Urban mapping using DMSP/OLS stable night-time light: a review

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ABSTRACT

The Defense Meteorological Satellite Program/Operational Linescane System (DMSP/OLS) stable night-time light (NTL) data showed great potential in urban extent mapping across a variety of scales with historical records dating back to 1990s. In order to advance this data, a systematic methodology review on NTL-based urban extent mapping was carried out, with emphases on four aspects including the saturation of luminosity, the blooming effect, the intercalibration of time series, and their temporal pattern adjustment. We think ancillary features (e.g. land surface conditions and socioeconomic activities) can help reveal more spatial details in urban core regions with high digital number (DN) values. In addition, dynamic optimal thresholds are needed to address issues of different exaggeration of NTL data in the large scale urban mapping. Then, we reviewed three key aspects (reference region, reference satellite/year, and calibration model) in the current intercalibration framework of NTL time series, and summarized major reference regions in literature that were used for intercalibration, which is critical to achieve a globally consistent series of NTL DN values over years. Moreover, adjustment of temporal pattern on intercalibrated NTL series is needed to trace the urban sprawl process, particularly in rapidly developing regions. In addition, we analysed those applications for urban extent mapping based on the new generation NTL data of Visible/Infrared Imager/Radiometer Suite. Finally, we prospected the challenges and opportunities including the improvement of temporally inconsistent NTL series, mitigation of spatial heterogeneity of blooming effect in NTL, and synthesis of different NTL satellites, in global urban extent mapping.

ARTICLE HISTORY

Received 1 October 2016
Accepted 5 December 2016

1. Introduction

Although the Defense Meteorological Satellite Program/Operational Linescane System (DMSP/OLS) was originally developed for the purpose of detecting the global distribution of clouds and cloud top temperature, it has become a predominate source for observing a series of faint emission sources since 1970s, such as city lights, shipping fleets, industrial sites, gas flares, and fires (Croft 1978; Elvidge et al. 1997b; Imhoff et al. 1997; Huang et al. 2014). The DMSP/OLS sensor contains two
spectral bands (visible/near-infrared – VNIR, 0.4 – 1.1 \( \mu \)m and thermal infrared – TIR, 10.5 – 12.6 \( \mu \)m) with a swath of \(~3000\) km (Doll 2008). In addition, this data set has a near global coverage (spanning from \(-180^\circ\) to \(180^\circ\) in longitude and \(-65^\circ\) to \(65^\circ\) in latitude), and it spans two decades (1992–2013). Through geolocation processing, the nominal resolution of DMSP/OLS data set is 30 arc second, which equals to 1 km in equator.

According to the latest World Urbanization Prospects (United Nations 2015), the percentage of global urban population has exceeded 54% in 2014, and this proportion is estimated to reach 66% by 2050. More importantly, most of the newly increased population in the near future is likely to occur in developing regions (Africa and Asia), which will lead to a series of environmental or ecological issues related to the rapid urbanization process (Li and Gong 2016b). Therefore, acquiring the historical record of urban sprawl or urban population change, as well as predicting its future trajectories, is of great importance to sustainable urban development. The DMSP/OLS night-time light (NTL) data provide a particular perspective with a unique data set to study urban expansion and relevant sociodemographic activities across a variety of spatial scales, such as population density (Zhuo et al. 2009; Sutton, Elvidge, and Obremski 2003; Sutton et al. 2001; Lo 2002; Amaral et al. 2006), physical urban extent mapping (Elvidge et al. 1997b, 2007; Zhou et al. 2014; Small, Pozzi, and Elvidge 2005), energy consumption (Doll and Pachauri 2010; Letu et al. 2010), socioeconomic activities (Chen and Nordhaus 2011; Zhao and Samson 2012), and environmental changes (e.g. light pollution) (Davies et al. 2013; Falchi et al. 2016). Presently, there are three categories of DMSP/OLS data sets, including the stable lights, the calibrated radiance, and the average digital number (DN) (Elvidge et al. 1999; Doll 2008; Elvidge et al. 2009). Among them, the stable NTL dataset is the most widely used one for regional or global urban studies (Huang et al. 2014) because (1) the radiance calibrated dataset is only available for specific years without continuous time series; and (2) the average DN dataset may contain other emissions sources (e.g. fires and other background noise) in addition to city light.

One of the most important applications of DMSP/OLS stable NTL dataset is mapping urban extent (or boundary) and its temporal dynamics at the regional or global scales (Elvidge et al. 2007; Huang et al. 2014; Zhou et al. 2014; Elvidge et al. 1997a). Although a wide range of relevant studies have been carried out, most of them focus on particular local or regional areas using varying ancillary datasets or mapping approaches (Huang et al. 2014; Liu and Leung 2015; Ma et al. 2014; He et al. 2006; Liu et al. 2012; Yi et al. 2014; Milesi et al. 2003). Potential challenges are still remaining for pursing a globally consistent mapping of urban area using the DMSP/OLS stable NTL dataset. These challenges include the sensitivity of threshold for obtaining urban clusters (Liu and Leung 2015; Zhou et al. 2014), saturated DN values in urban core regions (Zhang, Schaaf, and Seto 2013; Cao et al. 2009), temporally inconsistency of NTL dataset over years (Zhao, Zhou, and Samson 2015; Elvidge et al. 2009b), and complicated urban sprawl patterns with different development levels (Zhang and Seto 2011; Ma et al. 2012). Few efforts have been made to summarize the difference of current approaches or comparison of different mapping results, although there are some general works on meta-analysis or summary of specific applications of NTL data (Huang et al. 2014; Li, Zhao, and Xi 2016a).
Hence, a systematic methodology review on these topics is urgently needed, for achieving a globally consistent mapping of urban dynamics with NTL datasets over past 20 years (Elvidge et al. 2007; Zhou et al. 2015).

This article aims to provide a comprehensive review on methodologies of urban mapping using DMSP/OLS NTL data. The reminder of this article is organized as follows. In Section 2, we discussed the challenges and reviewed current studies in urban mapping using DMSP/OLS stable NTL data. Thereafter, a brief introduction of the upgraded Visible/Infrared Imager/Radiometer Suite/Day Night Band (VIIRS/DNB) data was presented in Section 3. At the end, we prospected future opportunities of spatiotemporal urban extent mapping using NTL data in Section 4.

2. NTL-based urban mapping and challenges

The definition of ‘urban extent’ is different when referring to different cases (Liu et al. 2014). For NTL relevant studies, the commonly used terms include impervious surface, human settlement, urban clusters, population density, human population, and urban boundary (Elvidge et al. 1997a; Sutton et al. 1997; Elvidge et al. 1999; Sutton et al. 2001; Henderson et al. 2003; Elvidge et al. 2007; Zhou et al. 2015). In this review, we covered three groups of studies in NTL-based urban mapping, including population density, urban extent, and impervious surface area (Figures 1(a)–(f)). The first is population density mapping in a perspective of land use (Figure 1(a)), by linking NTL data with census (e.g. demographic) data (Figures 1(d) and (e)). The second one is urban extent (Figure 1(b)), which indicates the boundary that separates urban areas from surrounding rural areas based on NTL images (Figure 1(e)). The third one refers to impervious surface mapping (Figure 1(c)), which excludes other land cover types (e.g. water, vegetation, and bare land) within the urban domain (Figures 1(e) and (f)). We included population density mapping in this review because (1) NTL datasets are often conjunctively used with demographic inventory (or census data), and the output of them can be used as an intermediate to map the urban extent (Elvidge et al. 2007; Lu and Weng 2006; Martinuzzi, Gould, and Ramos González 2007); and (2) population density essentially is a crucial indicator to describe the urban extent (Angel et al. 2005; Schneider, Friedl, and Potere 2010; Lo 2002).

Presently, studies on NTL-based urban mapping mainly focus on two domains as shown in Figure 2. Both spatial and temporal dimensions of NTL data have been extensively explored for urban mapping. At the spatial dimension, the inherent deficiencies of NTL dataset, that is, the saturated DN values in the urban core region and blooming effects on the urban–rural boundary, limit its application in urban mapping at a large extent (Zhang, Schaaf, and Seto 2013; Elvidge et al. 2007). At the temporal dimension, due to the lack of on-board calibration, additional processes on the annual composites of stable NTL data, such as intercalibration or temporal pattern adjustment, are needed to investigate the urban dynamics (Elvidge et al. 2009b; Zhang and Seto 2011). Consequently, a wide range of studies have been carried out to address these issues for consistent urban mapping at the regional or global scales. In this review, we discussed these issues in the following sections with more details.
2.1. Spatial dimension

2.1.1. Saturation of NTL luminosity
There exists a notable saturation effect of luminosity (i.e. the same or similar DN values in urban core area) in the DMSP/OLS NTL data because (1) the nominal resolution of

Figure 1. Night-time light (NTL)-based urban mapping: (a)–(c) are contents of NTL-based urban mapping; (d)–(f) illustrate necessary inputs for generating these maps.

Figure 2. Research domains on NTL-based urban mapping.

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1 km is resampled from the 2.7 km native resolution (Doll 2008); and (2) the limit of DMSP/OLS sensor sensitivity is 6 bit (i.e. DN value ranges from 0 to 63). Although DMSP/OLS radiance data with on-board gain setting is an accurate way to differentiate the saturated luminosity in the urban core region, it is still limited for dynamic urban mapping because the implementation of radiance calibration is difficult, and this data set is only available for limited years (Elvidge et al. 1999; Doll 2008; Elvidge et al. 2001; Letu et al. 2012). A variety of attempts have been made to mitigate this saturation effect by using ancillary data to retrieve the heterogeneity within the urban extent. In general, there are two widely used ancillary datasets, land surface features and census population data, for conjunctively use with NTL data to map urban extent.

The saturation effect of luminosity in urban core region can be mitigated by incorporating land surface features as an intermediate output to map urban impervious surface. For instance, vegetation cover is a useful variable to reduce the saturation effect of NTL, which has been confirmed by a variety of studies (Li and Gong 2016a; He et al. 2014; Zhang, Schaaf, and Seto 2013; Liu et al. 2015a; Zhou et al. 2014). Lu et al. (2008) proposed a human settlement index (HSI) that incorporated Moderate Resolution Imaging Spectroradiometer (MODIS) normalized difference vegetation index (NDVI) with NTL data for settlement mapping in the southeastern China. Zhang, Schaaf, and Seto (2013) proposed a vegetation-adjusted NTL urban index (VANUI), which is simple but efficient in revealing the heterogeneity in regions with saturated DN values (Ma et al. 2014; Shao and Liu 2014; Li et al. 2016b). Liu et al. (2015a) combined both NDVI and normalized difference water index (NDWI) with NTL to reduce the pixel saturation in HSI and VANUI with a new indicator of normalized urban areas composite index (NUACI). Through incorporating remotely sensed land surface index, regions belong to non-urban but with high DN values can be recognized and removed in further processing. In addition, land-use/land-cover (LULC) datasets at a finer spatial resolution (e.g. 30 m) is able to provide more details in saturated regions in NTL data (Zhou et al. 2014; Liu et al. 2012), which can be served as a fraction of urban area when aggregated them to the same resolution as NTL data, or a statistic of total urban area over a particularly region. These land surface features have been used in NTL-based urban mapping together using classification (e.g. Support Vector Machine (SVM), random forest or spatially adaptive regression) or threshold methods (Cao et al. 2009; Xiao et al. 2014; Liu and Leung 2015; Shao and Liu 2014; Li et al. 2016b; Huang, Schneider, and Friedl 2016).

Demographic features can also help mitigate the saturation issue in NTL data in urban core areas by incorporating additional socioeconomic information to get the density of population (Sutton et al. 1997, 2001; Lo 2002; Sutton, Elvidge, and Obremski 2003; Amaral et al. 2006). In general, these datasets are associated with specific census unit, which can be used to differentiate DN values that are saturated but have different demographic levels (e.g. population or density) (Zhuo et al. 2009). Spatially explicit demographic information (e.g. demographic level or zone) can be introduced to group saturated pixels in the raw NTL data for further applications (e.g. population density mapping). It is worth noting that this mitigation of saturation effect in NTL luminosity depends on scales (or resolutions) of census data (Sutton, Elvidge, and Obremski 2003). More sophisticated approach with incorporation of demographic features and land surface factors can improve the performance in differentiating saturated DN values. Zhuo et al. (2009) performed a polynomial regression to calibrate the
relationship between NTL and population at the county level in China, and then allocated the estimated population density to each pixel with the consideration of natural habitable condition (e.g. vegetation). The relationships between population and NTL vary among cases, and the spatial unit and level (e.g. state, province, county, and city) are a crucial factor influencing the relationship. In addition, NTL-derived population (or density) estimation can be used to delineate urban extent (Elvidge et al. 2007; Lu and Weng 2006; Martinuzzi, Gould, and Ramos González 2007).

2.1.2. Blooming effect in NTL
The blooming effect in the NTL data we discussed here specifically refers to the fact that outside of the actual urban extent, the DN values of NTL are still significantly above zeros. The blooming effect in NTL data increases difficulties to separate urban from its surrounding non-urban regions (Liu et al. 2015a; Zhang, Schaaf, and Seto 2013). A number of studies have been performed to address this issue for urban extent mapping (Henderson et al. 2003; Gallo et al. 2004; He et al. 2006; Cao et al. 2009; Liu et al. 2012). Among these studies, the approaches can be grouped roughly into two categories: (1) threshold based and (2) classification based.

Because of the blooming effect in NTL data, threshold-based approaches have been extensively used to extract urban extent from NTL data (see Figure 3) (Elvidge et al. 1997a; Imhoff et al. 1997; Henderson et al. 2003; He et al. 2006; Zhou et al. 2014; Liu et al. 2015a). Commonly, the status of urban and non-urban is determined by the threshold, that is, if the DN greater than the threshold, then it will be assigned as urban; otherwise it is classified as non-urban (see Figure 3, yellow rectangles). Essentially, the extracted urban extent is very sensitive to the threshold, and an optimal one is needed to

![Figure 3. Schematic diagram of threshold approach using NTL.](image-url)
maximally separate urban and non-urban regions using the NTL data (see Figure 3, red rectangles) (Zhou et al. 2014; Liu et al. 2012). Given that the spatial heterogeneity of urbanization features (e.g. urbanization level and urban size) over different regions, the optimal thresholds (see Figure 3, blue texts) vary across space and a scheme of dynamic (spatial and temporal) thresholds is required for large-scale and temporal dynamic urban extent mapping (Zhou et al. 2014; Elvidge et al. 1997b; Imhoff et al. 1997; Small, Pozzi, and Elvidge 2005; Elvidge et al. 2009b; Cao et al. 2009). Previous attempts on threshold approaches focused on NTL data only. For example, the ‘light picking’ approach was proposed to estimate the threshold for a local window based on the background information (Elvidge et al. 1997b), and urban shape (e.g. area or perimeter) was used to find the ‘sudden jump’ point through searching continuous thresholds (Imhoff et al. 1997; Liu and Leung 2015). More attentions have been given to determine those dynamic thresholds using ancillary information (He et al. 2006; Cao et al. 2009; Zhou et al. 2014; Liu et al. 2015a). For instance, He et al. (2006) iteratively searched optimal thresholds to match the statistical urban area at the province level. In a similar manner, statistical information of urban area of the region or city has been used to derive the optimal thresholds at these levels (Liu et al. 2012; Milesi et al. 2003; Yu et al. 2014). In addition, classified LULC data at a finer spatial resolution have been used to derive optimal thresholds over the conterminous space (Liu et al. 2015a; Li, Gong, and Liang 2015). Using the aggregated LULC information, Zhou et al. (2014) developed a method to derive dynamic optimal thresholds to map urban extent for each urban cluster, which was generated using a segmentation algorithm. This method was then extended to map urban extent at the global level (Zhou et al. 2015). Similarly, there are other site-based studies to estimate the empirical threshold based on the collected referred dataset (e.g. existing land-use cover data or impervious surface information) and the modified NTL indices (e.g. VANUI or NUACI) (Li et al. 2016b; Liu et al. 2015a).

Classification-based methods have always been used to extract the urban extent from NTL data with additional features such as NDVI and NDWI (Huang, Schneider, and Friedl 2016; Cao et al. 2009; Xiao et al. 2014). Cao et al. (2009) proposed a SVM-based region-growing algorithm to extract urban area using NTL data and Satellite Pour l’Observation de la Terre (SPOT) NDVI. Urban training samples were initially selected as seeds and thereafter they were iteratively updated through using newly classified urban pixels within a $3 \times 3$ window of these seeds to composite a new training set. This method outperforms those results derived from global-fixed or local-optimized approaches (Cao et al. 2009; Xiao et al. 2014). Huang, Schneider, and Friedl (2016) used a Random Forest regression model to estimate the urban percentage from stacked time series of NTL and MODIS NDVI data. In this method, urban percentage aggregated from Landsat-based land-cover data were used in the model training.

In addition to these two prevailing branches of methodology, there are other approaches to mitigate the blooming effect in NTL data. For instance, Townsend and Bruce (2010) developed an Overglow Removal Model (ORM) to correct the diffusion of NTL based on the empirical relationship between the light strength (sum of the total DN value) and the dispersion distance. But this relationship needed to be calibrated in advance with additional information (e.g. electricity use and population of each city). Su et al. (2015) adopted a neighbourhood statistics approach to detect the spatial difference of NTL data between urban and associated non-urban regions in the Pearl River
Delta (China). Pre-defined thresholds are not needed in this method, but the mapped urban extent is sensitive to the neighbourhood morphology (e.g. configuration and size) and NTL magnitude within the neighbourhood (e.g. maximum and minimum), which needs be examined when being applied in other regions. Tan (2016) developed a method to generate inside buffers based on the empirical relationship between surveyed urban area and lit area of NTL data for mitigating the blooming effect. These methods are similar with the approach of dynamic optimal thresholds in determining the buffers to separate urban and non-urban regions. However, it should be cautious when applying them in a large area with high spatial heterogeneity.

2.2. Temporal dimension

2.2.1. Intercalibration of annual NTL data

Due to the absence of on-board calibration, the DMSP/OLS stable NTL annual composites product derived from multiple sensors (F12–F16) and different years (1992–2013) are not comparable directly (Doll 2008). Therefore, intercalibration of annual NTL composites product is highly needed to investigate urban dynamics using the NTL data. Elvidge et al. (2009b) built the framework of intercalibration for annual NTL composites product, which is the most widely used framework currently (Elvidge et al. 2014; Ma et al. 2014; Liu and Leung 2015; Zhao, Zhou, and Samson 2015; Huang, Schneider, and Friedl 2016; Li et al. 2016b; Zhang, Pandey, and Seto 2016; Tan 2016; Yi et al. 2014). This proposed framework includes three procedures: (1) selection of the reference region; (2) determination of the reference satellite and year for calibration; and (3) model development for intercalibration. Currently, most works requiring intercalibration of NTL series followed these procedures.

The reference regions vary among different studies for particular applications at the regional or global scales. There are two criteria in selecting reference regions: (1) small changes in lighting over years and (2) covering a wide range of DN values (Elvidge et al. 2009b; Wu et al. 2013). Therefore, in addition to Sicily Island selected by Elvidge et al. (2009b) for an early calibration work, many other reference regions have been used to intercalibrate the annual NTL composites product for urban dynamics analyses. We surveyed literature on NTL-based intercalibration and summarized the hotspot map of reference regions (Figure 4). Presently, the collected reference regions in Figure 4 include different countries (Italy, USA, China, Japan, and India), covering both mainland and islands (Puerto Rico, Mauritius, and Okinawa) (Wu et al. 2013). Although these regions were selected for different purposes, they showed potential for intercalibration of NTL dataset at the global level. In addition, apart from those reference regions that contain a wide range of DN values, there are also some attempts using automatically or manually collected sites (or points) as references for intercalibration (Yi et al. 2014; Zhang, Pandey, and Seto 2016; Li et al. 2013). For instance, Li et al. (2013) used a linear regression model to iteratively filter out pixels that may be experienced a change of DN value to collect the referenced sites for intercalibration. This method is more appropriate for local applications because the iteration process is time consuming. Liu et al. (2015b) set a simple rule (i.e. DN >30) for sample collection in New York for multi-temporal NTL data intercalibration. However, it should be noted that those pixels involved in the
calibration process are very sensitive to the calibrated results (Zhang, Pandey, and Seto 2016).

The reference satellite and year are always determined based on the criterion that the sum (or averaged) of DN values in the reference region or the whole study area is the highest (Elvidge et al. 2009b; Pandey, Joshi, and Seto 2013; Ma et al. 2012). Other criterion in reference year/satellite selection is based on time-series of the NTL data, which aims to choose the year/satellite that lies in the middle of series for minimizing the effect of NTL change in the long time period (Zhang, Pandey, and Seto 2016). Once the reference year/satellite is selected, other NTL data were calibrated for achieving a comparable series over time. There are a variety of calibration models developed, such as six-order polynomial model (Bennie et al. 2014), second-order regression model (Elvidge et al. 2009b), simplified first-order regression model (Liu et al. 2015b) and power function (Wu et al. 2013). Among them, the second-order regression model has been extensively used to intercalibrate annual NTL composites product (Elvidge et al. 2009b; Zhao, Zhou, and Samson 2015; Ma et al. 2012; Liu et al. 2012; Liu and Leung 2015; Pandey, Joshi, and Seto 2013; Zhang, Pandey, and Seto 2016), and its formula can be expressed as Equation (1):

$$V_{\text{adjust}} = C_0 + C_1 \times V + C_2 \times V^2,$$

where $V_{\text{adjust}}$ is the calibrated DN value, $V$ is the original value, $C_0$, $C_1$, and $C_2$ are the coefficients, which were derived from the second-order regression model between DN values of reference image and others to be calibrated.

2.2.2. Temporal pattern adjustment

It is critical to evaluate the temporal pattern of the annual NTL data in terms of its consistency for tracing the urban sprawl process, particularly in rapidly developing regions (e.g. China and India) (Liu et al. 2012; Ma et al. 2014). Although it is a somewhat subjective modification of the intercalibrated NTL series, it is still needed because (1) the
intercalibration is likely to introduce errors for some sites with abnormal NTL sequences that are not consistent over time; and (2) the pathway of urban expansion in rapidly developing regions is more certain with continuously expansion and increasing lit areas, whereas the obtained NTL series may not follow this trajectory (Liu et al. 2012; Li, Gong, and Liang 2015; Mertes et al. 2015; Zhao, Zhou, and Samson 2015). Liu et al. (2012) proposed an inter-annual series correction to modify the abnormal pixels (see Figure 5(a)). In their study, based on the NTL series, temporally neighboured DN values are compared. Inconsistent pixels in the series were modified to achieve a continuously increasing pattern (see red and green circles in Figure 5(a)). Similar approaches can be found in Huang, Schneider, and Friedl (2016). Furthermore, to reduce the possible system errors caused by the initial year (e.g. 1992 in Figure 5(a)), Liu and Leung (2015) proposed a two-way modification of NTL series to combine sequences of 1992–2013 (i.e. green arrow in Figure 5(a)) and 2013–1992 (i.e. red arrow in Figure 5(b)). The mean of these two adjusted sequences was used in their studies based on the assumption that the positive and negative errors were offset (Zhao, Zhou, and Samson 2015; Liu and Leung 2015).

The adjustment of temporal pattern on the intercalibrated NTL series is needed for urban dynamics analyses in regions with rapid development while it may be not necessary for all areas. The natural pattern of NTL series may reflect multiple pathways (or archetypes) of urbanization, e.g. constant urban activity, earlier urban growth, de-urbanization, constant urban growth, and recent urban growth (Zhang and Seto 2011; Ma et al. 2012). Although most of these archetypes show temporally increasing total DN values, an opposite trajectory is also seen due to crisis such as war (e.g. Syria war) (Li and Deren 2014) or population migration due to poverty (Zhao, Zhou, and Samson 2015). The adjustment of intercalibrated NTL series is helpful in analysing dynamics of urban expansion, whereas the knowledge of the study area is needed for designing reasonable adjustment rules (i.e. linearly changed or not). Given that the land cover change from urban to non-urban rarely occurred (Li, Gong, and Liang 2015; Mertes et al. 2015), the temporal pattern adjustment is efficient for most urban lit areas on the planet. Nevertheless, it is still challenging to distinguish those pseudo changes from the actual expansion based on the calibrated NTL time series.

Figure 5. Temporal pattern adjustment of intercalibrated NTL time series: (a) 1992–2013 and (b) 2013–1992.
3. Successor of DMSP/OLS: VIIRS/DNB

The new generation of NTL, VIIRS, carried on the Suomi National Polar-orbiting Partnership (NPP) satellite (http://npp.gsfc.nasa.gov) was launched in 2011. Compared to the DMSP/OLS, the sensor DNB in the VIIRS is more advanced in (1) on-board calibration; (2) spatial resolution (about four times finer than DMSP); and (3) radiometric resolution (14 bit) (Miller et al. 2012; Elvidge et al. 2013). As a consequence, VIIRS is able to provide more details in terms of the detected night-time light (Small, Elvidge, and Baugh 2013). However, due to the short period since the VIIRS data were available, studies on urban mapping using VIIRS data are relatively limited currently. In addition, most of them centred around the comparison with DMSP/OLS data using similar approaches as we documented earlier, to enhance the benefits of VIIRS with improved spatial details. For example, Shi et al. (2014) evaluated the performance of VIIRS NTL data for extracting urban areas using the thresholds calibrated from statistical data based on 12 cities in China, and they found that the obtained accuracies were higher than that using DMSP/OLS data. Guo et al. (2015) integrated the VIIRS data with MODIS NDVI data to map the impervious surface area in China using the regression model. This procedure was similar to the approaches discussed in Section 2.1.1 to mitigate the saturation effect in NTL data with DMSP/OLS replaced by VIIRS. Sharma et al. (2016) made a similar attempt to estimate the thresholds at the global scale using data such as MODIS-derived ‘Urban Built-up Index (UBI)’ to estimate the thresholds. The thresholds for urban extent delineation in their work were determined based on region-specific values in each 10° × 10° tile for the whole globe. In addition, NTL-based observations with high spatial resolution (1 m) are emerging now, such as the Israeli EROS-B satellite (Levin et al. 2014), which is of great value in urban studies at the local scale.

4. Discussion and future opportunities

The DMSP/OLS NTL data showed great potential in urban extent mapping across a variety of scales with historical records dating back to 1990s. This article provides a systematic review on NTL-based urban mapping, including the saturation of luminosity, the blooming effect of NTL data, the intercalibration of NTL series, and adjustment of intercalibrated temporal patterns. Although NTL data are useful in urban extent mapping over large areas, it is worth to note that it is limited to its spatial resolution (1 km) and could be influenced by other light disturbance (e.g. gas) (Zhang and Seto 2013). The urban extent from NTL data may omit small city and include pseudo lit areas. However, the DMSP/OLS NTL data are highly recommended for global urban mapping studies. Compared to urban mapping using other datasets (e.g. MODIS, Landsat, and Orthophoto) (Schneider, Friedl, and Potere 2010; Gong et al. 2013; Small, Pozzi, and Elvidge 2005; Henderson et al. 2003; Zhou and Wang 2008), although they can provide more details of urban structure or extent, NTL data show advantages in generating a global consistent urban map series because of (1) more direct observations of night-time city light; and (2) less data volume requirement with globally consistent measurements (Zhou et al. 2015; Elvidge et al. 2007). However, due to the challenges discussed, there still lacks multi-temporal urban products based on a consistent mapping scheme from regional to global levels. These challenges also provide opportunities and open future
research avenues in temporal dynamic urban mapping from regional to global levels using NTL data.

(1) Improvement of temporally inconsistent NTL series. After Elvidge et al. (2009b) proposed the general framework for intercalibration of global inconsistent NTL series, few attempts have been made for multi-year global urban extent mapping. Recently, Zhang, Pandey, and Seto (2016) improved the intercalibration with carefully selected reference pixels to improve the initial NTL DN values. This study will undoubtedly promote the global mapping studies over multiple years. However, there are still two concerns to be addressed in this calibration framework in the future work. One is the notably disturbance of DN values through implementing the calibration model for almost all the pixels. Another is the shift of the initial pattern of NTL series over time after calibration (Wu et al. 2013). Novel methods are needed to reduce the uncertainty introduced from the calibration by detecting systematic errors of images of different satellites and years.

(2) Mitigation of blooming effect and its spatial heterogeneity in NTL. Presently, mapping approaches using NTL dataset at the global scale is still under development. The first global impervious surface map was built using a linear relationship and population data (Elvidge et al. 2007). However, the spatial heterogeneity of local socio-economic development was not well considered in this method. Zhou et al. (2015) used a logistic-model to estimate the optimal threshold for each urban clusters derived from NTL dataset for global urban extent mapping. Although spatial heterogeneities have been considered for each urban cluster, the finer resolution land cover data used in threshold estimation were merely based on two representative regions: China and USA. These challenging issues still exist in the global urban extent mapping using the NTL data, and more efforts are needed in the future.

(3) Synthesis of DMSP/OLS and VIIRS NTL datasets. The temporal coverage of DMSP/OLS NTL dataset is 1992–2013, and the continuing project of VIIRS is ongoing. The new satellite and sensor make it possible to detect more details of night-time city lights, whereas the inconsistent setting of sensors and resolutions between DMSP/OLS and VIIRS raise challenges to combine these two data sources for continuously monitoring of global urban expansion since 1990s. Although there are several studies have been carried out for comparison between VIIRS and DMSP/OLS datasets (Small, Elvidge, and Baugh 2013; Shi et al. 2014; Guo et al. 2015), few attempts have been made to integrate the DMSP/OLS and VIIRS/DNB for a consistent observation, which is of great importance to understand the dynamics of long-term urban expansion. More efforts are required to take advantage of them for a continuing mapping of urban dynamics at the global scale.

Acknowledgements

This work was supported by the NASA ROSES LULC Program ‘NNH11ZDA001N-LCLUC’. We thank three anonymous reviewers and editor for their valuable comments to improve this manuscript.

Disclosure statement

No potential conflict of interest was reported by the authors.
Funding

This work was supported by the NASA ROSES LULC Program ‘NNH11ZDA001N-LCLUC’.

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