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Research Article

Evaluating Urbanization and Spatial-Temporal Pattern Using the DMSP/OLS Nighttime Light Data: A Case Study in Zhejiang Province

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The application of DMSP/OLS nighttime light data provides an effective measure for characterizing urbanization and its spatial-temporal changes. Combined with the social economic statistics and calibrated nighttime data, the nighttime light imagery of Zhejiang province was fully intercalibrated during the period 1992–2013. The backgrounds were explained and the model of region light index (RLI) was built to make further research. The methods of mutation detection, regression analysis, and spatial analysis were adopted in this study. The results show that the urbanization progress of Zhejiang experienced a transformation from rapid development to steady improvement and was accompanied by a changing direction of urban expansion from coastal to inland areas from 2000. Further research indicated that Zhejiang province possessed a relative high level of urbanization, where a spatial pattern of urbanization with one center and four axes was initially formed. It is a novel attempt to investigate the urbanization of Zhejiang province on the basis of the DMSP/OLS night-lighting data, which may provide a significant guideline for the urban planning and development.

1. Introduction

Urbanization is a phenomenon that involves changes in land cover, the economy, and demographics; it is a shift from traditional agricultural society to a modern society which focuses on manufacturing industries and services. There was sluggish development in China before the policy of reform and openness due to various factors at home and abroad. However, the progress of urbanization in China accelerated from 1978; the urbanization rate in mainland China has risen from 26% in 1990 to 52.6% by the end of 2012 according to the National Bureau of Statistics of China. Urban areas concentrate people, economic activities, and the built environment; urbanization will also have a profound effect on the geography pattern [1–3].

Methods of qualitative and quantitative analyses were adopted by many researches when it came to urbanization. Nevertheless, there were many shortages on timeliness and reliability for the reason of uncertainty and lag of statistical data [4, 5]. Meanwhile, only a few researches have been made from the perspective of spatial and temporal patterns due to the lack of spatial information. Adopting remote sensing data can effectively avoid the above problems. Some scholars used remote sensing images of different resolutions to conduct urbanization-related researches and achieved a certain degree of success. High spatial resolution remote sensing data such as IKONOS, SPOT HRV, and Quick Bird images can reflect the details of the study regions but they come with high cost and complicated data processing procedure; due to the complexity of the ground objects that cause spectral differences, together with the limited resolution of the data, it is difficult to use lower resolution satellites like NOAA/AVHRR, EOS/MODIS, and Landsat TM/ETM+ images to identify the features of ground objects accurately, which renders the identification process more complicated [6–9]. This study highlights the utility of the Defense Meteorological Satellite Program/Operational Linescan System (DMSP/OLS) nighttime light data to analyze the urbanization in the selected regions.

The US Air Force Defense Meteorological Satellite Program's Operational Linescan System was designed to collect global clouds illuminated by moonlight. Different from other remote sensing satellites, the DMSP/OLS instrument can detect nocturnal artificial lighting in clear night conditions without moonlight owing to its low-light imaging capability. OLS has a wide view over the earth surface with a 3000 km swatch width and a spatial resolution of 2.7 km. The DMSP/OLS can distinguish other dark areas by capturing artificial lighting present on the earth's surface, such as that generated by human settlements, fishing boats, fires, and gas flares. This makes it convenient to analyze human activity and urban change from the perspective of space.

Since the 1980s, DMSP/OLS nighttime light data have gained widespread attention with related researches focusing on fields including technical methods exploration, population density estimation, energy consumption, land extraction, and urban sprawl monitoring [10–15]. Croft extracted the urban areas with the data of DMSP/OLS nighttime light for the first time in 1978 [16]. After this, more and more researches were made on a global and regional scale, but these researches were restricted by the influence of clouds and unstable light. Henderson et al. [17] extracted cities with different economic levels like Beijing, San Francisco, and so on by the method of threshold value and after comparing with that extracted from Landsat TM images, they drew the conclusion that DMSP/OLS nighttime light can be an effective data source to detect urbanization and urban areas. Chunyang et al. [18] found that DMSP/OLS nighttime light can reflect urbanization progress in China by rebuilding urbanization of mainland in China with nighttime data and related statistic data. Similar conclusion was also drawn by Liu et al. [19]. Yi et al. analyzed the land use pattern in northeast China by establishing the unit circle urbanization evaluation model and finally found that the Urban Light Index had a strong correlation with urban built-up areas and regional GDP [20]. The result indicating a stepwise transition of nighttime light brightness during urban expansion was found by Ma et al. through the brightness gradient and neighborhood analysis method [21]. By combining DMSP/OLS nighttime light data and remote sensing data, and using appropriate data calibration process model, the existing studies, to some extent, have overcome the impact of saturation and overflow and meanwhile shown certain practical significance by their successful application in various fields of society, production, economy, security, and so forth.

This paper detects the urbanization of Zhejiang province in 1992–2013 from a geographic perspective using the methods of mutation detection and spatial analysis and builds the region light index (RLI) to explore the relationship between light and urbanization, as well as the spatial-temporal changes of different land use patterns.

2. Data Preparing

2.1. Data Source. Three types of data were used in the study of urbanization in Zhejiang province. The first type is nighttime stable light data from 1992 to 2013 in the Version 4 global DMSP/OLS nighttime lights series dataset. The data were obtained from the National Geophysical Data Center (NGDC) Website (http://www.ngdc.noaa.gov/dmsp/downloadV4composites.html) and include datasets from five different satellites: F10 (1992-1993), F12 (1994–1996), F14 (1997–2003), F16 (2004–2009), and F18 (2010–2013). Background noises were identified and replaced with the value of zero, and the DN values for lit pixels ranged from 1 to 63. To reduce the differences between sensors and improve comparability of nighttime lights data from different satellites, the individual composites had to be calibrated via an empirical procedure.

The second type of data is socioeconomic census data, including the nonagricultural population, proportion of secondary industry and tertiary industry, and Gross Domestic Product (GDP). These data were obtained from the Zhejiang Statistical Yearbook (1992–2014). The third type is the auxiliary data related to boundaries, especially the administrative boundaries of the province and cities within Zhejiang province, as well as the boundary of China.

2.2. Intercalibration. The nighttime light data of Zhejiang province during 1992–2013 is composed of images covering 22 years and related to 5 different satellites. There is no on-broad calibration on the OLS; the data we chose is lacking in continuity and comparability, so they cannot be used to extract urban areas directly in this study unless calibrated. In the literatures related to this topic, the NTL data was often calibrated with the method proposed by Christopher Elvidge by applying regression models [22]. Wu et al. also put forward an approach called invariant regions-method to calibrate NTL images; the global NTL imageries were calibrated using this method [23]. This research adopts the approach proposed by Wu to realize the intercalibration of NTL images of Zhejiang province.

We captured the NTL images from the global NTL graphics downloaded from the NGDC website based on the method named Region of Interest (RIO). Many studies treated urban areas with stable nighttime lights as reference regions, because the DMSP images in these areas have signal saturation. In this article, we chose the reference region with the process of False Color Compositing by overlaying images from different years. The false color composited image covering 1992, 2003, and 2013 is shown in Figure 1 and areas in white are definitely the urban area which has signal saturation. Satellite F14 in 1999 was used as the reference and the data from other satellites were adjusted to match the F14 1999 data range by using second-order polynomial regression:

$$\mathrm{DN}_{\mathrm{cal}} = a + b \times \mathrm{DN} + c \times \mathrm{DN}^2, \quad (1)$$

where $\mathrm{DN}_{\mathrm{cal}}$ is the adjusted DN and $a, b,$ and c are coefficients.

The individual images were calibrated with (1) together with parameters in Table 1, and the influence of discontinuous

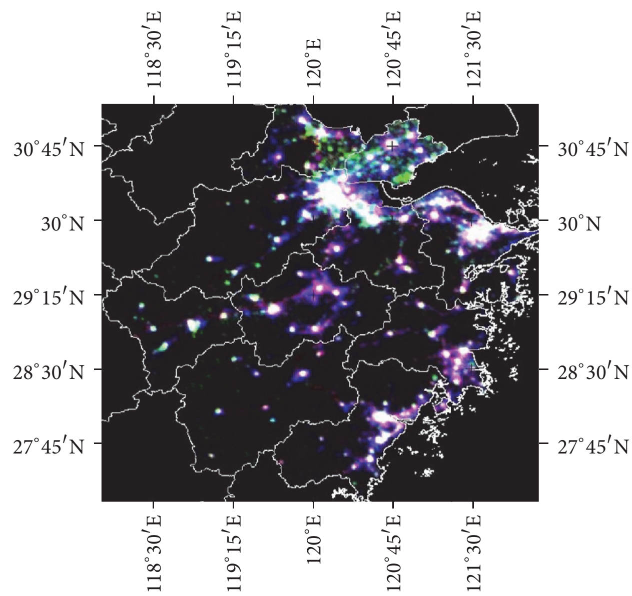


Figure 1: False color synthesis (1992: red; 2003: green; 2013: blue).

is eliminated in this way. The normalized conduction is also processed with

$$\mathrm{DN}_I = \frac{\left|X - \mathrm{DN}_{\min}\right|}{\mathrm{DN}_{\max} - \mathrm{DN}_{\min}}, \tag{2}$$

where DN_I is the value of pixels after normalization processing with the range between 0 and 1. $\mathrm{DN}_{\max}$ and $\mathrm{DN}_{\min}$ are the maximum and minimum values of normalized pixels. X is the DN value of each pixel.

3. Methods

The NTL data in this study were projected and resampled to a pixel size of 1 km, which means each pixel in the NTL image represents a region with an area of $1 * 1\,\mathrm{km}^2$. Each pixel is different in spatial attribution and has a DN value that equals the average brightness in the region. Meanwhile, the DN value in urban areas, especially the Central Business District (CBD), is higher than other regions, and the value decreases steadily when it comes to the edge of the city. Based on the above analysis, methods of Mutation Detection and Slop Calculation are adopted to extract urban and rural areas.

3.1. Mutation Detection. A few methods are available to extract urban information from NTL images, including an empirical thresholding technique, the thresholding technique based on Mutation Detection, and the statistics method with ancillary data. Of all these methods, the Mutation Detection is widely used because of its simplicity and reliability. Therefore, we used the Mutation Detection method to extract urban information in Zhejiang province.

Mutation Detection which was first proposed by Imhoff et al. is widely used to extract threshold of urban areas. In his theory, the changes in polygon perimeter along with the increase in threshold were compared. As the threshold rose, the polygons representing urban or lit areas shrank in size, while, at a certain point in the thresholding process, the urban polygons did not necessarily get smaller around their perimeter but began to break up internally. This point is the threshold of the urban area [24, 25].

Table 1: Distribution table of regression coefficient.

Satellites	Year	a	b	c	R^2
F10	1992	0.5614	0.2072	−0.002	0.792
	1993	−0.0325	0.2507	−0.0026	0.931
F12	1994	−0.1848	0.1497	−0.0008	0.967
	1995	0.3613	0.0848	0.0001	0.961
	1996	−0.7925	0.164	−0.0008	0.953
F14	1997	0.1617	0.1719	−0.0013	0.938
	1998	0.217	0.1289	−0.0005	0.965
	1999	0	1	0	1
	2000	−0.1921	0.098	0.0001	0.935
	2001	1.1786	−0.0072	0.0015	0.92
	2002	3.9886	−0.1798	0.0034	0.799
	2003	1.8356	−0.0923	0.0013	0.777
F16	2004	2.0823	−0.1012	0.0014	0.778
	2005	1.9593	−0.0984	0.0014	0.82
	2006	3.4457	−0.1801	0.0024	0.748
	2007	5.2046	−0.2214	0.0024	0.875
	2008	5.035	−0.2227	0.0025	0.82
	2009	−3.5291	0.1392	−0.001	0.652
F18	2010	4.8877	−0.1703	0.0015	0.671
	2011	−1.764	0.042	−0.0002	0.72
	2012	4.9955	−0.2903	0.0037	0.881
	2013	1.5588	−0.0654	0.0006	0.877

The process of Mutation Detection is shown in Figure 2. The first image in Figure 1 is the original NTL image of the selected area. When increasing the threshold the extracted urban areas change from image 2 to image 8. As the threshold rose to 0.81, the urban polygons began to break up; this means the value of 0.81 is definitely the threshold of the urban area in the study region.

3.2. Slop Calculation. As mentioned above, the DN values decrease when the distance from core city increases, but the variation tendency differs in different land use patterns. DN values in urban and rural areas change less due to the relative homogeneity in these regions, while the transition area between rural and urban has a quite drastic DN change and the spectral distribution curve is quite different (Figure 3).

Figure 3(a) is the X and Y profile segmentation of the study area and Figure 3(b) shows the spectral distribution curve of the profile. The transition region was confirmed by the drastic changes of DN values between red lines in Figure 3(b); then we analyzed the slop of the transition region and found out that the critical point is between rural and transition region. Figure 4 was the result of the regional segmentation.

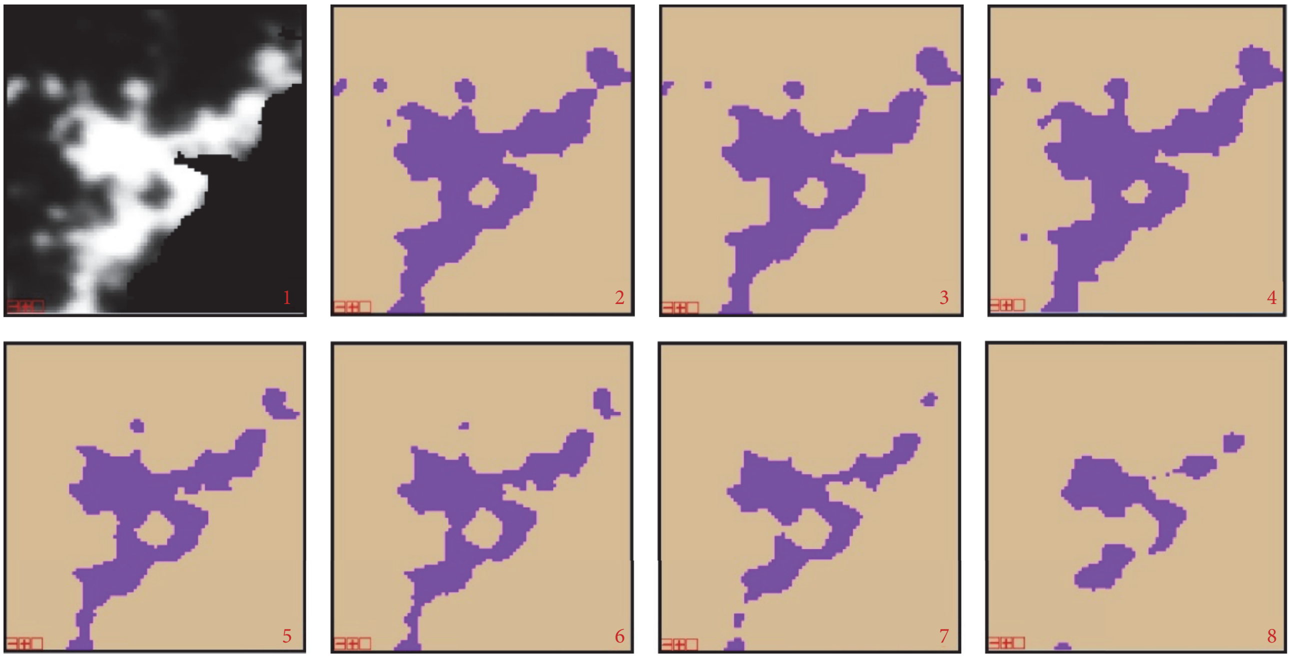
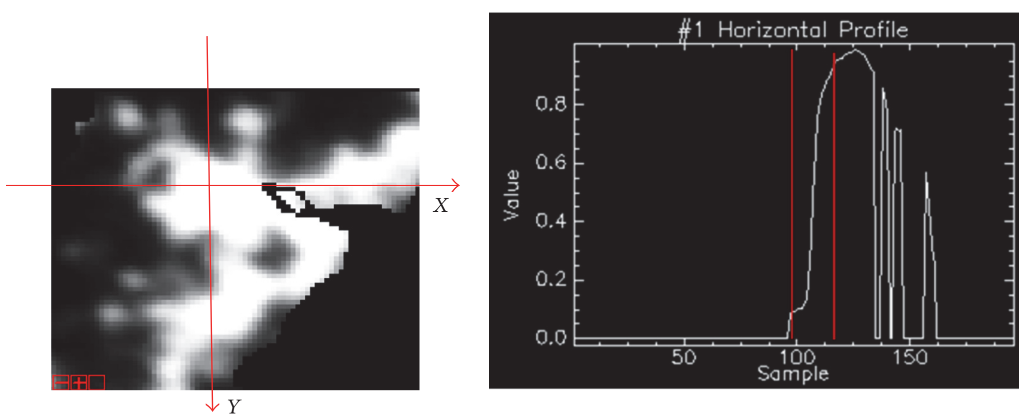


Figure 2: Images of mutation detection.



(a) (b)

Figure 3: (a) Images of profile segmentation and (b) spectral distribution curve.

3.3. The Region Light Index Model. The regions of rural, urban, and transition areas were extracted using methods of Mutation Detection and Slop Calculation. The study area composites pixels with different DN values; most pixels have quite low DN values which refer to farmland and forest [26]. In order to increase the accuracy and reliability of the study, pixels with DN values below 0.1 were abandoned for this research.

There are quite a lot of models to evaluate nighttime light features of cities, such as Urban Light Index (ULI) and Total Light Index (TLI), while few of these models focus on the effect of regional characteristics and land use patterns. The region light index (RLI) model provides an effective method to assess NTL intensity together with DN values and regional characteristics by

$$\mathrm{RLI} = \frac{S_u \times N_u \times a}{S} + \frac{S_r \times N_r \times b}{S} + \frac{S_t \times N_t \times c}{S}, \quad (3)$$

where S_u, S_r, and S_t are the areas of urban, rural, and transition areas; N_u, N_r, and N_t are pixels numbers of different land use patterns; a, b, and c refer to the average DN values of each region; S means the total area of the study region.

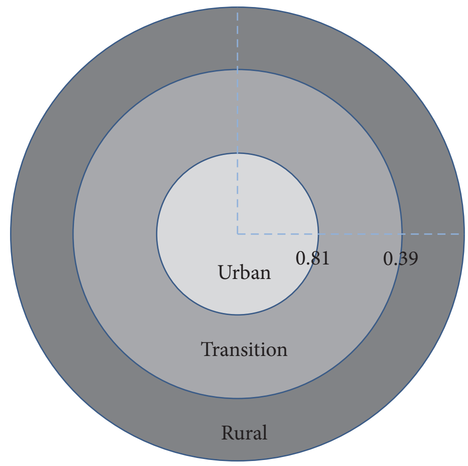


Figure 4: Result of region segmentation.

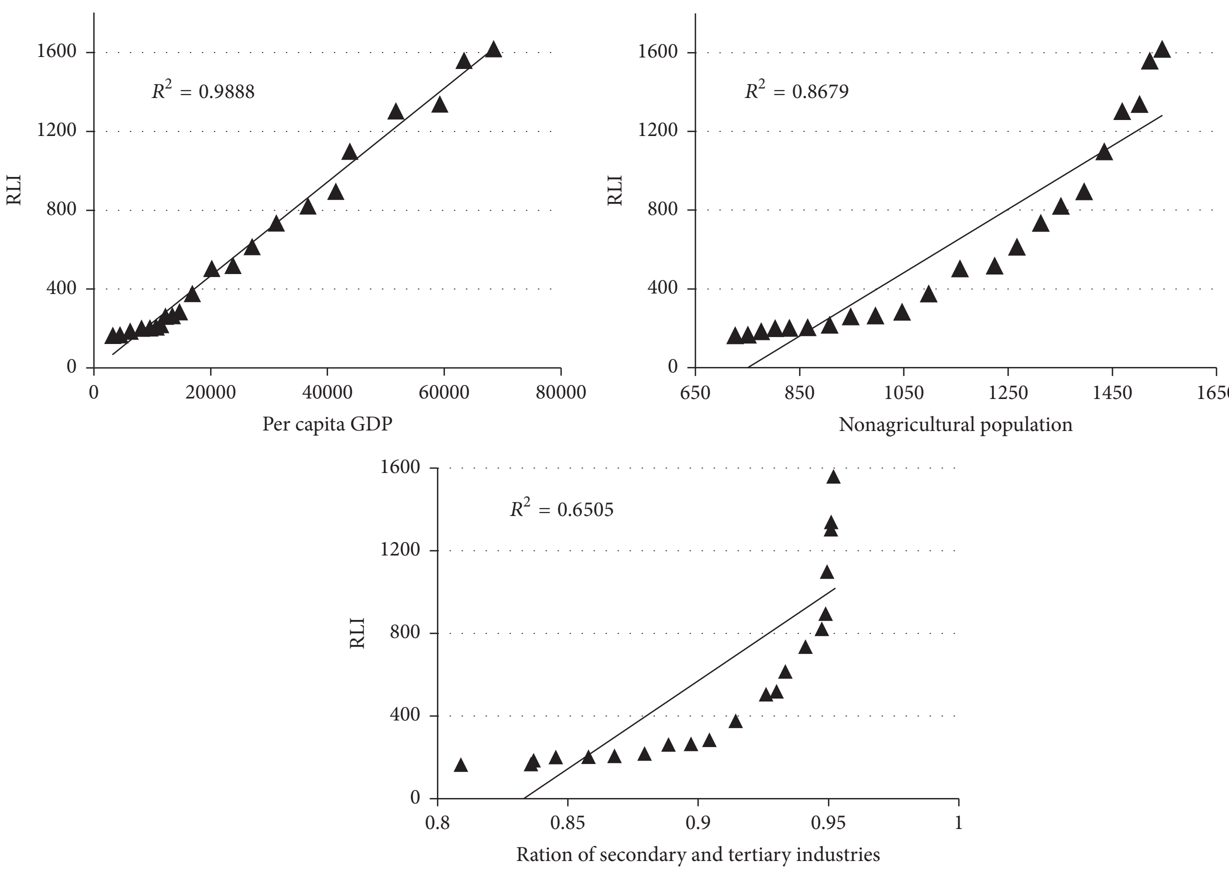


Figure 5: Correlations between RLI and urbanization indicators.

4. Result

4.1. The RLI and Urbanization. Urbanization is a complicated phenomenon related to demographic, economic, and land use changes. The distinguishable index of urbanization is concluded by two methods: one is the method of single or main index and the other is the compound indicator method.

The method of compound index is adopted to measure the relationship between RLI and urbanization in this study: indexes of per capita GDP, ration of secondary and tertiary industries, and nonagricultural population have also been selected in order to make further research [27].

The relationship between region light index (RLI) and urbanization level is measured based on the DMSP/OLS nighttime light data and ancillary economic statistical data with the method of regression analysis; the results are as in Figure 5.

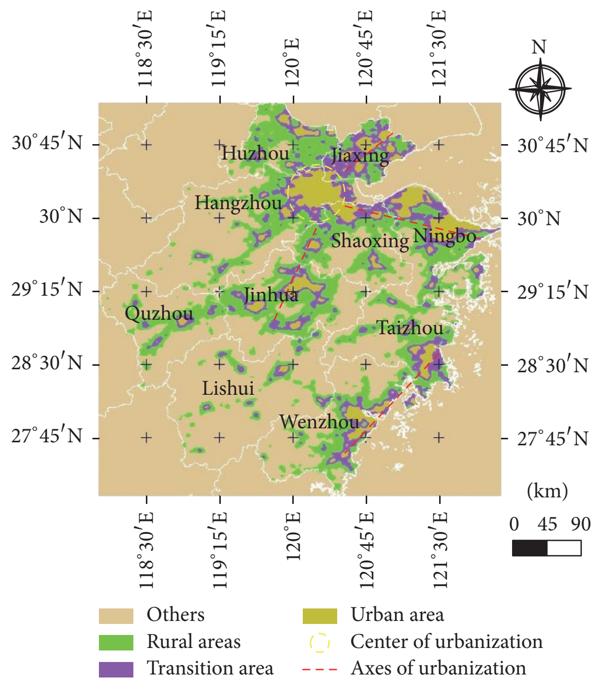


Figure 6: Spatial pattern of urbanization in Zhejiang province.

The regression analysis shows a strong positive relationship between RLI and indicators of urbanization level with high coefficients. Based on the analysis above, the model of region light index (RLI) can reflect urbanization level in regional scale precisely and can be used to measure the urbanization process in Zhejiang province.

4.2. Urbanization Pattern in Zhejiang Province. Figure 6 shows the spatial pattern of urbanization based on the latest DMSP/OLS NTL data of Zhejiang province. The urbanization pattern of "center-axes" in Zhejiang consists of the center of Hangzhou, axes of Hangzhou to Ningbo, Hangzhou to Jinhua (Lishui), Hangzhou to Jiaxing, and Wenzhou to Taizhou. With difference in economical level and regional geography, the brightness of NTL and urbanization levels vary from area to area. Based on the analysis of NTL images and new pattern of urbanization, it was found that areas around the Hangzhou Bay and near the coastal regions possess successional and brighter nighttime light, which means that the urbanization level in these areas is higher than other regions. Furthermore, the region brightness of NTL in Ningbo, Huzhou, Jiaxing, Hangzhou, and Jinhua in Figure 6 is much higher than other cities, as well as the urbanization level, which indicates that the urbanization process has expanded to inland from the coastal areas with changes of new patterns in geography.

4.3. Spatial and Temporal Variation of Urbanization in Zhejiang Province. The urban pattern in Zhejiang changed a lot in the process of urbanization, with agglomeration in urban cores and diffusion towards rural areas, as well as new spatial form in NTL images. Figure 7 shows the spatial and temporal change of urbanization pattern in Zhejiang province from 1992 to 2013 in selected years.

Table 2: Area statistic of RLI.

Year	Urban area	Transition area	Rural area	RLI
1992–1995	509.1549	2733.337	11057.4543	219.896
1996–1999	586.4639	2671.7617	11067.5625	213.8478
2000–2004	1397.9291	4529.9791	13241.7653	384.8646
2005–2008	2534.1677	8015.0679	16034.6284	743.3341
2009–2013	6143.4982	11962.9187	16772.6573	1384.89

Units: km^2.

There are 2 stages in the process of urbanization in Zhejiang province, the periods from 1992 to 2000 and 2000 to 2013. The urbanization area concentrated in the region of Hangzhou Bay which is located in the north of Zhejiang during the first stage, while, in the second stage, the urbanization level on the east coast and inland Zhejiang increased rapidly with the development of the economy and more and more metropolises appeared.

The direction of urban expansion also varies in different stage of urbanization. In the early urbanization period, the urban sprawls mainly focused on the horizontal direction, with more nonconstruction land converted into construction land. Nevertheless, the direction of urban sprawl transformed to vertical and more skyscrapers appeared when the urban area developed to a certain size, with the urban-land intensive utilization.

Table 2 is the data statistics of different areas based on the NTL data. As can be seen in the table, the areas of urban, transition area, and rural area increased from 1992 to 2013, especially the rural and transition areas. During the period of 2000–2008, the urban areas increased rapidly but the growth slowed down after that; this can be explained by the conversion of urban spatial expansion after the year 2000.

RLI can be used to reflect urbanization because of the strong relationship between RLI and indicators of urbanization. The RLI increases from 219.896 in the first stage (1992–1995) to 743.3341 in the fourth stage (2005–2008). However, the speed slowed down with an average value of 1384.89 in the fifth stage (2009–2013). On the strength of Table 2 and analysis above, the urbanization progress of Zhejiang has experienced a transformation from rapid development to steady improvement.

As can be seen in Table 2, the data statistics of rural area also increased a lot. This could have been caused by two different factors. Firstly, the pattern of rural area did not change in the process of urbanization, although there was migration movement from rural to urban areas. Secondly, rural development still exists along with urbanization.

5. Conclusion

DMSP/OLS data provide an accurate and comprehensive method to mirror urban growth, economic development, energy consumption, and so on. It also reduces the disadvantages of traditional qualitative and quantitative research

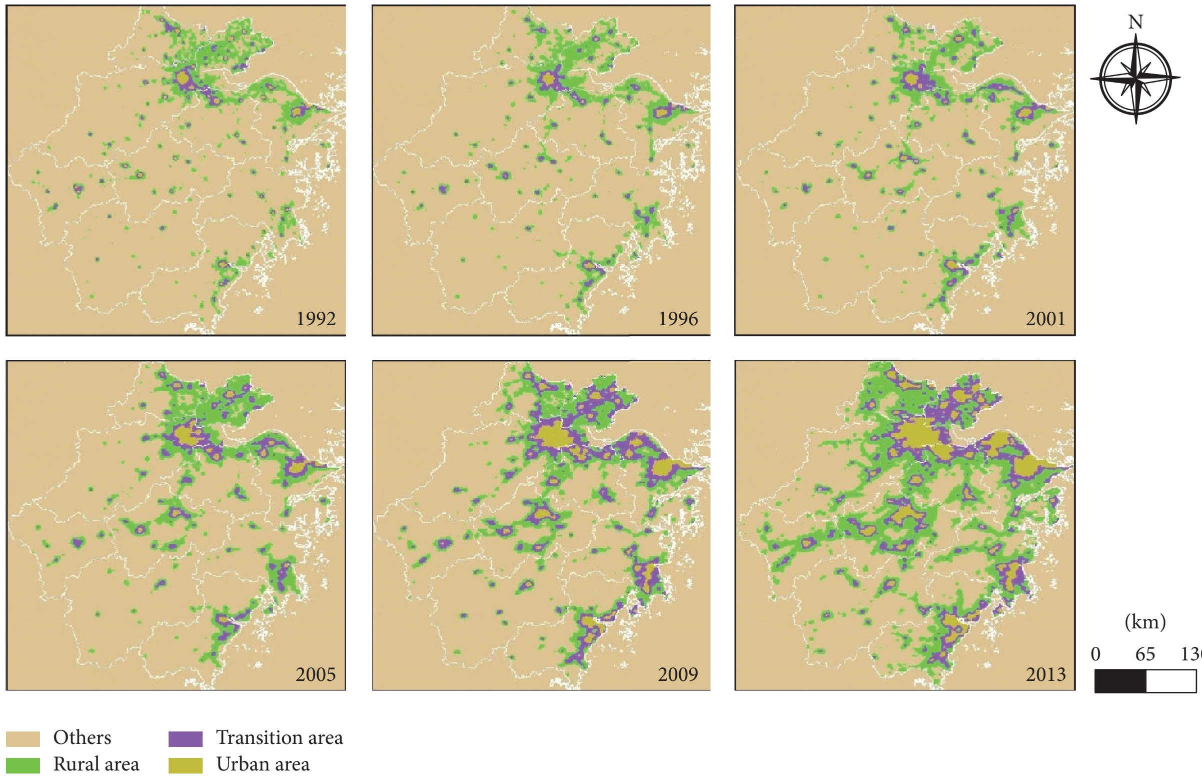


Figure 7: Spatial-temporal change of urbanization in Zhejiang province.

methods in data timeliness, spatial analysis, data processing, and so forth.

Based on the DMSP/OLS nighttime light data, the urbanization in Zhejiang province was analyzed from the perspective of geographic space. To reduce the differences between sensors, the invariant regions-method and regression method were selected to fully intercalibrate the data. The model of region light index (RLI) has now been established to make further research.

The results revealed that the RLI model has a strong relationship with urbanization indicators so it can be used to explain the development of urbanization in Zhejiang province. With the RLI model, the new "center-axes" pattern of urbanization was found. Meanwhile, the urbanization progress of Zhejiang has experienced a transformation from rapid development to steady improvement since 2000 and has been accompanied by a changing direction of urban expansion from coastal areas to inland areas. Based on the analysis above, the future of urbanization in Zhejiang should focus on the new "center-axes" pattern and pay more attention to the development of inland cities like Jinhua and Lishui, and enhanced cooperation is needed between cities to accelerate the economic society development.

It is a new attempt to analyze regional urbanization from geographical perspective; some valuable conclusions have been drawn based on the research. Nevertheless, this research only focuses on the regional level because of the limitation of relative statistics. Our hope is that, by using the DMSP/OLS nighttime light data, more researches that evaluate the urbanization and spatial-temporal changes over time can be made on the city level which is of great importance to the development, policy making, and planning of cities.

Disclosure

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Competing Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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