settlements, while the social media-derived NLR are representative measures of the local dynamics among the human population (as demonstrated in Figure 2). In spite of geographical shifts, these two variables typically show a strong quantitative relationship at the regional scale (Figure 3a–c). At the pixel level, however, the distributions of these two variables show less similarity (Figure 3d) due to the increased spatial heterogeneities of man-made lighting objects and the human population distribution. Two different sources of measurements could reflect distinctly different aspects related to the spatial patterns of human settlement at a fine scale, thereby providing us with a way to identify different types of areas with various human activities through the association between satellite-derived nighttime light radiances and social media–derived human population dynamics.

As exemplified by the city of Beijing (see Figure 6), we partitioned the bivariate plot into nine sub-regions (here, using the first and the third quartiles), and thus, all target pixels located in the city of Beijing were categorized into nine different types based on the association between the nighttime light radiance and the number of location requests: low-low (LL), medium-low (ML), high-low (HL), low-medium (LM), medium-medium (MM), high-medium (HM), low-high (LH), medium-high (MH), and high-high (HH). As shown in Figure 6a, three spatially consistent types (LL, MM and HH) account for the major proportion of all pixels (~68.2%). Only a minor proportion (~0.3%) of pixels is partitioned into two highly inconsistent types (HL and LH). Among all of the pixels, 15.9% of them are classified as types LM and MH, in which the observed NTL magnitude is less than the expected value for a given degree of the NLR with respect to the regional average (as represented by the red dashed line in Figure 6a). Approximately 15.5% of the pixels as identified as types ML and HM, both of which appear to show relatively higher NTL magnitudes and lower degrees of the NLR in comparison with the city-averaged level.

Comparing the partitioning results (Figure 6b) with the land use map (see Figure 6c, data are for 2015 and provided by the Institute of Geographical Sciences and Natural Resource Research [48]; here, three types of man-made land are involved because we mainly pay attention to the relationship between NTL and NLR over artificial lands), we can empirically find the following: (i) type LL pixels primarily cover remote, small residential sites with low-density human activity, (ii) type MM pixels mainly consist of outer suburban areas with medium-density human activity, (iii) type HH pixels are generally associated with urbanized areas with high-density human activity, (iv) type MH pixels mostly cover suburban areas with a high human population density and a medium nighttime light density, (v) type HM pixels are typically found in the peripheral areas of urbanized zones with a medium human population density and a high nighttime light density, (vi) type LM pixels appear to occur in large villages and hamlets; (vii) type LM pixels mostly cover townships and large settlements, (viii) type HL pixels seemingly occur in industrial areas with a high nighttime light density and a low human population density, and (ix) type LH pixels are generally found in remote areas in which notable human activity is captured by social media applications all day long but is not sensed by VIIRS DNB data at night. A plausible explanation for type LH pixels is that such areas generally have a high human population density and fewer artificial lighting features (e.g., scenic spots and resort areas) or that the infrastructure and socioeconomic status are under-developed in these areas.



**Figure 6.** (a) Illustration of the pixel-level partition based on the bivariate plot of the nighttime light radiance and the number of location requests in Beijing. Green solid lines represent the first and the third quartiles; (b) Partitioning result according to (a); (c) Landsat data-derived artificial land distributions.

# 3.6. City-Level Variations in the Spatial Consistency of the NTL and NLR Distributions

Our previous study has shown the utility of Tencent-derived big data for the hierarchical classification of human settlement based on partitioned VIIRS DNB nighttime light images [49]. In this study, we developed a bivariate plot-based approach associating nighttime lighting signal with human population dynamics information to perform a pixel-level partition of human settlement for 340 Chinese cities. The compositions of the different types of pixels enable us to investigate inter-city differences in the spatial patterns of human settlement through the joint characteristics of the intra-regional distributions of both the NTL and the NLR. As addressed above, the combination of three types (LL, MM, and HH) provide us with an approximate measurement of the spatial consistency of the distributions of the NTL and NLR magnitudes over a given human settlement. In this study, our results show that the proportion of LL+MM+HH (termed P0) might follow a rank-ordering distribution with two power-law parameters (also known as the discrete generalized beta distribution [50], DGBD, see Figure 7a for details). P0 is estimated to decrease orderly from 0.71 (Xiamen, the first) to 0.43 (Zhongwei, the last) across the 340 Chinese cities. From Figure 7a, we can further find that (i) the value of P0 shows a rapid decline from approximately 0.71 (Xiamen) to 0.57 (Changsha) at the head of the DGBD distribution across 52 cities, (ii) a slight decrease in P0 appears to occur for most of the cities ranked in the middle section of the DGBD distribution from approximately 0.54 (Zhangjiakou) to 0.49 (Shenyang), and (iii) the tail of the DGBD distribution shows a fast decay in P0 approximately after the city of Lianyungang. These findings jointly suggest a notable difference in the spatial consistency of patterns in both the dynamics of the human population and the artificial nighttime lighting features among a diverse selection of Chinese cities; this difference probably results from the variations in socioeconomic status and the sizes and forms of cities. In general, large cities with a high human activity density show

a relatively large P0 (see insets in Figure 7a), which implies a spatially proportional distribution of the NLR with respect to the corresponding NTL in these regions. A relatively small value of P0 appears to occur in most of the middle- to small-sized cities with medium-low averages of both the NTL and the NLR. In addition, the power behavior in the rank-ordered distribution (Figure 7a) might imply an inter-regional inequality in the characteristics of the NTL and NLR and the spatial co-distribution of these two variables across China's cities, which is probably due to the diversity in urbanization level and human population dynamics across the country.



**Figure 7.** (a) Rank-ordered distribution of P0 (here, a base-10 log scale is used) across 340 Chinese cities. Two insets show the relationships between P0 and the average nighttime light radiance (**left**) and the density of location requests (**right**) according to a power law; (b) Quantitative comparison between P1 and P2 (see main text and Figure 6a for definitions) among 340 cities in China.

Apart from the measurements of P0, a cross-regional comparison of the proportion of ML+HM+HL (P1) with the proportion of LM+MH+LH (P2) could further portray the variations in the spatial patterns of human settlement in terms of the spatial regularity of the NTL and NLR distributions across various city-level regions. As illustrated in Figure 6a, P1 and P2 are used as measures of the total proportions of local areas, which tend to have respectively higher and lower NTL values relative to their own NLR magnitudes based on the regional average. Figure 7b shows that there is a significant positive linear relationship between P1 and P2 across the 340 Chinese cities, and the deviation likely increases with increases in P1 and P2. This result indicates that the co-occurrence of two opposite types of local areas with respect to the spatial inconsistency between the distributions of the NTL and NLR is likely prevalent for all city-level regions. In general, cities with large urbanized areas show relatively low and similar P1 and P2 distributions. Relatively high P1 and P2 values likely occur in medium- and small-sized cities, in which the difference between P1 and P2 might vary inter-regionally.

### 3.7. Spatial Patterns in the NTL and NLR Distributions

According to the abovementioned results, nine typical cities (see Figure 8) with various sizes and features (see Figure 7) were selected to give a comparative characterization of the spatial patterns of human settlement in the context of the partitioning results based on the pixel-level bivariate relationship between the NTL and NLR. Generally, the spatial patterns of the NTL and NLR distributions are largely determined by the level of urbanization. As shown in Figure 8a, cities with relatively high proportions of MM and HH (e.g., Beijing, Xiamen, and Ningbo) generally appear to show

relatively low proportions of HL and LH, which represent two extreme types of inconsistencies in

the distributions of NTL and NLR across human settlements (see Figure 6a). Such regions commonly have a high proportion of urbanized area and peripheries with spatially concentrated, intense human activities (see Figure 6b), which could result in a high spatial consistency between the NTL and NLR distributions. By contrast, cites with geographically dispersed urbanized areas and human activities (e.g., Lianyungang, Nanchong, Cangzhou, and Kaifeng) might tend to show a relatively large proportion of HL and LH and a low spatial consistency between the NTL and NLR distributions. In these regions, most of the pixels showing a spatial inconsistency between the NTL and NLR likely occur in the transition zone between urbanized areas. This finding could imply a potential increase in the spatial consistency between the NTL and NLR with the growth of artificial land and the intensification of human activities driven by the urbanization process.



**Figure 8.** (a) Proportions of nine different types of pixels (as defined in Figure 6) for China and nine city-level regions; (b) Spatial distributions of the different types of pixels across nine city-level regions. Insets show the spatial distribution of urbanized areas. The setup of false-color ramp is the same as in (a).

#### 4. Conclusions

Satellite-derived observations of artificial lighting signals at night have been widely regarded as an efficient proxy measure of diverse human activities related to demographics, socioeconomics, and urbanization. In the present study, we used two of the most recent synchronous datasets derived from VIIRS DNB images and Tencent's social media applications to investigate the quantitative relationships between anthropogenic nighttime lighting signals and human population dynamics across China at four different levels: the provincial, the city, the country, and the pixel levels.

First, our results confirm the effectiveness of nighttime light data in terms of serving as a proxy measure of human population dynamics because there are statistically significant linear relationships between the NTL and NLR at the provincial, city, and county levels. Second, we also noted the existence of a marked dispersion between the VIIRS DNB nighttime lighting signals and social media application-derived quantity of human population dynamics, especially at the pixel level. Third, both variables exhibit a marked spatial autocorrelation at the city and county levels, which could provide a certain contribution to the corresponding regional-level association between the NTL and NLR and hence lead to an overestimation of the quantitative spatial response of nighttime light signals to the corresponding degree of human activity. Fourth, in spite of its statistical significance, the quantitative relationship between the NTL and NLR at the pixel level is likely insufficient to obtain a measure of the degree of human activity largely because of the spatial heterogeneity between artificial nighttime lighting sources and the distribution of human population dynamics at a fine scale. Fifth, our results suggest that the bivariate relationship between the NTL and NLR at the pixel level can be used to spatially partition human settlements based on the joint features of the magnitude of nighttime light signals and the degree of human population dynamics. Human settlements located in different areas might demonstrate varying characteristics resulting from underlying differences in urbanization. In addition, it is noteworthy that seasonal and monthly variations in both social media-derived human activity and VIIRS DNB nighttime light signals [34], and other driving factors for instance, cultural and demographic differences and the lighting technology [44–47], could affect the quantitative relationship between NTL and NLR and should be taken into account in future studies.

In conclusion, remotely sensed nighttime light data could further enhance our understanding of human activity, particularly regarding inter-level and geographical variations in the quantitative responses of nighttime lighting signals to the magnitudes of human activity and in association with the increasing availability of geo-located big data.

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# References

- Elvidge, C.; Baugh, K.; Kihn, E.; Kroehl, H.; Davis, E.; Davis, C. Relation between satellite observed visible-near infrared emissions, population, economic activity and electric power consumption. *Int. J. Remote Sens.* **1997**, *18*, 1373–1379. [CrossRef]
- 2. Elvidge, C.D.; Baugh, K.E.; Kihn, E.A.; Kroehl, H.W.; Davis, E.R. Mapping city lights with nighttime data from the DMSP Operational Linescan System. *Photogramm. Eng. Remote Sens.* **1997**, *63*, 727–734.
- 3. Chen, X.; Nordhaus, W.D. Using luminosity data as a proxy for economic statistics. *Proc. Natl. Acad. Sci. USA* **2011**, *108*, 8589–8594. [CrossRef] [PubMed]
- 4. Zhang, Q.; Seto, K.C. Mapping urbanization dynamics at regional and global scales using multi-temporal DMSP/OLS nighttime light data. *Remote Sens. Environ.* **2011**, *115*, 2320–2329. [CrossRef]

- 5. Small, C.; Sousa, D.; Yetman, G.; Elvidge, C.; MacManus, K. Decades of urban growth and development on the Asian megadeltas. *Glob. Planet. Chang.* **2018**, *165*, *62*–89. [CrossRef]
- 6. Sutton, P.; Roberts, D.; Elvidge, C.; Baugh, K. Census from heaven: An estimate of the global human population using night-time satellite imagery. *Int. J. Remote Sens.* **2001**, *22*, 3061–3076. [CrossRef]
- Sutton, P.C. A scale-adjusted measure of "urban sprawl" using nighttime satellite imagery. *Remote Sens. Environ.* 2003, *86*, 353–369. [CrossRef]
- 8. Small, C.; Pozzi, F.; Elvidge, C.D. Spatial analysis of global urban extent from DMSP/OLS night lights. *Remote Sens. Environ.* **2005**, *96*, 277–291. [CrossRef]
- Amaral, S.; Câmara, G.; Monteiro, A.M.V.; Quintanilha, J.A.; Elvidge, C.D. Estimating population and energy consumption in Brazilian Amazonia using DMSP night-time satellite data. *Comput. Environ. Urban Syst.* 2005, 29, 179–195. [CrossRef]
- 10. Doll, C.; Muller, J.; Morley, J. Mapping regional economic activity from night-time light satellite imagery. *Ecol. Econ.* **2006**, *57*, 75–92. [CrossRef]
- 11. Small, C.; Elvidge, C.D. Mapping decadal change in anthropogenic night light. *Procedia Environ. Sci.* **2011**, *7*, 353–358. [CrossRef]
- 12. Elvidge, C.; Baugh, K.; Anderson, S.; Sutton, P.; Ghosh, T. The night light development index (NLDI): A spatially explicit measure of human development from satellite. *Soc. Geogr.* **2012**, *7*, 23–35. [CrossRef]
- 13. Huang, Q.; Yang, X.; Gao, B.; Yang, Y.; Zhao, Y. Application of DMSP/OLS nighttime light images: A meta-analysis and a systematic literature review. *Remote Sens.* **2014**, *6*, 6844–6866. [CrossRef]
- Kyba, C.C.M.; Kuester, T.; Sánchez de Miguel, A.; Baugh, K.; Jechow, A.; Hölker, F.; Bennie, J.; Elvidge, C.D.; Gaston, K.J.; Guanter, L. Artificially lit surface of Earth at night increasing in radiance and extent. *Sci. Adv.* 2017, *3*, e1701528. [CrossRef] [PubMed]
- 15. Ghosh, T.; Powell, R.L.; Elvidge, C.D.; Baugh, K.E.; Sutton, P.C.; Anderson, S. Shedding light on the global distribution of economic activity. *Open Geogr. J.* **2010**, *3*, 148–161.
- 16. Li, X.; Ge, L.; Chen, X. Detecting Zimbabwe's decadal economic decline using nighttime light imagery. *Remote Sens.* **2013**, *5*, 4551–4570. [CrossRef]
- 17. Xu, T.; Ma, T.; Zhou, C.; Zhou, Y. Characterizing spatio-temporal dynamics of urbanization in China using time series of DMSP/OLS night light data. *Remote Sens.* **2014**, *6*, 7708–7731. [CrossRef]
- Ma, T.; Zhou, Y.; Zhou, C.; Haynie, S.; Pei, T.; Xu, T. Night-time light derived estimation of spatio-temporal characteristics of urbanization dynamics using DMSP/OLS satellite data. *Remote Sens. Environ.* 2015, 158, 453–464. [CrossRef]
- 19. Bennett, M.M.; Smith, L.C. Advances in using multitemporal night-time lights satellite imagery to detect, estimate, and monitor socioeconomic dynamics. *Remote Sens. Environ.* **2017**, *192*, 176–197. [CrossRef]
- Miller, S.D.; Hawkins, J.D.; Kent, J.; Turk, F.J.; Lee, T.F.; Kuciauskas, A.P.; Richardson, K.; Wade, R.; Hoffman, C. NexSat: Previewing NPOESS/VIIRS imagery capabilities. *Bull. Am. Meteorol. Soc.* 2006, 87, 433–446. [CrossRef]
- 21. Hillger, D.; Kopp, T.; Lee, T.; Lindsey, D.; Seaman, C.; Miller, S.; Solbrig, J.; Kidder, S.; Bachmeier, S.; Jasmin, T. First-light imagery from Suomi NPP VIIRS. *Bull. Am. Meteorol. Soc.* **2013**, *94*, 1019–1029. [CrossRef]
- 22. Elvidge, C.D.; Baugh, K.; Zhizhin, M.; Hsu, F.-C.; Ghosh, T. VIIRS night-time lights. *Int. J. Remote Sens.* 2017, 38, 5860–5879. [CrossRef]
- Small, C.; Elvidge, C.D.; Baugh, K. Mapping urban structure and spatial connectivity with VIIRS and OLS night light imagery. In Proceedings of the 2013 Joint Urban Remote Sensing Event (JURSE), Sao Paulo, Brazil, 21–23 April 2013; pp. 230–233.
- 24. Elvidge, C.D.; Baugh, K.E.; Zhizhin, M.; Hsu, F.-C. Why VIIRS data are superior to DMSP for mapping nighttime lights. *Proc. Asia-Pac. Adv. Netw.* **2013**, *35*, 62–69. [CrossRef]
- Falchi, F.; Cinzano, P.; Duriscoe, D.; Kyba, C.C.; Elvidge, C.D.; Baugh, K.; Portnov, B.A.; Rybnikova, N.A.; Furgoni, R. The new world atlas of artificial night sky brightness. *Sci. Adv.* 2016, *2*, e1600377. [CrossRef] [PubMed]
- 26. Li, X.; Xu, H.; Chen, X.; Li, C. Potential of NPP-VIIRS nighttime light imagery for modeling the regional economy of China. *Remote Sens.* **2013**, *5*, 3057–3081. [CrossRef]
- 27. Ma, T.; Zhou, C.; Tao, P.; Haynie, S.; Fan, J. Responses of Suomi-NPP VIIRS-derived nighttime lights to socioeconomic activity in China's cities. *Remote Sens. Lett.* **2014**, *5*, 165–174. [CrossRef]

- 28. Shi, K.; Huang, C.; Yu, B.; Yin, B.; Huang, Y.; Wu, J. Evaluation of NPP-VIIRS night-time light composite data for extracting built-up urban areas. *Remote Sens. Lett.* **2014**, *5*, 358–366. [CrossRef]
- 29. Shi, K.; Yu, B.; Huang, Y.; Hu, Y.; Yin, B.; Chen, Z.; Chen, L.; Wu, J. Evaluating the ability of NPP-VIIRS nighttime light data to estimate the gross domestic product and the electric power consumption of China at multiple scales: A comparison with DMSP-OLS data. *Remote Sens.* **2014**, *6*, 1705–1724. [CrossRef]
- 30. Ma, T.; Zhou, Y.; Wang, Y.; Zhou, C.; Haynie, S.; Xu, T. Diverse relationships between Suomi-NPP VIIRS night-time light and multi-scale socioeconomic activity. *Remote Sens. Lett.* **2014**, *5*, 652–661. [CrossRef]
- Yu, B.; Shi, K.; Hu, Y.; Huang, C.; Chen, Z.; Wu, J. Poverty evaluation using NPP-VIIRS nighttime light composite data at the county level in China. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* 2015, *8*, 1217–1229. [CrossRef]
- 32. Jing, X.; Shao, X.; Cao, C.; Fu, X.; Yan, L. Comparison between the Suomi-NPP Day-Night Band and DMSP-OLS for correlating socio-economic variables at the provincial level in China. *Remote Sens.* **2016**, *8*, 17. [CrossRef]
- Sharma, R.C.; Tateishi, R.; Hara, K.; Gharechelou, S.; Iizuka, K. Global mapping of urban built-up areas of year 2014 by combining MODIS multispectral data with VIIRS nighttime light data. *Int. J. Digit. Earth* 2016, 9, 1004–1020. [CrossRef]
- 34. Levin, N. The impact of seasonal changes on observed nighttime brightness from 2014 to 2015 monthly VIIRS DNB composites. *Remote Sens. Environ.* **2017**, *193*, 150–164. [CrossRef]
- 35. Levin, N.; Zhang, Q. A global analysis of factors controlling VIIRS nighttime light levels from densely populated areas. *Remote Sens. Environ.* **2017**, *190*, 366–382. [CrossRef]
- 36. Dou, Y.; Liu, Z.; He, C.; Yue, H. Urban land extraction using VIIRS nighttime light data: An Evaluation of Three Popular Methods. *Remote Sens.* **2017**, *9*, 175. [CrossRef]
- Zhao, N.; Hsu, F.-C.; Cao, G.; Samson, E.L. Improving accuracy of economic estimations with VIIRS DNB image products. *Int. J. Remote Sens.* 2017, *38*, 5899–5918. [CrossRef]
- Li, X.; Li, D.; Xu, H.; Wu, C. Intercalibration between DMSP/OLS and VIIRS night-time light images to evaluate city light dynamics of Syria's major human settlement during Syrian Civil War. *Int. J. Remote Sens.* 2017, 38, 5934–5951. [CrossRef]
- 39. Zheng, Q.; Deng, J.; Jiang, R.; Wang, K.; Xue, X.; Lin, Y.; Huang, Z.; Shen, Z.; Li, J.; Shahtahmasse, A.R. Monitoring and assessing "ghost cities" in Northeast China from the view of nighttime light remote sensing data. *Habitat Int.* **2017**, *70*, 34–42. [CrossRef]
- Román, M.O.; Wang, A.; Sun, Q.; Kalb, V.; Miller, S.D.; Molthan, A.; Schultz, L.; Bell, J.; Stokes, E.C.; Pandey, B.; et al. NASA's black marble nighttime lights product suite. *Remote Sens. Environ.* 2018, 210, 113–143. [CrossRef]
- 41. Song, C.; Qu, A.; Blumm, N.; Barabasi, A.-L. Limits of predictability in human mobility. *Science* **2010**, 327, 1018–1021. [CrossRef] [PubMed]
- 42. Lu, X.; Bengtsson, L.; Holme, P. Predictability of population displacement after the 2010 Haiti earthquake. *Proc. Natl. Acad. Sci. USA* **2012**, *109*, 11576–11581. [CrossRef] [PubMed]
- Devile, P.; Linard, C.; Martin, S.; Gilbert, M.; Stevens, F.R.; Gaughan, A.E.; Blondel, V.D.; Tatem, A.J. Dynamic population mapping using mobile phone data. *Proc. Natl. Acad. Sci. USA* 2014, *111*, 15888–15893. [CrossRef] [PubMed]
- 44. Román, M.O.; Stokes, E.C. Holidays in lights: Tracking cultural patterns in demand for energy services. *Earth's Future* **2015**, *3*, 182–205. [CrossRef] [PubMed]
- 45. Kyba, C.C.; Kuester, T.; Kuechly, H.U. Changes in outdoor lighting in Germany from 2012–2016. *Int. J. Sustain. Light.* **2017**, *19*, 112. [CrossRef]
- 46. De Miguel, A.S. Differential photometry study of the European light emission to the space. In Proceedings of the World Conference in Defence of the Night Sky and the Right to Observe the Stars, La Palma, Spain, 20–23 April 2007.
- 47. De Miguel, A.S. Spatial, Temporal and Spectral Variation of Light Pollution and Its Sources: Methodology and Resources. Ph.D. Thesis, Institute of Astrophysics of Andalusia, Madrid, Spain, 2015.
- 48. Liu, J.; Liu, M.; Tian, H.; Zhuang, D.; Zhang, Z.; Zhang, W.; Tang, X.; Deng, X. Spatial and temporal patterns of China's cropland during 1990–2000: An analysis based on Landsat TM data. *Remote Sens. Environ.* **2005**, *98*, 442–456. [CrossRef]

- 49. Ma, T.; Yin, Z.; Zhou, A. Delineating spatial patterns in human settlements using VIIRS nighttime light data: A watershed-based partition approach. *Remote Sens.* **2018**, *10*, 465. [CrossRef]
- 50. Petersen, A.M.; Stanley, H.E.; Succi, S. Statistical regularities in the rank-citation profile of scientists. *Sci. Rep.* **2011**, *1*, 181. [CrossRef] [PubMed]



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