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Spatio-temporal Dynamics of Urbanization in China Using DMSP/OLS Nighttime Light Data from 1992–2013

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Abstract: Understanding the dynamics of urbanization is essential to the sustainable development of cities. Meanwhile the analysis of urban development can also provide scientifically and effective information for decision-making. With the long-term Defense Meteorological Satellite Program's Operational Linescan System (DMSP/OLS) nighttime light images, a pixel level assessment of urbanization of China from 1992 to 2013 was conducted in this study, and the spatio-temporal dynamics and future trends of urban development were fully detected. The results showed that the urbanization and urban dynamics of China experienced drastic fluctuations from 1992 to 2013, especially for those in the coastal and metropolitan areas. From a regional perspective, it was found that the urban dynamics and increasing trends in North Coast China, East Coast China and South Coast China were much more stable and significant than that in other regions. Moreover, with the sustainability estimating of nighttime light dynamics, the regional agglomeration trends of urban regions were also detected. The light intensity in nearly 50% of lighted pixels may continuously decrease in the future, indicating a severe situation of urbanization within these regions. In this study, The results revealed in this study can provided a new insight in long time urbanization detecting and is thus beneficial to the better understanding of trends and dynamics of urban development.
Keywords: Defense Meteorological Satellite Program's Operational Linescan System (DMSP/OLS) nighttime light; urbanization; pixel level detection; spatio-temporal dynamics; future trends

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1 Introduction

As an important phenomenon related with human development, urbanization is generally considered as important processes, by which towns and cities are formed and become larger since more people begin living and working in central areas, and it has also arisen as a hot point among researchers (Liang and Yang, 2019). According to the official publication of World Urbanization Prospects in 2018 (http://www.un.org), the proportion of world's population living in urban areas will expand from 55% to 68% till 2050, indicating an inevitable urbanization trend of human development. Along with the rapid development, various urban related problems started to emerge, such as increasing population, crowded public space, vegetation degeneration, water pollution and so on. Thus, acquiring accurate information about the urbanization is essential and beneficial to the healthy and sustainable development of our cities (Ma et al., 2012; Wei and Ye, 2014).

Various data and methods have been applied, especially those statistics data from government, such as Gross Domestic Product (GDP), impervious surface area and demographics (Li and Gong, 2016). However, these data can only provide limited regional assessments of urban development, which are insufficient in timely

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and spatial detections. Fortunately, with the development of the technique of remote sensing, more and more information of ground surface can be monitored easily due to the ability of providing direct and frequent temporal coverage of the study regions and making the spatial temporal detection available. In this research, the nighttime light images from the Defense Meteorological Satellite Program's Operational Linescan System (DMSP/OLS) were chosen to assess the long-term dynamics of national development of China.

The DMSP/OLS nighttime light images were first designed to monitor global clouds illuminated by moonlight in the 1970s (Croft, 1978; Imhoff et al., 1997; Román et al., 2018). Different from other remote sensing satellites, the DMSP/OLS instrument can detect nocturnal artificial lighting in clear night without the assistance of moonlight owing to its low-light imaging capability. Meanwhile, the images consist pixels with location and illuminance information of ground surface. Both advantages make the DMSP/OLS images one of the most widely used data source in human activities detecting, such as population density detecting (Archila Bustos et al., 2015; Ceola et al., 2015; Tripathy et al., 2017; Li et al., 2019; Yin et al., 2020), urbanization process monitoring (Hu et al., 2017; Gu et al, 2019; Xu et al., 2020), regional GDP estimating (Propastin and Kappas, 2012; Bennett and Smith, 2017), electricity consumption modeling (Cao et al, 2014; Jasiński, 2019) and so on (Li and Li, 2014; Xu et al, 2019).

With the superiorities of the data source, a great number of researches related to urbanization monitoring at different regional scales have been made, Imhoff identified the urban areas of the continental United States, and found that the light sources was feasible to detect location of urban areas (Imhoff et al., 1997). Hu mapped the development patterns of urbanization in Beijing-Tianjin-Hebei Urban Agglomeration using the nighttime light data (Hu et al., 2017). Zhang captured the full continuum of urban expansion process in 30 major metropolitans of China using the DMSP-OLS nighttime light data (Zhang and Su, 2016). Zhang and Seto mapped urbanization dynamics in India, China, Japan, and the United States based on the sum of nighttime light (Zhang and Seto, 2013). Although these regional level detections provided direct and accurate information of the extension and patterns of urbanization, few of them focused on the processes, the details of long-term dynamics or future trends of urbanization. Moreover, due to the limitations of traditional geographical research methods, pixel level detections of time series from the perspective of basic spatial resolution were insufficient in general, and the dynamics of pixel vales were usually ignored. Studies in different perspectives were needed to determine the general laws related to the temporal and spatial dynamics of nighttime light and to excavate detailed information about urban changes.

In view of this, we focus on the detecting of variation regularity for the evolution characteristics of nighttime light at pixel level. The mathematical methods of coefficient of variation (*CV*), the Mann-Kendal test (*MK* test) and the Theil-Sen median trend analysis were applied using the calibrated DMSP/OLS nighttime light data, and the spatio-temporal dynamics of urbanization within China from 1992 to 2013 were fully analyzed. The objective of this study is to improve the understanding of long-term urban development and provide much more detailed information related with the characteristics of urbanization, and also appropriate decision-making towards future urban development.

2 Data and Methods

2.1 Study area

In this study, China was selected as the research case, and Taiwan, Hong Kong, Macao and South China Sea were not considered in this study. As a country with land area more than 9 600 000 km², China has experienced a remarkable development in social-economics, urban development and so on during the past two decades, and has also shown great regional difference (Lin, 2007; Chen et al., 2013). To demonstrate the long-term dynamics and trend of nighttime light of China, a regional comparing was also performed. The eight-region division proposed by the State Council was accordingly accepted (Fig. 1). The strategy was developed based on the traditional east-central-west division which is widely accepted in the State Council reports as well as other research fields (Fan and Qi, 2010; http://www.gov.cn/), including regions of Northeast (NE), North Coast (NC), East Coast (EC), South Coast (SC), Central Yellow River Delta (CYRD), Central Changjiang River Delta (CCRD), Great Southwest (GSW) and Great Northwest (GNW).

Fig. 1 Distribution of eight-region division of China. Hong Kong, Macao and Taiwan of China are not included

2.2 Data collection and processing

The annual stable DMSP/OLS nighttime light images of version 4 from the website of NOAA/NGDC (https://www.ngdc.noaa.gov) were accepted in this research, the images are 30 arc second grids (about 1 km²), spanning 180°E to 180°W and 65°S to 75°N, and the brightness of each pixel is recorded with a digital number (DN) range of 0 (no light) to 63 (maximum light). The DMSP/OLS nighttime light images can record light information derived from a variety of natural and man-made phenomenon on the surface of earth, which can provide both brightness and geospatial details of these activities, and thus widely accepted in natural and social sciences detections (Yi et al., 2014; Li et al., 2016).

To make the long-term detecting of light dynamics, the DMSP/OLS images from 1992 to 2013 were accepted, since these images were derived from 5 different sensors, covering 22 yr, and a calibration method is needed to reduce the inconsistency and make the data series comparable (Ma et al., 2014; Liu and Leung, 2015). In this stage, the widely used inter-calibration method proposed by Elvidge in 2009 was applied (Elvidge et al., 2009). The Jixi City in Heilongjian Province was chosen as the reference region, and the image of F121997 was chosen for reference due to its stable light dynamics during the study period. The model of second order regression was developed to perform the calibration process. The time series can thus be calibrated with the following model in Eq. (1):

$$DN_c = a \times DN^2 + b \times DN + c \tag{1}$$

where DN is the pixel value of original pixel, DN_c is the calibrated results, a, b and c are coefficients.

In addition, an average strategy was also applied to calibrate images for different sensors in the same year.

2.3 Methods

In this research, we studied the variations and dynamics of nighttime light on a pixel perspective with a spatial resolution of 1 km × 1 km, and the statistical change of each pixel was calculated. And the statistical analysis of coefficient of variation (CV), the Mann-Kendal test (M-K test), the Theil-Sen median trend analysis and Hurst index were further utilized to investigate the characteristics of spatial-temporal dynamics of light within China from 1992 to 2013.

2.3.1 The coefficient of variation

The coefficient of variation (CV) was typically used to describe the extent of variability related with the mean value of the population (Milich and Weiss, 2000). In this research, CV was adopted to analyze the spatial-temporal pattern and distribution of light dynamics within the study area, and it can be calculated with the following equation:

$$CV_{DMSP} = \frac{\sigma_{DMSP}}{\overline{DMSP}} \tag{2}$$

where CV_{DMSP} is the calculated pixel level coefficient of variation of DMSP/OLS nighttime light during 1992–2013. σ_{DMSP} stands for the standard deviation and $\overline{DMSP}$ is the mean value of light intensity. Pixels with higher value of CV_{DMSP} indicates a much scattered distribution of data among different years, as well as more active dynamic of light intensity; otherwise, the data distribute could be highly concentrated, showing a very stable process of variation.

2.3.2 The Mann-Kendall trend test

The Mann-Kendall (*MK*) trend test is a non-parametric test which is often used to detect the trend of a series. It is an important trend test strategy developed by Mann and Kendall (Mann, 1945; Kendall, 1975; Hamed and Rao, 1998). The *MK* test has been widely accepted and used by researchers in hydrology, ecology, meteorology to detect whether there is a significant monotonic trend (increase or decrease) in time series data (Fensholt et al., 2012; Yang et al., 2017). In this study, the *MK* trend test was initially adopted to illustrate the pixel level trend of light dynamics (Z), and the equations are as follows:

$$Z=\begin{cases} \dfrac{S-1}{\sqrt{\mathrm{var}(s)}} & S>0 \\ 0 & S=0 \\ \dfrac{S+1}{\sqrt{\mathrm{var}(s)}} & S<0 \end{cases} \tag{3}$$

$$S=\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\mathrm{sign}(DMSP_j - DMSP_i) \tag{4}$$

Variance can be also calculated with the following equation:

$$\mathrm{var}(s)=\frac{n(n-1)(2n+5)}{18} \tag{5}$$

$$\mathrm{sign}(DMSP_j - DMSP_i)=\begin{cases} 1 & DMSP_j - DMSP_i > 0 \\ 0 & DMSP_j - DMSP_i = 0 \\ -1 & DMSP_j - DMSP_i < 0 \end{cases} \tag{6}$$

In which $DMSP_i$ and $DMSP_j$ are the light intensity value of pixel during the study years of i and j; n is the length of time series; sign is the sign function. Z is the measurement of significance of the trend within the range of $(-\infty,+\infty)$. With the chosen significance level of α, if the calculated $|Z|$ is larger than $Z_{\alpha/2}$, then the trend is significant. In this study, the trends were tested under the significance level of 0.05 and $Z_{0.05}$ of 1.96, and the results can be classified into significance variation ($|Z| >$ 1.96) and slight variations ($|Z| <$ 1.96) (Karmeshu, 2012; Zhao et al., 2019).

2.3.3 Theil-Sen median trend analysis

As a famous non-parametric statistics method, the Theil-Sen median trend analysis was usually combined with the Mann-Kendall trend test to determine the trend of time series data (Sen, 1968; Theil, 1992). It is a robust fitting method which can be calculated efficiently and also inventively to outliers, the formula is:

$$t_{DMSP} = \mathrm{median}\left(\frac{DMSP_j - DMSP_i}{j-i}\right) \quad 1992 \le i \le j \le 2013 \tag{7}$$

where t_{DMSP} is the trend of *DMSP* time series, when $t_{DMSP} > 0$, the time series show an increasing trend, otherwise, a decreasing trend is identified.

2.3.4 The Hurst index

The Hurst index—a measurement of long-term memory and sustainability of time series, was first developed in the study field of hydrology by Hurst in 1951, and has been widely applied for quantitative analyses of the sustainability of time series data, especially in meteorology, ecology, and economics (Hurst, 1951; Mandelbrot and Wallis, 1969; Qian and Rasheed, 2004). In this analysis, the Hurst index was also accepted to try to figure out the future sustainability of pixel level light dynamics.

First of all, we need to define the light time series of $\{DMSP_t\}$, t = 1, 2, …, n. Then the mean sequence of the light time series can be calculated with the Equation (8).

$$\overline{DMSP_{(\tau)}} = \frac{1}{\tau}\sum_{t=1}^{\tau} DMSP_{(\tau)} \qquad \tau = 1, 2, \ldots, n \tag{8}$$

Then we calculate the accumulated deviation in Eq. (9), build the range sequence in Eq. (10) and create the standard deviation sequence with the Eq. (11) followed.

$$X_{(t,\tau)} = \sum_{t=1}^{t}\left(DMSP_{(t)} - \overline{DMSP_{(\tau)}}\right) \qquad 1 \le t \le \tau \tag{9}$$

$$R_{(\tau)} = \max_{1\le t\le\tau} X_{(t,\tau)} - \min_{1\le t\le\tau} X_{(t,\tau)} \qquad \tau = 1,\ 2,\ \ldots, n \quad (10)$$

$$S_{(\tau)} = \left[\frac{1}{\tau}\sum_{t=1}^{\tau}(DMSP_{(t)} - DMSP_{(\tau)})^2\right]^{1/2} \qquad \tau = 1,\ 2,\ \ldots, n \quad (11)$$

Finally, the Hurst index can be calculated with the following formula.

$$\frac{R_{(\tau)}}{S_{(\tau)}} = (c\tau)^H \quad (12)$$

$R_{(\tau)}$ and $S_{(\tau)}$ are respectively the range and standard deviation of the data, c is a constant. The variable H is the Hurst index, and it can be changed by fitting with a logarithm method and further calculated with the least squares method (Granero et al., 2008). As illustrated in other studies, the value of H can be classified into three categories: if $0.5 < H < 1$, then the time series is persistent and sustainable series, and the future change will be the same with the previous; if $H = 0.5$, the time series is relatively random, the dynamics trend in the future will be unrelated with that in the study period; if $0 < H < 0.5$, the future change will be opposite since the time series show an anti-persisted and unsustainable feature (Jiang et al., 2015; Jiapaer et al., 2015).

3 Results and Analyses

3.1 Temporal variations of nighttime light of China

It was found that the numbers of pixels with DN > 0 nearly doubled in the past few decades, and light intensity increased significantly based on the index of total night light (TNL), sum of light (SOL), night light mean (NLM) and so on. While the non-normal distribution of lighted pixels made it not enough to be convincing based merely on the basic arithmetic average results, since the percentage of pixels with low light values is much more than that with high values. Thus, a stratified statistics methodology was applied to eliminate the influence with an interval of 20 of DN values.

As illustrated in Fig. 2a, the percentage of pixels with DN value larger than 20 increased dramatically, especially those larger than 40, indicating a huge boost of pixels with high light intensities during the period. It was found that the total number of lighted area nearly doubled during the study period. Fig. 2b further reveals the dynamics of mean DN values with error bars in each category, and the steady increasing trends for pixels with DN larger than 40 and smaller than 20 can be observed as well. Based on the stratified statistics analysis, both the lighted areas and light intensity of China increased from 1992 to 2013. To further reveal the characteristics of light dynamics, the CV and trends of long time changes were also obtained below.

3.2 Variability and distribution of pixel-level light dynamics of China

CV of long-time series DMSP/OLS light intensity was applied to detect pixel level light dynamics of China from 1992 to 2013. To better illustrate the light dynamics, the CV intensities were firstly divided into four categories (Fig. 3) and named as higher fluctuation ($CV > 4.0$), high fluctuation ($4.0 > CV > 2.5$), moderate

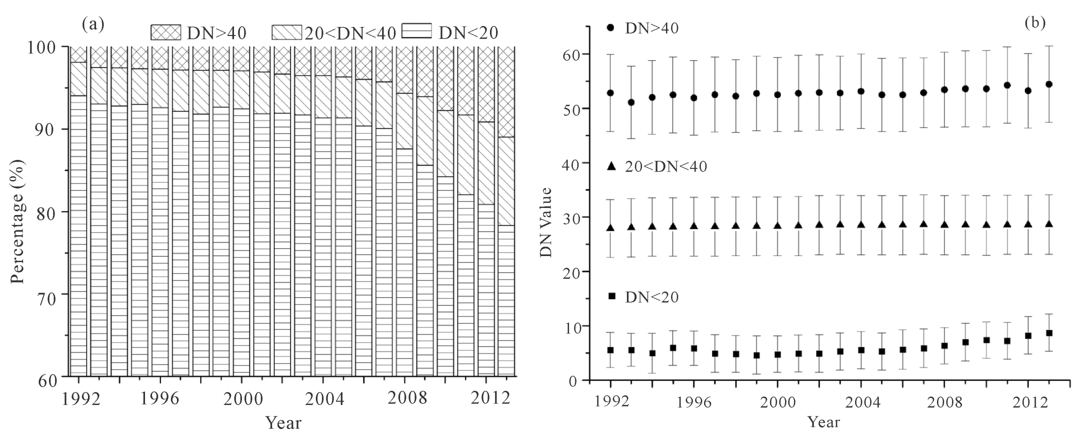

Fig. 2 Long time light intensities of China: (a) Percentages of pixels of different values from 1992–2013 and (b) dynamics of DN values from 1992–2013

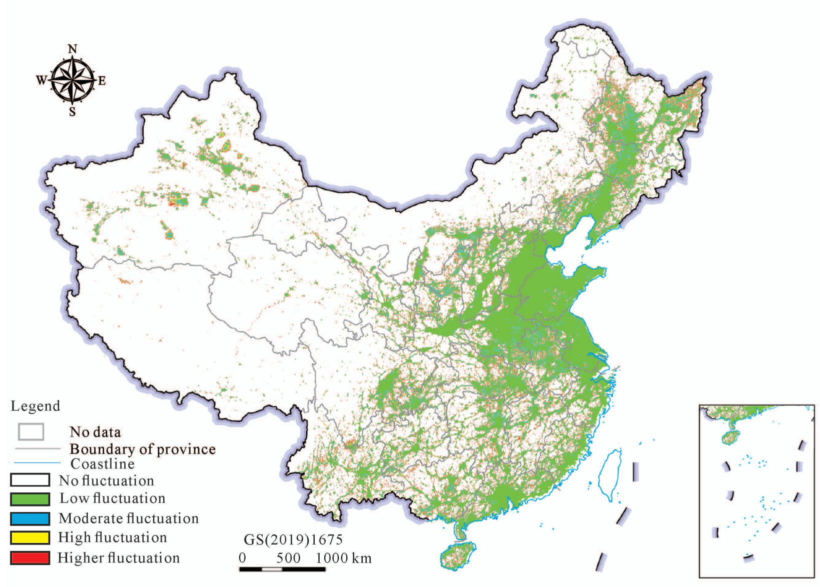

Fig. 3 Spatial distribution of the coefficient of variation of China from 1992–2013. Hong Kong, Macao and Taiwan of China are not included

fluctuation (2.5 > *CV* > 1.0) and low fluctuation (1.0 > *CV* > 0). Pixels with small value of *CV* also showed relatively smaller light intensity fluctuations. Based on the distribution characteristics of *CV* in Fig. 3, it was found that among regions with light changes, the pixels close to and within urban agglomerations tend to have smaller values of *CV*, such as those in Beijing-Tianjin-Hebei Urban Agglomeration, or in Yangtze River Delta Urban Agglomerations. This showed a relatively stable changes of urban development, which is related with the high level of urbanization in the past few decades. While in small cities and regions away from core cities, especially those of inland China, the significant light dynamics indicated quite obvious developing process and urban dynamics.

To further detect the regional difference of light dynamics, the *CV* distribution and proportions of different *CV* intensities were also discussed (Fig. 4). Among lighted pixels, the light fluctuations in most parts of China were obvious and showing great regional disparities. The general variability of light intensity in the eastern China is relatively smaller and distribute much more consecutively than the western China, and showing a mean *CV* order of NC < EC < SC. In regions of GNW and GSW, although abundance pixels were found with no light, significant light fluctuations can still be found. In addition, the drastic fluctuations of light dynamics founded in regions of CYRD, CCRD and NE indicate significant changes of light emanation and urban development within these regions.

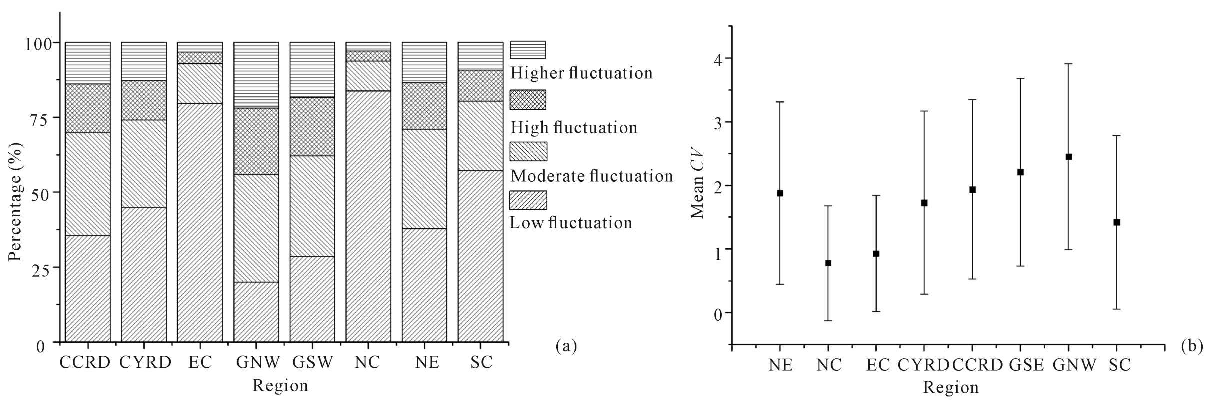

Fig. 4 *CV* of long-time light intensities of China: (a) Percentages of pixels with different coefficients of variation in each region and (b) mean *CV* in each region. NE (Northeast), NC (North Coast), EC (East Coast), SC (South Coast), CYRD (Central Yellow River Delta), CCRD (Central Changjiang River Delta), GSW (Great Southwest) and GNW (Great Northwest)

3.3 Variations and distributions of light of China

Together with the results of *MK*-trend test and Theil-Sen Median analysis, the general monotonic trend and slopes of light dynamics of each pixel with resolution of 1 km × 1 km can be effectively detected, and four categories of light dynamics types, named as significant increase, slight increase, slight decrease and significant decrease respectively can be thus summarized. As demonstrated in Fig. 5, the light intensity of pixels with light emission of China significantly increased during the study period. And it is obvious that the pixels within coastal regions and around core cities increased more significantly than those of the others. Moreover, among all the pixels with light changes, more than 97% display increased light intensities, and over 90% of which are significant. On the other hand, regions with decreased light intensity are mostly located in the natural resource-based area such as Shanxi and Liaoning provinces. And this might be associated with the phenomenon of 'ghost cities', which might be caused by the forbidden mining of mineral resources within these regions.

From a regional perspective, we also detected the trend of light variation in each divided region. The increasing trends of light variations in each study area were oboviously shown in Fig. 6. The percentage of increased pixels are quite high, especially in coastal areas, such as the regions of EC, NC, CCRD and SC, showing that the urban development of these regions were quite obvious and active (Fig. 6a). While the light variations are much gentle and a lot of pixels with light decrease were even found in regions of GNW, NE, GSW and CYRD, this could be due to the different developing strategies of these regions.

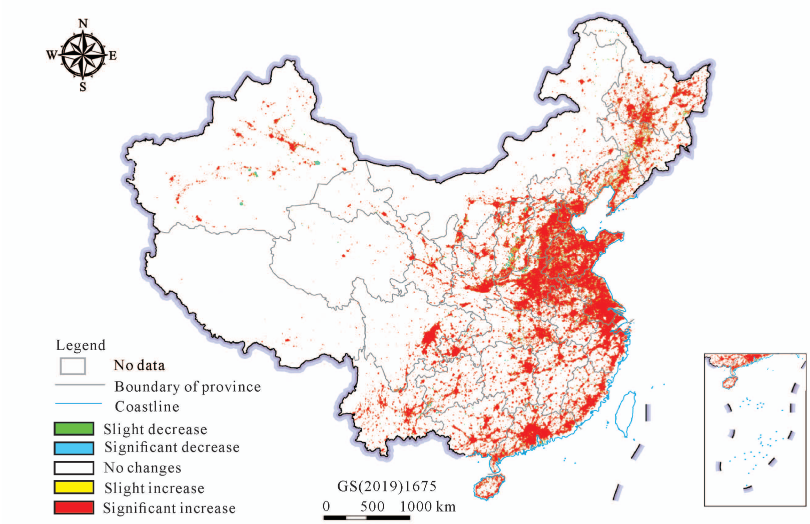

Fig. 5 Spatial distribution of the variation trend of China from 1992–2013. Hong Kong, Macao and Taiwan of China are not included

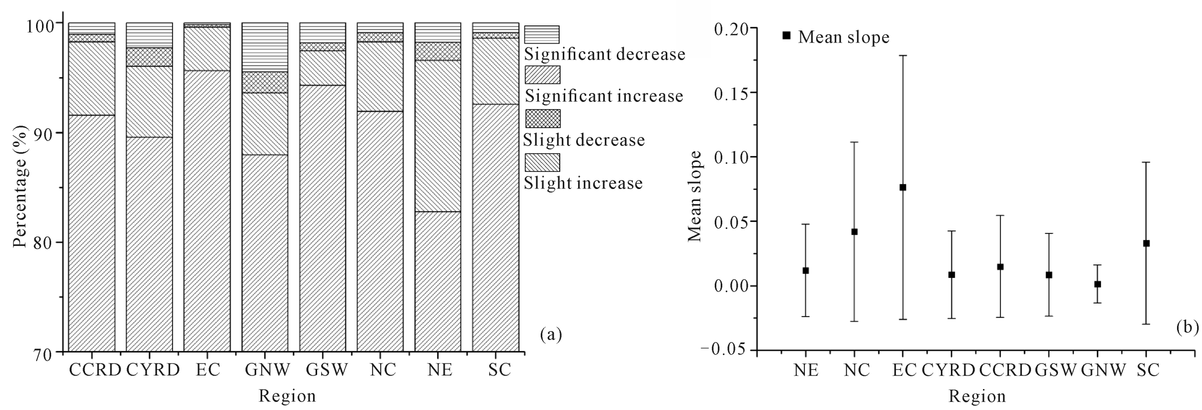

Fig. 6 Light trend of China: (a) Percentages of pixels with different variation trends in each region and (b) mean slope in each region. NE (Northeast), NC (North Coast), EC (East Coast), SC (South Coast), CYRD (Central Yellow River Delta), CCRD (Central Changjiang River Delta), GSW (Great Southwest) and GNW (Great Northwest)

3.4 Sustainability of nighttime light dynamics of China

An initial effort was also made in this research to predict the future trends of nighttime light dynamics at pixel level based on the long-term data. To achieve this goal, the widely used method of Hurst index was applied, as well as the results of *MK*-trend test and Theil-Sen Median analysis. From the detecting results of all three methods, the future trends of lighted pixels were further divided into four categories: 1) sustainable and significant increase; 2) sustainable and slight increase; 3) sustainable and slight decrease and 4) sustainable and significant decrease. In Fig. 7, the average value of Hurst index of China is about 0.68, indicating that the future light and urbanization will remain at the current trend. In details, in regions such as east and north coast China, the lighted pixels exhibits sustainable significant increase especially those within and around big cities. While in most regions of northeast and south China, sustainable decreases were observed around big cities. Indicating the disappearing of small cities and emergent growth of urban agglomerations in the future.

To further demonstrate the future dynamics of light, statistical comparison at region level was further presented in Fig. 8. Significant regional differences were found. And it was clear that in coastal regions of China, more than 60% pixels with light emanation show sustainable and significant increasing trend in the future, especially in regions of EC, NC and SC. While in the less developed regions of GSW, GNW and NE, nearly 50% of lighted pixels were found with sustainable decrease trends in the future, indicating a severe situation of development within these regions.

4 Discussion

Pixel level spatial-temporal detection provides a new insight into the dynamics and changes of the nighttime light images, and the detected urbanization dynamics and spatial patterns in this study are relatively consistent with that found in previous studies (Yi et al., 2016; Jia et al., 2017; Xin et al., 2017). While the pixel level detecting in this study is more superiority, since the detection on the dynamics of each pixel provides more reliable and believable evidence than traditional methods. Moreover, with the 1 km × 1 km spatial resolution, more detail information can be found at pixel level. Besides, pixel level detections can also make intra-regional comparison possible, which is unique from the current studies.

When the data of DMSP/OLS was utilized, the phenomenon of saturation was a major drawback in urbanization detection. Although there are some methods to eliminate saturation, the availability and effectiveness in

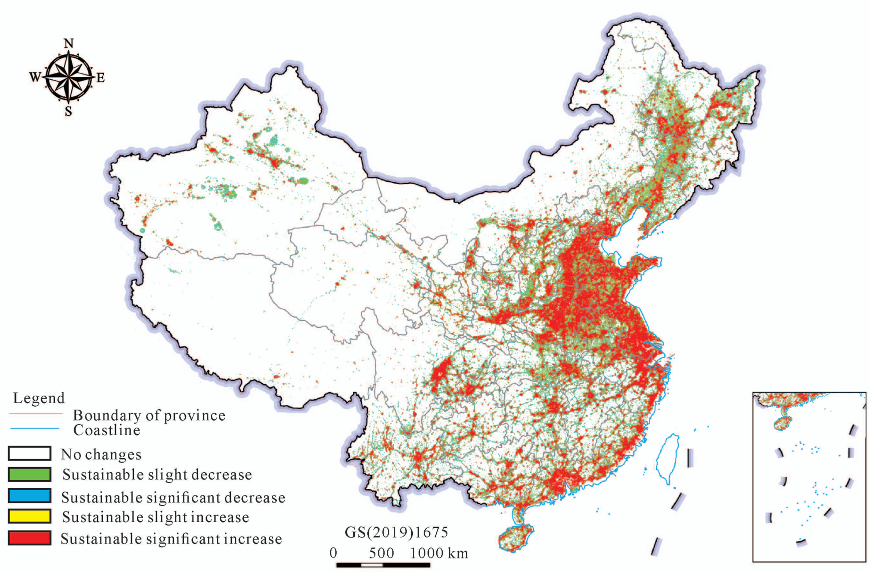

Fig. 7 Sustainability of the variations for nighttime light in China from 1992–2013. Hong Kong, Macao and Taiwan of China are not included

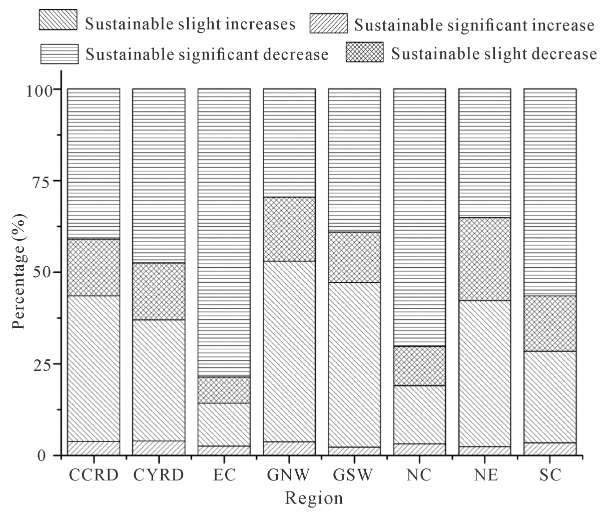

Fig. 8 Proportion of the sustainability in each region of China. NE (Northeast), NC (North Coast), EC (East Coast), SC (South Coast), CYRD (Central Yellow River Delta), CCRD (Central Changjiang River Delta), GSW (Great Southwest) and GNW (Great Northwest)

large scale remain unknown. The saturated regions are usually found in urban cores which are also highly urbanized. Moreover, according to a mathematical calculation, the saturated pixels with DN value of 63 are only less than 1% of pixels with light emission of China in each year, so we can believe that these saturated regions will not change the results of this study.

With the index of *CV* and calculations of slopes, the urbanization fluctuation and dynamics were revealed. In regions such as traditional big cities, the detected *CV* is quite small, this does not mean that the urban dynamics of these pixels are stable, on the contrary, the urbanization level is quite high and can be explained by the characteristics of the index and saturation phenomenon of the data source (Zhang and Seto, 2013; Hsu et al., 2015; Li and Zhou, 2017). Different regions respond differently to *CV*, and nearly 3% of lighted pixels were detected with a decrease trend of light dynamics, and most of them located in or around the resource-based cities. Indicating a significant phenomenon of 'ghost cities', which means that the urban region within these regions is far exceeds the actual demand of human habitat (Zheng et al., 2017). This might be associated with the forbidden mining of mineral resources and loss of population, and researches should focus on this phenomenon in future studies. Based on the current results, we found that in regions of GNW and GSW, which covers most areas of China, the total variations were insignificant and the trends were relatively slow, indicating a severe difference in regional development among these regions, and different development strategies should be applied. Combining the results of trend analyze and Hurst index, we can also predict the future trend of light variations, and also draw a brief picture of future regional development which so far has not been done in previous studies.

With the long-term nighttime light variations of China, the characteristics and patterns of light variations and trends in different regions were detected at pixel level, while there are still few limitations needed to be concerned. For example, due to the existence of saturation and blooming phenomenon of nighttime light images, the land features might be distorted in some pixels which cannot be solved by far. Moreover, the future trends in this study were detected based on the light history of time series and the results greatly depends on the quality of the time series.

5 Conclusions

Nighttime light data provide an accurate and effective measurement to exam the process of urbanization. Together with the methods of *CV*, *MK* test and Hurst index, the spatio-temporal dynamics and future trends of urban development of China from 1992–2013 have been detected at pixel level using the long-term series DMSP/OLS data. The results indicated that the urban development in most region of China experienced significant increases during 1992–2013, especially in regions of coastal and metropolitans. The increasing trend in North Coast China, East Coast China and South Coast China were quite drastic, while in inland areas, thus the trends were relatively stable, great regional differences could be found. In addition, the future trends of regional development were further predicted based on the historical nighttime light data from 1992–2013, and an agglomeration trend of urban development was detected. Besides, in less developed regions, nearly 50% of lighted pixels were found with sustainable decrease trends. This study effectively demonstrates the light dynamics of China at pixel level, which we believe is beneficial to better understanding the process of regional development.

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