ESTIMATING INDUSTRIAL STRUCTURE CHANGES IN CHINA USING DMSP - OLS NIGHT-TIME LIGHT DATA DURING 1999-2012

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ABSTRACT:

The Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) night-time light imagery has been proved to be a powerful tool to monitor economic development with its relatively high spatial resolution at large scales. Night-time lights caused by human activities derived from DMSP-OLS satellite imagery are widely used in socioeconomic parameter estimations and urbanization monitoring. In this paper, DMSP-OLS night-time stable light data from 1999 to 2012 are utilized to analyze inter-annual variation in GDP of per unit light intensity (R_{GDP}) in China. Furthermore, R_{GDP} was compared with statistical data of the tertiary industry structure for 28 provincial regions. The results show that the provincial R_{GDP} decreased abruptly in 2001-2002, 2008-2009 and 2011-2012, which is consistent with the proportional growth of the tertiary industry in GDP. These results indicate that the changes in R_{GDP} can reflect tertiary industry structural changes in China's province-level regions.

1. INTRODUCTION

In recent decades, rapid economic development, growth of energy consumption and accelerated urbanization have been occurring in China. Gross domestic product (GDP) is the basic indicator for measuring the economic development of countries and regions. The continuous development of remote sensing technology, especially the night-time light imagery derived by satellite provides an ideal data source for research on urbanization, economic activity, and population(Bennett and Smith, 2017; Lu et al., 2018). Some researchers have found a strong correlation between night-time light and socio-economic parameters such as GDP, population , electric power consumption(Dai et al., 2017; Elvidge, 2000; Elvidge et al., 1997; He et al., 2014; Letu et al., 2010; Li et al., 2013a; Sutton et al., 2007; Zhang et al., 2017; Zhao et al., 2011; Zhu et al., 2017).
The night-time light imageries derived by Operational Linescan System (OLS) sensors carried by the Defense Meteorological Satellite Program (DMSP) provide a powerful tool to monitor economic activities at a large scale with its relatively high spatial resolution (1 km×1 km)(Zhao et al., 2014). DMSP-OLS was designed for meteorological monitoring and detecting clouds under moonlight. However, the photomultiplier tube (PMT) carried on the sensor is able to detect weak near-infrared radiation on the surface(Elvidge et al., 1997). Therefore, night-time light data are used as an effective proxy of socioeconomic activity, and these data are an ideal data source for investigating economic activity and energy consumption. Elvidge et al.(Elvidge et al., 1997) conducted a regression analysis of GDP, population, electric power consumption, and night-time light for 21 countries based on DMSP-OLS night-time light data. The results show that there is a strong correlation between night-time light and human activities. Then, the correlation was confirmed for other national areas(Elvidge, 2000; Elvidge et al., 2001; Shi et al., 2016). Further studies show that night-time light data can be used to estimate socio-economic parameters such as GDP, population and electric power consumption at the sub-national level(Dai et al., 2017; Ebener et al., 2005; Letu et al., 2010; Sutton et al., 2007; Zhao et al., 2014). The studies above were carried out on single-year night-time light data at national and sub-national scales. Townsend et al.(Townsend and Bruce, 2010) monitored the variation trend for electric power consumption in Australia using time series night-time light data, but they neglected the correction of incompatibility and discontinuity of time series night-time light data. Zhao et al.(Zhao et al., 2012) combined population data to estimate provincial-level electric power consumption from 1995 to 2009 based on corrected night-time light data. However, these studies did not make a distinction for socio-economic parameters of different industries. Wu et al.(Wu et al., 2013) discussed numerous factors affecting the relationship between night-time light and GDP on global scales from 1995 to 2009 and concluded that agriculture was approximately 25.4% of total light consumption. Han et al.(Han et al., 2012) calculated GDP generated by the tertiary industry utilizing night-time light, and they considered that night-time light was representative of human economic activity especially in the service industry. These studies mainly established correlations between night-time light and socioeconomic parameters for estimation, spatialization and dynamic analysis. However, they did not combine night-time light with socioeconomic parameters.
The intensity of night-time light generally refers to the intensity of the regional light and previous studies have shown that the total digital number (DN) values of night-time light imageries in a region have a strong positive correlation with GDP(Dai et al., 2017; Doll et al., 2006; Elvidge et al., 1997; Elvidge et al., 2009; H et al., 2015; Ma et al., 2012; Qi et al., 2017; Yue et al., 2014). However, few studies focus on the analysis of changes in industrial structure by combining time-series night-time light

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with socio-economic parameters. This topic provides a novel idea for investigating the industrial structure via combining time-series night-time light data with GDP. Night-time light, a proxy of human activities(Tripathy et al., 2017), is related to many factors such as economy, urbanization and energy consumption. Moreover, the industrial structure, a component of the economy, is related to night-time light. In China, the main sources of light produced by urban streets, business districts, residential areas and the development of urban streets are closely related to the city's tertiary industry (service industries and tourism mainly). We assume that the tertiary industry in a region produces more intense or wide light when the intensity of night-time light increases rapidly relative to GDP in one year. Therefore, we considered that the proportion of the tertiary industry increases when the province-level R_{GDP} decreases abruptly during the year. Importantly, the assumption in this paper is unidirectional. When the proportion of provincial tertiary industry increases, R_{GDP} does not always decrease. However, the growth in proportion of the tertiary industry does not always result in light intensity having a rapid increase relative to GDP.

We obtained the spatiotemporal distribution of night-time light intensity firstly. Then, the variation trend of industrial structure at province-level across China based on long-time series DMSP-OLS night-time light data was analyzed, and the proportion of the provincial tertiary industry is compared with the variation trend of R_{GDP} in this paper.

2. MATERIALS AND METHODS

2.1 Data sources

The version 4 DMSP-OLS night-time stable light products from 1999 to 2012 were obtained from the National Oceanic and Atmospheric Administration's National Geophysical Data Center (NGDC). The DMSP satellite orbits earth every 101 minutes at an altitude of 833 km above the surface of the earth and passes the same location twice a day. The reference of night-time stable light imageries is WGS-84 covering the range from -180◦ to 180◦ longitude and -65◦ to 75◦ latitude(Baugh et al., 2010). The study area in this paper contains provincial administrative regions in China. It is difficult to obtain statistical data for Hong Kong, Macao and Taiwan. At the same time, the statistical data are inaccurate and lacking owing to the underdeveloped economies of Tibet, Qinghai and Ningxia. Therefore, we chose 28 provinces in China excluding Hong Kong, Macao, Taiwan, Tibet, Qinghai and Ningxia.

The administrative boundary provided by the Database of Global Administrative Areas (GADM). GDP and industrial proportion at the province level come from the China Statistical Yearbook (2000-2013) released by National Bureau of Statistics of the People's Republic of China. Detailed data sources are shown in Table 1.

Data	Source
GDP, Industrial proportion	National Bureau of Statistics of People's Republic of China （http://www.stats.gov.cn/）
Administrative boundary	GADM （http://www.gadm.org/country）
DMSP-OLS Stable light data	NGDC https://www.ngdc.noaa.gov/eog/dmsp/downloadV4composites.html

Table 1. Data source list

2.2 Inter-calibration

The night-time stable light data used in this paper are global imagery composites, so we obtained the imagery of China firstly. The original data are in the WGS-84 coordinate system, and the footprint of 30 arc-second grids decreases as latitude increases. All data were projected into the Albers Equal Area Projection to avoid the impact of area distortion and resampled to a spatial resolution of 1 km×1 km (cell size).

The imageries adopted in this article are from 1999 to 2012 and contain a total of 23 night-time light imageries taken from five different sensors (F12, F14, F15, F16 and F18). The DN values of the imageries collected vary from one satellite to another, as well as from one year to another for the same satellite due to changes in ground conditions or gain values of the sensors(Doll, 2008).

Invariant region method was adopted to correct the night-time stable light imageries, and the imagery collected by the F12 sensor in 1999 was selected as the reference imagery. The method selected Sicily, Italy, as invariant region. A quadratic regression equation was established to adjust the DN value of pixels in the original imagery and match with the reference imagery. The inter-calibration equation obtained by this method was used to correct all the imageries. The inter-calibration equation is as shown in Equation 1:

$$DN_{cal} = a + b \times DN + c \times DN^2 \qquad (1)$$

where DN indicates the DNs in the original imagery; DN_{cal} indicates the DN values after inter-calibration; and a, b and c indicate parameters in the quadratic regression equation.

2.3 Incompatibility and discontinuity correction

The night-time light data possess a single DN value for each pixel in some years, such as F16 2008, F16 2009 and F18 2012. However, there are different DN values for the same pixel in some years such as 1994 and 1997-2007. In short, a large number of inconsistent bright-value pixels are present in the imageries of different sensors in the same year. The value of pixels obtained from the same year for different sensors should be consistent in number and location. The night-time light imageries used are annual average products in this paper, so when a pixel value is 0, we can consider that no light is generated in the region. Therefore, when performing imagery operations on night-time light imageries acquired by different sensors in the same year, as both DN values are not 0, the two values are averaged; if one of the two DN value is 0, then the final value is 0. Corrections between satellites in the same year use following equation:

$$DN_{i,n} = \begin{cases} (DN_{i,n,a} + DN_{i,n,b})/2 & (DN_{i,n,a} \neq DN_{i,n,b} \neq 0) \\ 0 & (DN_{i,n,a} = 0) \ or \ (DN_{i,n,b} = 0) \end{cases} \qquad (2)$$

where $DN_{i,n}$ is DN value of the ith lit pixel of intra-annual composite in the nth year; and $DN_{i,n,a}$ and $DN_{i,n,b}$ are DN values of the ith lit pixel from two NSL data in the nth year respectively. According to the characteristics of night-time light in developing countries, China, which is one of the fastest-growing developing countries in the world, has enjoyed a period of steady development over the past two decades. Therefore, we further assumed that lit pixels detected in earlier night-time light imageries should be maintained in the later night-time light imageries, and DN values of lit pixels detected in an earlier night-time light image should not be greater than their DN values in the later imagery based on the premise of China's development. Liu et al.(Liu et al., 2012) extracted urban built-up areas based on the above assumptions. DN values of multi-year imagery were corrected according to following equation.

$$DN_{i,n} = \begin{cases} DN_{i,n-1} & (DN_{i,n-1} > DN_{i,n}) \\ DN_{i,n} & others \end{cases} \quad (3)$$

where $DN_{i,n}$ and $DN_{i,n-1}$ are DN values of the *i*th lit pixel of night-time light data in the nth and the n-1th years, respectively.

2.4 Analysis of time series night-time light and statistical data

The unlit regions outside city and water areas were affected by the urban light. Therefore, there are DN values larger than 0 for unlit area in the time series DMSP-OLS imageries. Sutton et al.(Sutton et al., 2007) selected a DN value threshold of 30 for night-time light imageries to delimit urban extents. Liu et al.(Liu et al., 2012) divided China into eight economic regions, and determined the optimal thresholds, which are 27 – 62, for each economic region. We believe these thresholds are too high for China, which is a low-urbanized developing country. However, GDP comes from not only cities, but also the countryside. Those large thresholds will ignore light information from small cities and countryside, which are also contributor to GDP when the threshold is too large. The blooming effects of the imageries will be hard to minimize and some regions without light are also counted when the selected threshold is too small. For the study of Zhao et al.(Zhao et al., 2012), the authors found that 10 is the maximal DN value that can delimit all the county extents in Qinghai, which is the most economically underdeveloped province in China. Therefore, a DN value threshold of 10 was selected to minimize the effects of blooming. According to Equation 2, to minimize the effects of blooming:

$$DN_{adj} = \begin{cases} 0 & DN < 10, \\ DN & DN \geq 10, \end{cases} \quad (4)$$

where DN_{adj} indicates the DN values in night-time imageries after adjusting, and *DN* indicates the DN values in the original imageries.

We combined GDP and night-time light data to obtain GDP of per unit light intensity. We assumed that the tertiary industry in the region has been developed to produce more intense or wide lights when the intensity of night-time light increases rapidly relative to GDP in one year. We analyzed the time series province-level GDP of per unit light intensity to investigate the variation trend of the tertiary industry structure in different provinces. R_{GDP} was obtained according to following equation.

$$R_{GDP} = \frac{GDP_i}{DN_i} \quad (5)$$

where R_{GDP} is GDP of per unit light intensity, GDP_i indicates *i*th provincial GDP, and DN_i indicates sum of DN of the *i*th province. We investigated the correlation between variations of the proportion of the tertiary industry and R_{GDP} based on comparative analysis of time series R_{GDP} and the annual proportion of the tertiary industry in each province.

3. RESULTS AND DISCUSSION

3.1 The corrected night-time light products

There are two obvious flaws in the original night-time light data: DN value discontinuity in different years; and the incompatibility between two night-time light imageries obtained by different sensors in the same year. Figure 1 shows the change in night-time light total DN value taken by five different sensors during the period of 1999 to 2012 in China. We determined that the night-time light imagery captured at F14 from 1999 to 2002 is dimmer than other two sensors. In addition, the total value of F15 in 2003, F16 in 2005 and 2008, and F18 in 2011 had a downward trend. The former may be caused by different gain values of different sensors, and the latter may be caused by sensor degradation.

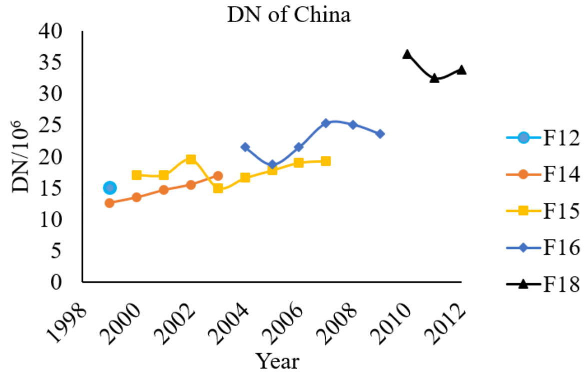

Figure 1. Sum of DNs in China during 1999-2012 from five different satellites

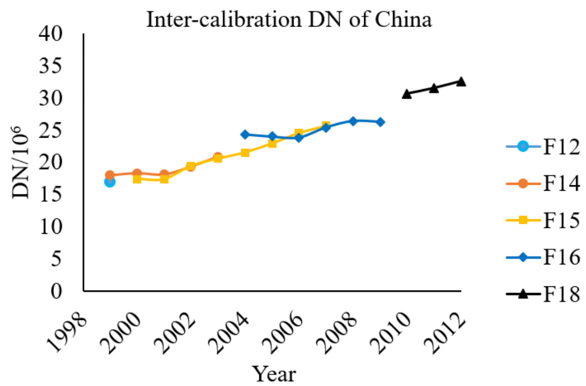

Figure 2. inter-calibration sum of DNs in China during 1999-2012 from five different satellites

After the correction, as shown in Figure 2, we can see that the total DN value of night-time light imageries obtained by different sensors are close to each other in the same year, and the effect caused by sensor degradation had been reduced. This result is in line with the development of China, which was a rapidly developing country from 1999 to 2012. After the correction, night-time light imagery data of the long time series are comparable, and each period of the imageries weakened the DN value saturation.

3.2 Spatiotemporal distribution of DN

Night-time light, which is a proxy of human activity, indicates the degree of urbanization and economic development. The studies have shown that the sum of province-level DN values has a strong positive correlation with province-level GDP. We assumed that DN values in night-time light imageries products are also constantly increasing, which means that the DN value of each pixel the following year should be greater than or equal to the DN value of the previous year with the continuous development of China's economy. From Figure 3, DN values in most provinces maintain a relatively steady growth. In terms of space, the provinces with larger DN sums are concentrated in the eastern coastal provinces, followed by the central and northeastern regions, and the DN sums in the western region are generally small. In terms of time, the increment of DNs varied from province to province during 1999-2012.

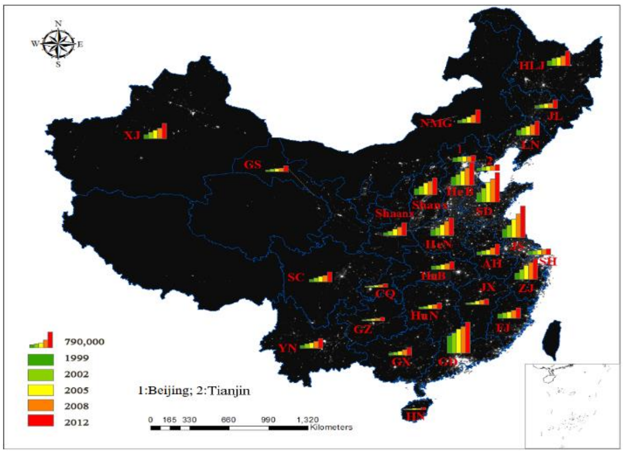

Figure 3. Spatiotemporal distribution of DN in China (Background image: night-time light image of China in 1999;BJ = Beijing; TJ = Tianjin; HeB = Hebei; Shanx = Shanxi; NMG = Inner Mongolia; LN = Liaoning; JL = Jilin; HLJ = Heilongjiang; SH = Shanghai; JS = Jiangsu; ZJ = Zhejiang; AH = Anhui; FJ = Fujian; JX = Jiangxi; SD = Shandong; HeN = Henan; HuB = Hubei; HuN = Hunan; GX = Guangxi; HN = Hainan; CQ = Chongqing; SC = Sichuan; GZ = Guizhou; YN = Yunnan; Shaanx = Shaanxi; GS = Gansu; and XJ = Xinjiang.)

These temporal and spatial variations are closely related to the geographical location, climate conditions and national policies of each province. Among them, DN values of Jiangsu in 2001-2002; Sichuan, Hebei, Heilongjiang and Liaoning in 2008-2009; and Tianjin in 2009-2010 increased significantly. The reason for these increases is probably that tertiary industries in these provinces were developed and produced more intense or wider ranges of lights.

In addition, the proportion of the tertiary industry of Jilin did not increase (38% -37.9%) when DN values increased significantly in 2008-2009; DN values of Henan also increased significantly from 2005 to 2006 with the GDP maintaining at relatively steady growth. However, the proportion of the tertiary industry did not increase from 2005 (30%) to 2006 (29.8%); similarly, DN values of Shanxi increased significantly in 2003-2004 with a steady increase in GDP for the corresponding year. However, the proportion of the tertiary industry decreased significantly in Shanxi province from 2003 (34.7%) to 2004 (32.2%). In addition, DN values in Anhui increased significantly from 2009 to 2010, but the proportion of the tertiary industry declined (36.4% - 33.9%). Therefore, a significant increase in DN values of provincial-level night-time light does not represent an increase in the tertiary industry proportion. It is difficult to obtain the variation trend of the tertiary industry structure utilizing the provincial-level DN values individually.

3.3 Inter-annual variation in R_{GDP} and industrial structure

In this paper, we analyzed the inter-annual variation in R_{GDP} in each province (Figure 4). The study time range started from 1999, and we explored the abrupt point in the R_{GDP} interannual variation. However, we did not explore and explain the phenomenon when R_{GDP} started to decrease from 1999 to 2000, owing to the trend of R_{GDP} before 1999 that was not obtained.

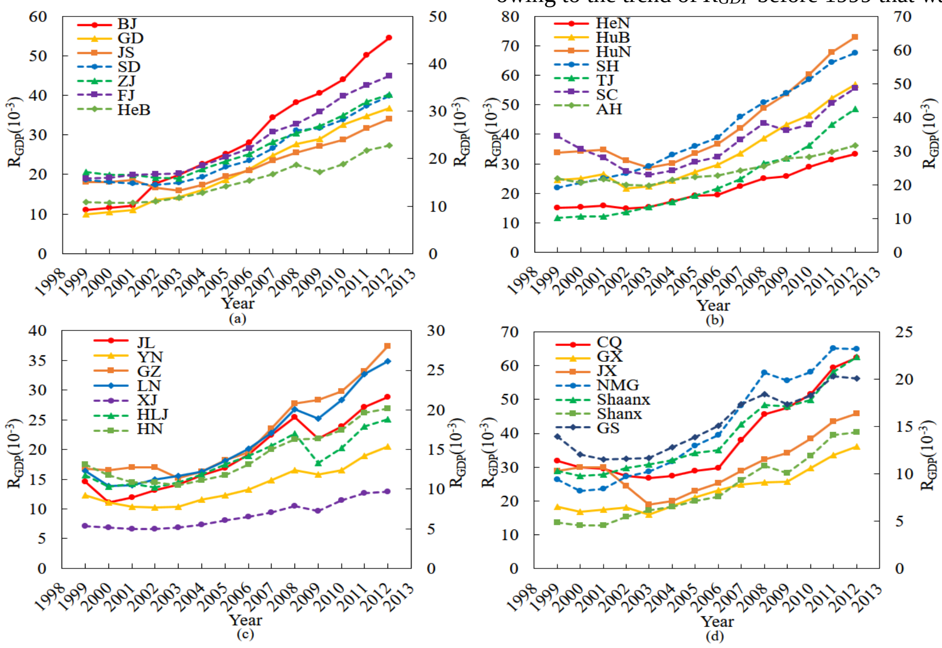

Figure 4. Inter-annual variation in R_{GDP} for 28 provinces in China during 1999-2012

As shown in Figure 4, R_{GDP} of Jiangsu, Henan, Hubei, Hunan and Anhui provinces decreased abruptly from 2001 to 2002 indicating that DNs had a larger increase than GDP in 2002, while the proportion of the tertiary industry increased (Table 2). However, it is difficult to judge variation in the tertiary industrial structure from GDP and DN in 2001-2002 (Figure 4). As the first year of the Tenth Five-Year Plan in 2001, the government made strategic adjustments to the economic structure. The main tasks were optimizing the industrial structure and comprehensively raising the level and efficiency of agriculture, industry and service industries. Based on this background, the five provinces adjusted their industrial structure to increase the proportion of the tertiary industry in the national economy. The R_{GDP} of Inner Mongolia and Gansu decreased abruptly from 2011 to 2012, and the proportion of the tertiary industry increased (Table 2). Jiangsu is located in the eastern region with an economy in second place for many years, and it has a higher level of economic development than the other six provinces. Hubei, Hunan, Henan and Anhui are located in the central region with lower economic development than the Jiangsu. Inner Mongolia and Gansu are located in the western region with economic development slightly weaker than the other five provinces (The four major economic regions of China come from National Bureau of Statistics of the People's Republic of China). The proportion of the tertiary industry increased when the R_{GDP} decreased abruptly whether in the eastern coastal provinces with higher levels of economic development or the central provinces and the western provinces.

The R_{GDP} of Jiangxi decreased abruptly in 2001-2002 and kept decreasing in the following year (Figure 4), but the proportion of the tertiary industry did not increase (Table 2). The R_{GDP} of Jiangxi has significant variation in 2001-2003 compared with other provinces, while the GDP of Jiangxi maintained a relatively steady growth in line with other provinces. In addition, the DN of the Jiangxi had significant variation, which may be caused by the error of night-time light data or industrial policy.

The R_{GDP} of Guizhou and Guangxi decreased abruptly in 2002-2003, then it maintained steady growth. However, the proportion of their tertiary industry did not increase (Table 2). Economic growth in both provinces was affected in 2002-2003: Guizhou's GDP growth rate during this period (14.71%) was close to the growth rate of previous year (14.61%) and much lower than the growth rate of next following year (17.63%); Guangxi's GDP during this period was far less than the growth rate in the previous year (13.11%) and the following year (21.71%). The R_{GDP} of Guizhou and Guangxi declined by the impact of GDP growth.

Province (municipality)	**Proportion of tertiary industry (%)**		**R_{GDP} (10^{-3})**	
	2001	**2002**	**2001**	**2002**
Jiangsu	37	37.3	18.72	16.59
Hubei	35.5	36.6	26.42	21.56
Anhui	34.2	34.9	21.78	19.96
Hunan	39.8	40.5	34.69	31.11
Henan	31	31.3	15.90	14.88
Jiangxi	40.5	39.3	29.91	24.38
	2011	**2012**	**2011**	**2012**
Inner Mongolia	34.9	35.5	20.68	19.83
Gansu	39.1	40.2	18.37	17.35
	2002	**2003**	**2002**	**2003**
Guizhou	36.2	35.3	16.94	15.23
Guangxi	40.5	39.3	18.11	16.08

Table 2. The variation in proportion of tertiary industry and R_{GDP}

Province (municipality)	**Proportion of tertiary industry (%)**		**R_{GDP} (10^{-3})**	
	2008	**2009**	**2008**	**2009**
Xinjiang	33.9	37.1	7.85	7.27
Hebei	33.2	35.2	18.68	17.24
Liaoning	34.5	38.7	26.73	25.17
Inner Mongolia	33.3	38	20.68	19.83
Heilongjiang	34.4	39.3	16.97	13.30
Gansu	39.1	40.2	18.37	17.35
Yunnan	39.1	40.8	16.52	15.80
Sichuan	34.8	36.7	38.19	36.07
Shaanxi	32.9	38.5	17.28	17.09
Shanxi	34.2	39.2	10.81	10.07
Jilin	38	37.9	25.46	21.82

Table 3. The variation in proportion of tertiary industry and R_{GDP} during 2008-2009

The R_{GDP} of Xinjiang, Hebei, Liaoning, Inner Mongolia, Heilongjiang, Gansu, Yunnan, Sichuan, Shaanxi and Shanxi decreased abruptly from 2008 to 2009 (Figure 4). The DNs of the ten provinces had a greater growth than the growth of GDP in

2009, and the proportion of tertiary industries increased (Table 3). Ten provinces are distributed in various economic regions of China, Hebei is located in the eastern region, Shanxi is located in the central region, Liaoning and Heilongjiang are located in the northeast region, and the others are located in the western region. It is difficult to judge the variation in the industrial structure from GDP and DN of the ten provinces. China was affected by the global economic crisis caused by the subprime crisis of the United States in 2008, and GDP growth of most provinces slowed down. However, the economic crisis not only posed a challenge but also provided opportunities for industrial restructuring and upgrades. When responding to the economic crisis, China seized the opportunity to upgrade its industrial structure and actively develop its tertiary industry. In addition, the R_{GDP} of Jilin decreased abruptly in 2008-2009; however, the proportion of the tertiary industry did not increase (Table 3). DNs in Jilin substantially increased from 2008 to 2009, while GDP grew more slowly. The night-time light of Jilin substantially increased in 2008-2009, which may have been caused by the development of infrastructure (streetlights, etc.), but the tertiary industry had not been developed.

4. ERROR AND LIMITATIONS

We found that the process of inter-calibration may generate some errors. We used the invariant region method to inter-calibrate raw night-time light imageries because of the lack of on-board calibration for DMSP-OLS. The method assumed that night-time lights in Sicily, Italy, did not experience any significant changes, which seems to be impossible. The sum of the lights from the two satellites were not coincident (Figure 2). Future work will consider improving the methods to reduce the impact of the lack of on-board calibration.

In addition, the single threshold of 10 for controlling 'blooming effects' may lead to some errors. Zhao et al. found that threshold of 10 was better than threshold of 20 and 30 to delimit urban extents(Zhao et al., 2012). To reduce the impact of a single threshold, future work can determine the threshold accurately utilizing multisource data for each year and each province.

Another kind of error may come from the discontinuity correction. Regions that are dependent on resources and heavy industry may experience a decrease in night-time light intensity. However, night-time stable light data are the annual average product with a spatial resolution of 1 km, we believed that pixels with a decrease in night-time light intensity were only a small part.

5. CONCLUSIONS

The prosperity of tertiary industry is an important feature of the modern economy. Therefore, it is significant to understand variation trends of the tertiary industrial structure. This paper analyzed spatiotemporal distributions in night-time light intensity and the variation trend of industrial structures at the province-level across China based on long-time DMSP-OLS night light data from 1999 to 2012.

In this paper, we assumed that the tertiary industry has been developed to produce more intense or wide lights in a region when night-time light increases rapidly relative to GDP in one year. Therefore, we considered that the tertiary industry structure increased when the R_{GDP} of a province-level decreased abruptly in a year. The results show that inter-annual variation in R_{GDP} can reflect the variation of the tertiary industry structure in the provincial region. Among them, the R_{GDP} of Jiangsu, Anhui, Hubei, Hunan and Henan in 2001-2002; Xinjiang, Heilongjiang, Liaoning, Inner Mongolia, Heilongjiang, Gansu, Yunnan, Sichuan, Shaanxi and Shanxi in 2008-2009; and Inner Mongolia and Gansu in 2011-2012 decreased abruptly, and the proportion of the tertiary industry increased. In addition, the proportion of the tertiary industry in four provinces did not increase when the R_{GDP} of these provinces decreased abruptly, and we analyzed the reasons above. The 4 provinces only account for a small part compared with the other 17 provinces. Therefore, we believed the assumption above was valid.

This article explored variation trends of the tertiary industry structure via night-time light data obtained by satellites in a new perspective and provided a reference for the economic development and industrial structure of province-level regions of China. The Visible Infrared Imaging Radiometer Suite (VIIRS) sensor on the Suomi National Polar-orbiting Partnership (NPP) Satellite launched in October 2011 has become a new satellite used to monitor night-time light(Li et al., 2013b). Future study can apply this method to NPP-VIIRS satellite.

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