Mapping urbanization dynamic of mainland china using dmsp/ols night time light data

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Abstract. Knowledge of spatial-temporal changes of urbanization is highly required nowadays and DMSP /OLS nigh time light provides new insights to detect changes of urbanization in the global and regional scale. However, most researches focus on the spatial pattern while ignoring the temporal dynamics of urbanization process. In this study, the raw Night time Light data (NTL) were calibrated to form a comparable time series. New metrics of GNTL (growth of NTL), max GNTL, min GNTL, mean GNTL, GNTL amplitude and accumulated GNTL derived from time series DMSP/OLS data were applied to detect the urbanization dynamics of Mainland China from 1992 to 2013. The results show that NTL-derived metrics are good indicators to trace the urban dynamics on the contexts of both spatial and temporal scales, from which the urbanization dynamic features can be detected. With the combined utilization of NTL and NTL derived metrics, 3 types of urbanization are summarized, namely constant rapid urbanization, active improving urbanization and steady improving urbanization. Classification methods were also applied to test the performance of NTL derived metrics for urban structure discrimination. The study reported here is a novel attempt to trace urbanization process using the NTL derived metrics, and we foresee its wide applications in future in relevant studies.

1. Introduction

Urbanization is a process that concentrates people and relative social activities; it refers to the population shift from rural to urban areas as well as the shift of living condition of traditional agricultural society to a modern society; it has also been described as one of the most remarkable developments around the world [1].

China has experienced unprecedented economic growth and urbanization after the launch of the policy of reform and openness in 1978. More than half of the people in China have been living in urban areas since 2012 according to the National Bureau of Statistics of China and the trend is stilling accelerating [2-3]. Urban concentrates people, economic activities, and the built environment, while it has also led to many ecological and environmental problems [4]. Obtaining accurate information about the process of urbanization provides direct observations to these problems, which is crucial and beneficial to the development of our cities nowadays.

At present, methods of qualitative and quantitative analyses were accepted by most researches when it came to urbanization and the socio-economic statistical data provides powerful evidence. Many research have been made with the socio-economic data related to process of urbanization [5-7]. While there are still many shortages on timeliness and reliability for the reason of uncertainty and lag of statistical data which limits the contents of research [8-9]. In order to overcome these shortages
mentioned before and map the urbanization process precisely from the perspective of spatial and temporal, many researchers adapted the remote sensing images of different resolutions and achieved a certain degree of success.

Remote sensing data provide us with an easy and direct way to figure out ground objects and detect spatial-temporal characteristics of them. A lot of studies on urbanization have been made with remote sensing images such as Landsat TM/ETM+, SPOT HRV, IKONOS and Quick Bird. However, fine resolution datasets are often less popular at global and national level studies due to the high cost and complicated data processing procedure [10-12].

The DMSP/OLS instruments are first used to monitor the global distribution of clouds and cloud top temperatures in the early 1970s. Different from remote sensing images, the DMSP/OLS records visible and near-infrared light from the earth's surface at night, together with the presence of photomultiplier tube, the nighttime visible band signal was exactly intensified. And in doing so provides not only visually arresting images of the earth at night but also a geospatial time series of data that has proved to be a valuable source for both the natural and social sciences [13]. Since the establishment of the open access digital archive in 1992 by the National Oceanic and Atmospheric Administration/National Geophysical Data Center (NOAA/NGDC), these nighttime data have been widely used by the scientific community [14].

The DMSP/OLS night time data was first used in 1978 to identify human activities by Croft [15]. Since then, more and more attention has been paid on the applications of the dataset with the ability in capturing artificial lighting presented on the earth surface, especially in the early 2010s, such as urbanization detection [16-19], energy consumption [20-21], Social-economic activities detection [22-23], disease analysis [24-25], war detection [26-27] and so on. Among the various applications of DMSP/OLS night time data, the detection of urban and urbanization draws the most attention especially in the recent years. Long-term archives of DMSP/OLS night time imagery can provide uniform, consistent and valuable data sources for investigating urban dynamics, mounts of studies have been made for quantitatively tracing and mapping urban growth and patterns [28]. Zhang mapped the urbanization dynamics in India, China, Japan, and the United States at regional and global level based on the linear correlation between NTL and urbanization indicators [29]; Demetris found that DMSP/OLS nighttime light data can reflect urbanization progress in Europe by calculating the Sum of Lights (Sol) index in different regions [30]. Henderson also drew the conclusion that DMSP/OLS nighttime light can be an effective data source to detect urbanization and urban areas after comparing with results extracted from Landsat TM images [31]. Previous researches with different approaches were made at different scale and the results suggested that DMSP/OLS NTL data are efficient in urbanization related activities detecting.

NTL provided new insights to detect urban development at local and national level, but most of them are pattern-based analysis which mainly focuses on the snapshot of urban development of different years. To trace the dynamics of urbanization in mainland China, new methods should be introduced. In this study, we derived metrics from NTL to detect detail changes of urbanization dynamics at a provincial scale. The main objectives of the research described in this paper are (1) to introduce the new metrics derived from NTL to map the urbanization dynamics. (2) to trace the urbanization process with the derived metrics of mainland China from 1992-2013. To achieve these goals, the raw NTL data was calibrated; urbanization and urban growth pattern were mapped at the provincial and pixel level. In order to make a full understanding of urbanization with the DMSP/OLS nighttime light images, variations of urbanization based on NTL-derived metrics were summarized, and we also found that the supervised classification is more effective in detecting urban structure compared with unsupervised method.
2. Data and methodology

2.1. Data source

The nighttime stable light of Version 4 global DMSP/OLS nighttime lights series dataset from 1992-2013 obtained from the National Geophysical Data Center (NGDC) (http://www.ngdc.noaa.gov/dmsp/downloadV4composites.html) was adopted in this study to map the urbanization dynamics in mainland China (Figure 1). The archive data set consists of low resolution global and the imagery recorded along a 3000km scan with 0.55 km spatial resolution which are aggregated and composited to 30 arc second grids, containing lights from cities, towns, and other sites with persistent lighting, including gas flares, background noise was also identified and replaced with values of zero and the final data values range from 0-63. NTL raw images contain all the continuous impervious surface area, while part of them cannot be detected as urban or urban related area due to the low values and effect of over glow. So in this study, pixels with DN>13 were adopted as urbanization areas compared with images from Google Earth [32-33].

![Figure 1. False color composite image of Mainland China (red:1992; green:2003; blue:2013).](image1)

![Figure 2. DMSP/OLS night time data from 5 different satellites.](image2)

The DMSP/OLS nighttime data we use in this study include datasets from 6 different satellites (Figure 2): F10 (1992-1994), F12 (1994–1999), F14 (1997–2003), F15 (2000–2007), F16 (2004–2009) and F18 (2010–2013), the data cannot be used directly due to the differences between sensors and low comparability of nighttime lights data from different satellites, the individual composites had to be calibrated via an empirical procedure before they can be used.

In this study, we also use socioeconomic census data, including the nonagricultural population, the proportion of secondary industry and tertiary industry, and Gross Domestic Product (GDP) (obtained from the Chinese Statistical Yearbook (1992–2014)), Land-Use and Land-Cover Change (LUCC) data from The Institute of Remote Sensing and Digital Earth (RADI), Chinese Academy of Sciences (CAS) (http://www.resdc.cn/) was also adopted to detect the accuracy of the study. As well as Google Earth images and auxiliary data related to boundaries, especially the administrative boundaries of the province and the boundary of China.

2.2. Data processing

Due to the absence of on-board calibration of the sensor, the images we downloaded from the website are lacking in comparability and consistency, so they cannot be used directly to investigate the urbanization until calibrated.

In order to calibrate the data effectively, the second order regression model was first proposed by Elvidge [34], method of invariant region [35], improved intercalibration method [36] and coefficient based inter-calibration method [37] were also proposed based on the effort of Elvidge. Methods mentioned above can reduce the discontinuity of NTL effectively and these methods have been
utilized by many scholars in various research fields. In this study, we adapt a second order regression model to realize the inter-calibration of NTL images.

Areas with stable NTL with little changes over time and covering a quite wide range of DN values are always selected as the reference regions. In this study, we adopt the image of satellite F14 in 1999 as the reference image and Jixi as the reference region based on a thorough analysis and the second order regression model (equation 1) was employed to adjust data from other images to match the F14 1999 data range.

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

Where \( DN_{cal} \) is the calibrated DN values of pixels and a, b and c are coefficients of the second order regression model.

The process of inter-calibration was implemented based on the method above and the influence of discontinuous is effectively eliminated. But there still exist problem that images of the same year are from different satellites, thus an inter-annual calibration is needed (equation 2).

\[
\begin{align*}
DN_{(n,i)}^a = 0 & \quad |DN_{(n,i)}^a + DN_{(n,i)}^b|/2 \\
DN_{(n,i)}^b = 0 & \quad |DN_{(n,i)}^b| = 0 \\
\text{Others} & \quad |DN_{(n,i)}^a| = |DN_{(n,i)}^b| 
\end{align*}
\] (2)

\( DN_{(n,i)}^a \) and \( DN_{(n,i)}^b \) are DN values of the ith pixel of the nth year from satellite a and satellite b; \( DN_{(n,i)} \) is the inter-annual calibrated ith pixel value of the nth year; n means the ear of 1992, 1993, ……,2012, 2013.

Meanwhile, images after the two calibration methods are at different mathematical bases and in order to improve the comparability of data, the method of normalization was also adopted (Equation 3).

\[ DN_i = \frac{|X - DN_{min}|}{DN_{max} - DN_{min}} \] (3)

\( DN_i \) is the normalized value of Ith pixel with a range of 0-1 and the value of 1 means saturation; \( DN_{max} \) and \( DN_{min} \) are minimum and maximum values of an individual image.

Table 1. Metrics derived from NTL temporal profile.

| Metrics | Definition |
|---------|------------|
| GNTL | The metric of GNTL is the basic index of the metrics derived from NTL which means the growth of NTL between consecutive years. The equation of GNTL is as followed: \( GNTL = NTL_i - NTL_{i-1} \). This metric provides an index of the largest growth of the NTL between consecutive years. |
| Max GNTL | Metric of minimum GNTL describes the least growth of the NTL. |
| Min GNTL | The mean GNTL indicates the annual average increase of NTL values of the study region in the research time of 1992-2013. GNTL amplitude provide an index to describe the difference between the maximum and minimum GNTL which is different in different urbanization periods and urbanization regions. |
| GNTL amplitude | GNTL differs during the whole period of urbanization progress, which means that the growth of NTL is different. In this research, we built the GNTL threshold to help to describe kinds of GNTL based on the threshold. |
| GNTL threshold | Accumulated GNTL of a certain year indicate the total growth of NTL from the beginning of investigate urbanization period till the certain year. And the accumulate area of the graph is definitely the growth of NTL during the period. |
| Accumulated GNTL(AGNTL) | |

Table 1. Metrics derived from NTL temporal profile.
2.3. Metrics derived from NTL temporal profile
NTL can detect urbanization preciously to some extent, and most researches nowadays focus on the pattern or the phenomenon of urbanization, while the dynamics of urbanization dynamic process as well as the NTL growth pattern of different years didn’t draw much attention. Mimicked the metrics derived from NDVI by Wang and Tenhunen in 2004 [38], we developed the NTL-based derived metrics from NTL temporal profiles to focus on the dynamics or growth of NTL of different years, the metrics are listed in detail in Table 1.

2.4. Classification
Remote sensing provides us an easy and accurate way to detect the characteristic of land surface from the perspective of geography. Technologies of classification are always applied to detect the classes of ground features and there are two basic categories in classification methods: supervised and unsupervised.

The unsupervised classification method is used to describe the hidden structure or characteristics of unlabeled data. Unsupervised classification method identifies groups of pixels with similar NTL and GNTL properties using the approach of clustering. This method has been applied to identify patterns of urbanization dynamics in China, India, the USA and Japan, with DMSP/OLS nighttime light data in 2014 [29].

Similarly, supervised classification assigns pixels in a data set into classes corresponding to user-defined training data and specifies a classification method. In this analysis we select the simplest classification method called minimum distance classification method; the minimum distance technique uses the mean vectors of each endmember and calculates the Euclidean distance from each unknown pixel to the mean vector for each class. Then, all pixels are classified to the nearest class in which the distance is minimized. In this research, both of the two methods were applied to map the urbanization in the study region.

3. Results

3.1. NTL-derived metrics and urbanization dynamics at the province and city level

![Figure 3. correlation between GNTL and growth of GDP and Growth of Population at province (a) (b) and city level (c) (d).](image)

NTL images from DMSP/OLS give us a unique proxy to detect urban dynamics, many research have evaluated the correlation between NTL and urbanization indicators at different scale [39-40]. The relationship detected between NTL and urbanization suggested that the NTL time series data can be employed to map the pattern as well as the dynamics of urbanization, and the urban population and
GDP have been proved to be relevant to urban expansion. Therefore, we evaluated the relationship between NTL-derived metrics and urban dynamics with the indicators of GNTL, growth of GDP and growth of urban population at province and city level from year 1992 to 2013. The results(Figure 3(a)(b)) indicated that the metric of GNTL correlated well with growth of GDP and growth of urban population with correlation coefficients of 0.82 and 0.85 at provincial level; while Figure 3 (c) and (d) show the correlation of them at city level, in which 80 cities were selected randomly from different provinces (expect for cities such as Beijing, Shanghai, Shenzhen and so on, which are greatly influenced by the politics and favourable policy), and the result show that the metric of GNTL correlate well with urbanization indicators at both province and city level.

3.2. Urbanization dynamics in the study area

3.2.1. Urbanization in China. The urbanization pattern of 2013 and the urban dynamics process from 1992 to 2013 at provincial level of mainland China is mapped bellow in Figure 4 and Figure 5 according to the DN values of individual pixels.

According to Figure 4 and Figure 5, the urbanization pattern can be detected with the most urbanized regions concentrate mainly in the east China especially the coastal areas. And the three regions with highest NTL values as well as urbanization level are the Beijing-Tianjin Urban Agglomeration in the north region containing main cities of Beijing and Tianjin, the Yangtze River Delta Urban Agglomeration in the middle region with cities of Shanghai, Hangzhou and Nanjing as well as the Pearl River Delta Urban Agglomeration in the south region around the city of Guangzhou, and these three regions are the top 3 of mainland China in terms of non-agricultural population, proportion of secondary industry and tertiary industry, and Gross Domestic Product (GDP) according to the Chinese Statistical Yearbook. Meanwhile, urbanization hot points are prone to concentrate around the provincial capital in the study region of mainland China and regions around the capital are also at a quite high urbanization level, which might be caused by the radiating and exemplary role of the capital areas.

3.2.2. Urbanization Growth pattern. The urbanization pattern of mainland China in 2013 was mapped with NTL metrics. Moreover, based on the metrics of GNTL we developed above, the dynamics of NTL from year 1992 to 2013 was mapped to detect the growth of urbanization in mainland China (Figure 6).

From the detection of GNTL pattern, the mainland China experienced a rapid urbanization process from the year 1992 to 2013 and the urban developed quite a lot through the country. Coastal regions, especially the Yangtze River Delta Urban Agglomeration with main cities of Shanghai, Hangzhou and Nanjing experienced the largest urban growth owing to the location advantages which can be defined via the remarkable values of GNTL. And areas of provincial capitals are still the highpoints of urban growth compared with other regions in an individual province. The coarse pattern of urban dynamics can be detected from Figure 6, but in order to explore the details of urban growth from the perspective of regional and temporal, more relative researches are needed.
Figure 4. Urbanization pattern of Mainland China in 2013.

Figure 5. Average NTL values of different provinces of Mainland China from 1992-2013 (Horizontal axis is the year from 1992-2013; vertical axis is the NTL values of individual province).

Figure 6. GNTL pattern of Mainland China from 1992-2013.

Figure 7. Metrics derived from GNTL.
3.3. NTL derived metrics in Mainland China

3.3.1. Metrics derived from NTL. Metrics derived from NTL provide good indicators to describe and detect urbanization process. Figure 7 demonstrates the basic metrics of Max GNTL (the yellow line), Min GNTL (the red line), mean GNTL (the blue line) and the GNTL Amplify (the green line). Based on the figures of NTL-derived metrics, characteristics of the urban dynamics process can be easily detected. Values of GNTL above or below the mean GNTL line represent the growth speed of NTL, and GNTL values of year 1995, 2003, 2007-2013 are above the mean GNTL line, which means that urban growth in these years experienced a huge leap. Moreover, the curve in black means the growth of NTL values in different years and the areas between the curve and the horizontal axis are exactly the value of accumulated GNTL as well as the total NTL of the chosen year, and this can provide a direct understanding of urban dynamics through the process. With the metrics mentioned in Figure 8, the urbanization dynamics of individual provinces can also be mapped.

3.3.2. Urbanization dynamics based on GNTL. The metrics of GNTL give us good measures to detect the urbanization process of individual regions. In this study, we calculated the GNTL year by year, and the dynamics of GNTL in 31 provinces from 1992-2013 were mapped to confirm the process of urban development.

![Figure 8](image_url)

Figure 8. Dynamics of GNTL in Mainland China from 1992-2013 (Horizontal axis is the year from 1992-2013; vertical axis is the GNTL values of individual province).

Figure 8 maps the GNTL dynamics of 31 provinces in Mainland China, the growth of provinces in each year as well as the total NTL can be indicated. Provinces such as Shanghai, Chongqing, Tianjin and Beijing experienced a quite steady urbanization process with steady GNTL changes; while the urbanization dynamic process of Zhejiang, Jiangsu, Liaoning, Heilongjiang, Henan, Hebei, Guangdong and Fujian are quite acute with great changes of GNTL. Compared to the traditional urbanization process detect method, GNTL-based urbanization dynamics provide us an easy and quite direct method from a temporal perspective, and it can also be applied in other related researches.

3.4. Variations of urbanization

Based on the analysis of section 3.2, urbanization processes were mapped with the observation of GNTL dynamics. It can be observed that provinces in mainland China experienced different progresses of urban sprawl and models of urbanization can also be detected based on the metrics
derived from NTL of each province. Urbanization models of individual provinces were detected with the integrated utilization of metrics of mean NTL and mean GNTL in Figure 9.

Three models of urbanization dynamics are established: the model of constant rapid urbanization; model of active improving urbanization; and model of steady improving urbanization. Provinces include Shanghai, Tianjin and Beijing experienced constant rapid urbanization with high value of both average mean NTL and average mean GNTL; while Shandong, Jiangsu and Zhejiang province belong to the active improving urbanization model which are high in average mean GNTL but low in average mean NTL, these provinces experienced obvious improving of NTL from low to high compared with provinces of other models. The rest with low average mean GNTL and low average mean NTL are provinces of steady improving urbanization model.

![Figure 9. Urbanization models of 31 provinces in Mainland China.](image)

3.5. Classification results

With methods of supervised and unsupervised classification, an inner structure of urbanized areas and others from NTL image, AGNTL image and composite NTL and AGNTL image of 2013 mainland China were detected; the overall accuracy and Kappa coefficient were also calculated to examine the accuracy of classification. Images from Google Earth and Land-Use and Land-Cover Change (LUCC) data from The Institute of Remote Sensing and Digital Earth (RADI) released from the Chinese Academy of Sciences were adopted as the primary land cover reference images sources.

Supervised and unsupervised classification methods were performed based on the four types of urban structure: the urban core, urban transition, isolate towns and other areas, and the accuracy of classification are detected with the confusion matrices below (Table 2).

From Table 2, the conclusion that relative performance of classification based on NTL+AGNTL composite image is better than when it is based on NTL image and AGNTL image either in supervised or unsupervised classification method can be drawn. The supervised classification of NTL is better than that of AGNTL with an overall accuracy of 82.4617% and Kappa Coefficient of 0.7264; while the unsupervised method based on AGNTL with an overall accuracy of 72.1660% and Kappa Coefficient of 0.5494 performs better. Moreover, with the application of composite NTL and AGNTL image, both unsupervised and supervised classifications show remarkable improvement in accuracy with overall accuracies of 80.8696% and 90.2442% and Kappa coefficients of 0.2476 and 0.8140, respectively.

Based on the result of two classification methods related to three types of images, GNTL provided a new insight to detect the urbanization to some extent and the combination of traditional NTL and derived GNTL metrics can help to improve the mapping accuracy which is also beneficial to relative studies of urbanization.
Table 2. Confusion matrices of different classification methods (%).

| Method                         | Urban core | Urban Transition | Isolate towns | Others |
|-------------------------------|------------|------------------|---------------|--------|
| Unsupervised NTL              | 100        | 86.41            | 79.4          | 0.32   |
| (Overall Accuracy = 69.1398%; Kappa Coefficient = 0.5292) |            |                  |               |        |
| Urban core                    | 0          | 13.55            | 20.37         | 15.86  |
| Urban Transition              | 0          | 0                | 0             | 0      |
| Isolate towns                 | 0          | 0.05             | 0.59          | 83.81  |
| Others                        | 0          |                  |               |        |
| Unsupervised AGNTL            | 90.16      | 55.81            | 19.54         | 0      |
| (Overall Accuracy = 72.1660%; Kappa Coefficient = 0.5494) |            |                  |               |        |
| Urban core                    | 5.14       | 34.44            | 12.39         | 0.34   |
| Urban Transition              | 0          | 0.04             | 0.03          | 0.12   |
| Isolate towns                 | 4.70       | 9.71             | 68.05         | 99.53  |
| Others                        |            |                  |               |        |
| Unsupervised NTL+AGNTL        | 0          | 0.15             | 0.26          | 1.09   |
| (Overall Accuracy = 80.8069%; Kappa Coefficient = 0.2476) |            |                  |               |        |
| Urban core                    | 28.92      | 93.78            | 56.02         | 0.05   |
| Urban Transition              | 71.08      | 3.14             | 0.13          | 0.03   |
| Isolate towns                 | 0          | 2.92             | 43.59         | 98.83  |
| Others                        |            |                  |               |        |
| Supervised NTL                | 99.70      | 24.63            | 18.28         | 0      |
| (Overall Accuracy = 82.4617%; Kappa Coefficient = 0.7264) |            |                  |               |        |
| Urban core                    | 0.30       | 28.99            | 24.93         | 0.02   |
| Urban Transition              | 0          | 34.87            | 38.03         | 0.38   |
| Isolate towns                 | 0          | 11.51            | 18.76         | 99.60  |
| Others                        |            |                  |               |        |
| Supervised AGNTL              | 71.93      | 11.46            | 5.83          | 0      |
| (Overall Accuracy = 66.1434%; Kappa Coefficient = 0.5095) |            |                  |               |        |
| Urban core                    | 18.18      | 44.33            | 13.70         | 0      |
| Urban Transition              | 4.31       | 33.67            | 12.33         | 0.34   |
| Isolate towns                 | 5.59       | 10.54            | 68.14         | 99.66  |
| Others                        |            |                  |               |        |
| Supervised NTL+AGNTL          | 91.12      | 0.90             | 0             | 0      |
| (Overall Accuracy = 90.2442%; Kappa Coefficient = 0.8140) |            |                  |               |        |
| Urban core                    | 8.88       | 76.27            | 27.94         | 0      |
| Urban Transition              | 0          | 19.62            | 28.34         | 0.06   |
| Isolate towns                 | 0          | 3.21             | 43.72         | 99.94  |
| Others                        |            |                  |               |        |

4. Discussion

4.1. NTL-derived metrics in urbanization dynamics detecting

The work in this paper provides a new insight for urbanization mapping and urban dynamics detection with the DMSP/OLS nighttime light data. In the studies performed before, NTL-based urbanization mapping mainly focus on the distribution and pattern of individual years or a limited period, and
affiliate data sources are always needed due to the saturated DN values in the urban core regions, the application of the raw data were thus limited [41-42]. The saturated pixels are areas with DN value of 63 and these are always the fully urbanized areas especially the urban cores. In this study, we detected the characteristics of NTL light and derived the NTL-based metrics which focus on the dynamics of NTL. Urbanization is a dynamic process with an expansion of urban land and intensity of emerging of new city regions, with the dynamic-oriented metrics derived, the influences of saturation within urban cores can be minimized and the changes in other urbanized regions are fully highlighted.

In addition, few research investigated the process of urbanization of mainland China year by year from the perspective of geography, the research hotspots are always the urban sprawl pattern or the dynamics of a given period which ignored the details of changes before [43-44]. In this study, the initial effort of overall descriptions of the urban process was performed. With the metrics of GNTL, max GNTL, min GNTL, average GNTL, mean GNTL, accumulated GNTL and GNTL threshold derived from NTL, the urbanization process can be fully detected like an individual living cell with different characteristics in the different growing period. The findings of urbanization process reported here are consistent with those of previous studies. Moreover, 3 types of urban dynamics were also established based on the intensity of NTL and GNTL, compared with urbanization models established by other researchers before [45-46], the model we established are much more efficient which made a comprehensive consideration of both the value of NTL and the growth of it.

4.2. Classification with GNTL Metrics

Inner structures detection of urbanized areas is an important aspect of urbanization description, and it’s also the most popular topic among DMSP/OLS nighttime light related urbanization studies. There are mainly 2 types of urban structure detection methods, NTL model based detection and affiliate RS data source based detection, NTL-based index can detect the urban areas from transition area and rural area easily, but the accuracy of the classification should be improved [47]. While the affiliate RS data source based detection are much precise, but the data amount needed is quite large and the data processing process is rather complex. Both of these two kinds of method are commonly used today, but they are also greatly limitedly by the quality and accuracy of original images and statistical data, the reliability of these methods should be detected.

To detect the inner structure of urbanized regions, remote sensing classification methods were adopted. And the result shows that the classification accuracy of both the supervised and unsupervised classification methods of NTL and AGNTL composed images are higher than that of either NTL images or AGNTL images. The reason can be explained that within the composed image, the short comings of raw NTL data can be overcome, both the saturated areas (with DN values of 63) and urban change area are highlighted and these features can be easily captured, which provide a precious and easy solution to map the inner structures of urbanized area.

4.3. Limitations and future prospects

In this study, the urbanization dynamics of mainland China were detected using metrics derived from the DMSP/OLS nighttime light. Meanwhile, classification methods were also applied to test the relative performance of NTL derived metrics for urban structure discrimination. Nevertheless, the study was also confined by various limitations.

First, the accuracy of NTL-derived metrics is limited, since the metrics proposed in this study were derived from DMSP/OLS nighttime light with a resolution of 1km. However, it is still difficult to reflect the details of urban development and detect the urban dynamics at the city level through the metrics, detailed data source are needed. Meanwhile, although previous studies have justified a strong correlation between NTL and urban land, and between NTL and population, the relationships between GNTL and change of urban land, change of population are still unknown. Last but not least, to map the urbanization dynamics precisely, indicators such as NDVI, land surface temperature and LUCC(land use and land cover change) should also be adapted in future studies.
5. Conclusions

With the advantages of DMSP/OLS NTL data, we mapped the urbanization process of 31 provinces in mainland China. The raw data was fully calibrated with methods of inter-calibration and inter-annual calibration; new metrics from NTL were also derived to make further research. The result verifies that both the NTL and the GNTL can be utilized to detect the urban development and the maps of GNTL give us a good description on the growth pattern of urban dynamics. With the NTL and derived metric of GNTL, distributions of urbanization hot point regions and highpoints of urban growth were detected. Classification methods were also applied to detect the characteristics of metric of GNTL and the result shows that with the combination of NTL and GNTL, the overall accuracies of both unsupervised and supervised classifications show remarkable improvement.

It’s a new attempt to map urbanization process with metrics derived from NTL, some basic descriptions and conclusions can be drawn from the analysis. But with the basic characteristics of DMSP/OLS nighttime light, the research from the provincial scale is still coarse, plenty of useful information remains to be discovered, detailed data source such as VIIR is needed in the future work.

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