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Nighttime light remote sensing for urban applications: Progress, challenges, and prospects

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ABSTRACT

Nighttime light (NTL) remote sensing data offer unique capabilities to characterize both the extent and intensity of human activities and have been extensively used to understand urbanization since 1992. The recent proliferation of NTL sensors, algorithms, and products creates new opportunities to understand contemporary urbanization and the associated socioeconomic and environmental changes. We conducted a comprehensive literature review of 688 peer-reviewed papers published between 1992 and 2022 to understand the trends in how NTL data have been used to study urbanization (e.g., with which data products, during which time span, and in which geographies) and to synthesize the progress and challenges of key urban application topics. Based on our review, we identified four research directions for future NTL-based urban applications: (1) a better understanding of scale effects and sources of variations in NTL data; (2) integrating multi-source NTL data and synergizing NTL data with other types of geospatial data for improved NTL utilization; (3) more research on the Global South; and (4) developing new urban applications with new NTL data products. Addressing research gaps in these areas will generate new insights into the urbanization process under different geographical and socioeconomic settings.

1. Introduction

The ongoing global urbanization is expected to bring 2.6 billion new urban dwellers by 2050 (United-Nations, 2019), while about 60% of the urban land area required to accommodate these new dwellers has yet to be built (Seto et al., 2011). A global study of future urban growth estimates that urban areas will increase by 0.6-1.3 million km^2 between 2015 and 2050, an increase of 78%-171% over the urban footprint in 2015 (Huang et al., 2019). Monitoring changes in urban extent, as well as urban infrastructures, intra-urban areas, and socioeconomic sectors, is crucial given the pressing need for sustainable development in cities and human settlements. Monitoring these changes is closely pertinent to UN Sustainable Development Goals (SDGs), especially Goal 11 (to make cities and human settlements inclusive, safe, resilient, and sustainable).

The Anthropocene has seen an unprecedentedly changing nightscape in human settlement areas, from pitch dark to brightly-lit. In the past three decades, remotely sensed nighttime light (NTL) images have become a global icon depicting this changing nightscape t in a spatially explicit way (Croft and Colvocoresses, 1979; Elvidge et al., 1997a; Román et al., 2018). The arresting contrast between brightness and darkness presented in NTL images makes them an ideal proxy of human activities (Stokes et al., 2021). This unique nature of NTL data distinguishes it from "daytime" remote sensing data in meeting the demand for understanding urbanization. NTL data cannot only represent the spatial extent of urbanization (e.g., urban extent), as most "daytime" remote sensing data can do, NTL intensity is also a direct indicator of human activities. The NTL intensity can reveal the intra-urban variations of urbanization intensity and shows a strong correlation to socioeconomic variables, thus suitable to model and spatialize these variables. These capabilities of NTL are key to understanding urbanization, which is barely achievable via "daytime" remote sensing data (Li et al., 2016).

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The year 2022 marks the 30th anniversary since the first digital archiving of NTL remote sensing data, DMSP-OLS, in the NOAA National Geophysical Data Center in 1992 (Elvidge et al., 1997a). The thirty-year record of cross-sectional research has demonstrated the powerful capabilities of NTL images in understanding urbanization, such as mapping urbanization processes (Zhou et al., 2018), modelling and spatializing socioeconomic (e.g., gross domestic product and electricity consumptions) and environmental variables (e.g., CO_2 emission) (Chen and Nordhaus, 2011; Li et al., 2015), presenting human activities changes during disasters, armed conflicts and holidays (Li et al., 2013; Roman and Stokes, 2015), and monitoring light pollution and its impacts on the ecosystems and human health (Gaston et al., 2015; Kyba et al., 2017; Meng et al., 2022).

The recent proliferation of NTL-based urban applications points to the need for a systematic review of published literature. While there are existing reviews focusing on different aspects of NTL (Elvidge et al., 2022; Levin et al., 2020; Li, & Zhou, 2017; Pandey et al., 2017; Zhao et al., 2019a), they are subject to at least one of the following issues: (1) the review concentrates solely on one specific urban application; (2) the review focuses on methodological issue; or (3) challenges in the research have not been well defined. Moreover, there are urgent needs for obtaining new scientific knowledge from NTL data to understand contemporary urbanization and the associated socioeconomic and environmental changes, given its unprecedented scale and pace. Recent advancements in NTL sensors, data products, and methods have brought new potential for fulfilling these demands in urban observations, but in parallel with new challenges that have not been discussed or foreseen in previous reviews. Against these backdrops, we provide a systematic review of the trend, progress and challenges in NTL-based urban applications, and propose directions that we hope to inspire future research. The remainder of this review is organized as follows: Section 2 introduces the review method; Section 3 presented the trends in how NTL data have been used for studying urbanization with bibliometric analysis; Section 4 reviews the progress and challenges of key topics of urban NTL remote sensing; and Section 5 proposes research directions for future NTL-based urban applications.

2. Review methods

2.1. Inclusion criteria

We used the PRISMA approach to conduct a systematic literature review on urban NTL remote sensing (Page et al., 2021). We began by collecting literature from the Artificial Light at Night (ALAN) Research Literature Database and Web of Science (WoS) database using keywords including nighttime light, night lights, urban, urbanization, and built-up areas. As of July 1, 2022, our initial search yielded 6,490 articles, which we subsequently narrowed down using the following criteria. We included only peer-reviewed English articles published after 1992, that used remotely sensed NTL data, and focused on urban areas. We excluded studies that solely relied on field measurements or lab experiments, as well as those that focused solely on NTL in natural ecosystems. We also removed duplicative or inaccessible articles. The final literature collection consists of 688 articles for our subsequent bibliometric analysis and literature review (Fig. 1; see Supplementary Data 1 for the full list of reviewed articles).

2.2. Metrics for bibliometric analysis

We reviewed all 688 articles in the final literature collection and collected the following information for bibliometric analysis: title, publish year, journal, corresponding author country, NTL imagery used, study period, study area, study spatial scale (e.g., pixel, city, state, county, global, etc.), study type (method/algorithm development or application), study topic and sub-topic, preprocessing approach used, main methodology, input/output spatial resolution, and input/output

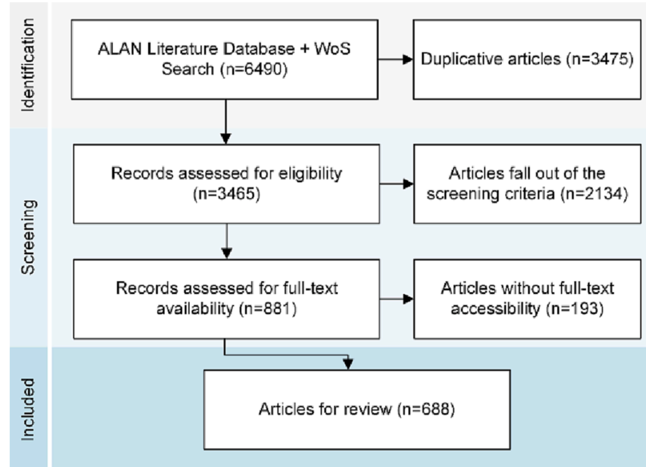

Fig. 1. Reporting diagram of PRISMA literature review framework.

temporal resolution. Additionally, we obtained the urban population and the latest list of Global North and Global South countries from the United Nations (UN, 2018, 2022).

3. Trends of urban applications with NTL data

3.1. Data products

Since the 1990s, various NTL data products have been publicly released, including those from DMSP-OLS and VIIRS, as well as airborne NTL images, multi-spectral and high-resolution NTL observations, and NTL images taken from International Space Station (ISS) (Table 1 and Fig. 2). Urban applications of NTL data have been evolving along with the emergence of these new observation platforms and products, as well as the advancements made available thanks to their performance improvements. Here, we review the trends in how these NTL data products have been used for urban applications.

The earliest remote sensing NTL observation can be traced back to the 1970s with DMSP-OLS satellite (Croft, 1978; Croft and Colvocoresses, 1979). However, it was not until 1992, when the satellite was fully digitized, processed, and made publicly available for applications by NOAA's Earth Observation Groups (EOG), that the widespread urban applications of DMSP-OLS were kicked off (Elvidge et al., 1997a; Imhoff et al., 1997). While a few other NTL datasets, such as ISS images and SAC-C/D images, have been used for local-scale studies, their use has been largely limited (Colomb et al., 2004) (Fig. 3a).

Nevertheless, DMSP-OLS was originally designed for meteorological monitoring rather than urban applications, and its application potential was limited by outdated sensor technology, particularly its data storage capacity and calibration system. Issues such as data saturation and inter-annual inconsistency across DMSP-OLS satellites limited its effectiveness. To address the data saturation issue, EOG released an alternative product – "radiance calibrated" DMSP-OLS (DMSP-OLS_{rad}) – which blends operational stable light DMSP-OLS product with certain fixed-gain DMSP-OLS images calibrated to images with a high gain setting (Hsu et al., 2015). DMSP-OLS_{rad} exhibits a significantly higher dynamic range than the original DMSP-OLS product and is free of the saturation issue (Table 1). It should be noted that DMSP-OLS_{rad} is still unitless and inter-annually inconsistent due to the inherent absence of an onboard calibration system. Various methods have been applied to desaturate DMSP-OLS data. The most commonly used one was to create an NTL-index by integrating DMSP-OLS image with spectral indices (e.g., NDVI, EVI, and NDWI) derived from "daytime" satellite images (Liu et al., 2015; Zhang et al., 2013). In addition, calibration models have been proposed to address the inter-annual inconsistency among DMSP-OLS satellites, among which pseudo-invariant features (PIFs) based

Table 1
Space-borne NTL datasets: platforms, their corresponding products and key performance parameters.

Platform	Product	Spatial resolution	Spatial coverage	Temporal resolution	Temporal coverage	Spectral ranges	Dynamic range	Low-light detection limit (W/cm^2/sr)	Accessibility	Reference
DMSP-OLS	Version 4 product	30 arcsec	180°W to 180°E, 65°S to 75°N	Yearly	1992–2013	0.5–0.9 µm	6 bit	5.0E-10	Free	Elvidge et al. (1997)
	Radiance calibrated product	30 arcsec	180°W to 180°E, 65°S to 75°N	Yearly	1996,1999,2000,2002,2004,2006,2010,2011	0.5–0.9 µm	≫ 6 bit	5.0E-10	Free	Hsu et al. (2015)
	Monthly product	30 arcsec	180°W to 180°E, 65°S to 75°N	Monthly	1992–2013	0.5–0.9 µm	6 bit	5.0E-10	Free	Elvidge et al. (1997), Li et al., (2017)
	DMSP NTL Extension	30 arcsec	180°W to 180°E, 65°S to 75°N	Monthly Yearly	2013-	0.5–0.9 µm	6 bit	5.0E-10	Free	Ghosh et al. (2021)
Suomi-NPP VIIRS	Version 1 Product	15 arcsec	Global	Monthly Yearly	2012-	0.5–0.9 µm	14 bit	2.0E-11	Free	Elvidge et al. (2017)
	Version 2 Product	15 arcsec	Global	Daily Yearly	2012-	0.5–0.9 µm	14 bit	2.0E-11	Free	Elvidge et al. (2021)
	Black Marble Product	15 arcsec	Global	Daily Monthly Yearly	2012-	0.5–0.9 µm	14 bit	2.0E-11	Free	Román et al. (2018), Wang et al., 2022
	Black Marble HD	<30 m	Local-to-Regional	Daily Monthly Yearly	2012-	0.5–0.9 µm	–	2.0E-11	On-demand	Román et al. (2018)
	Black Marble NRT	15 arcsec	Global	Daily	2012-	0.5–0.9 µm	14 bit	2.0E-11	Free	Román et al. (2018)
NOAA-20 VIIRS	VIIRS	15 arcsec	Global	Daily	2018-	0.5–0.9 µm	14 bit	2.0E-11	Free	Wang et al. (2021)
Luojia-1	Luojia-1	129 m	Regional	16 days	2018–2019	0.46–0.98 µm	12 bit	9.0E-09	Free	Li et al. (2019)
Jilin01	Jilin01-3B/4/5/6/7/8	0.92 m	Local-to-Regional	On-demand	2017-	0.43–0.72 µm (RBG)	8 bit	7.0E-07	On-demand	Zheng et al. (2018b)
SDGSAT-1	SDGSAT-1	10 m: Pan 40 m: RGB	Global	11 days	2022	0.44–0.91 µm (Pan) 0.42–0.89 µm (RGB)	≥12bit	1.6E-07	Free	Lin et al. (2022)
Lookup-1	Lookup-1	60 m	Local-to-Regional	On-demand	2021-	0.42–0.7 µm	~9 bit	7.0E-10	On-demand	Zhu et al. (2022)
EROS-B	EROS-B	0.65 m	Local-to-Regional	On-demand	2013–2022	0.45–0.9 µm	10 bit	–	On-demand	Levin et al. (2014)
ISS	ISS	5–200 m	Regional	Irregular	2003-	RGB	–	–	Free	Sánchez de Miguel et al. (2019)

Note that we excluded the platforms that have not been reported in peer-review articles, such as Aerocube-4/5 and SAC-C/D.

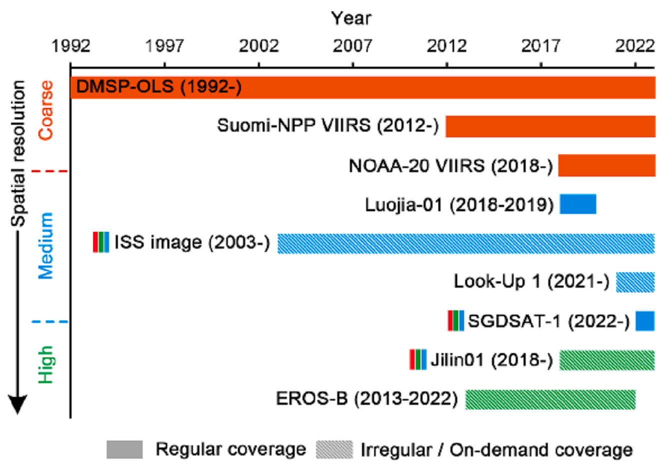

Fig. 2. Illustrative diagram of space-borne NTL platforms and their key features, including spatial resolution, temporal coverage, and coverage pattern. Platforms that provide multispectral NTL images are also labelled.

regression method was used most frequently. This method trains a regression model using the uncalibrated NTL intensity of PIFs in a reference year and other years, and applies the model to calibrate all other DMSP-OLS images to the image of the reference year (Pandey et al., 2017). While these issues were once bottlenecks of NTL studies, there are now many well-acknowledged solutions available to address them.

The Day/Night Band (DNB) of Suomi-NPP satellite's VIIRS sensor, launched in 2011, represents a revolutionary milestone in NTL remote sensing (Elvidge et al., 2017; Shi et al., 2014). VIIRS is the first satellite sensor specially designed for global-scale NTL observations, with its sensor features head and shoulders above DMSP-OLS, including a higher spatial resolution, dynamic range, low light detection sensitivity, and an onboard calibration system (Elvidge et al., 2013). Consequently, the annual usage of VIIRS has increased sharply to 65% in 2022, while the proportion of DMSP-OLS-based studies has declined from 87% to 22% between 2012 and 2022 (Fig. 3a). Many studies previously relied on DMSP-OLS have now "transplanted" to VIIRS data (Chen and Nordhaus, 2015; Shi et al., 2014). Despite the declining usage of DMSP-OLS, we believe it will continue to play an indispensable role in future NTL studies, primarily due to the need for long-term observations. We observed a rising demand in long-term NTL observations, with approximately 30% and 16% of articles' study periods spanning at least 10 and 20 years, respectively (Fig. 4b). Among these articles, more than 51 articles employed both DMSP-OLS and VIIRS (Fig. 3b). Thus far, combining DMSP-OLS (1992–2013, V4 product) and VIIRS (2012-present) is still the only solution to long-term NTL observations.

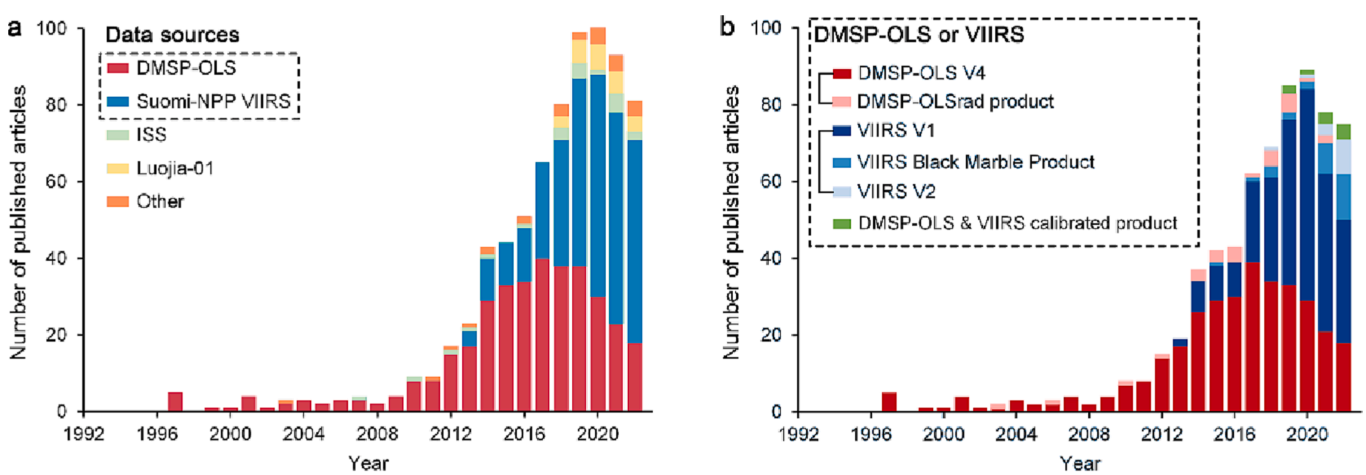

Fig. 3. (a) Number of published articles using different data sources. (b) A closer comparison between different data products of DMSP-OLS and VIIRS.

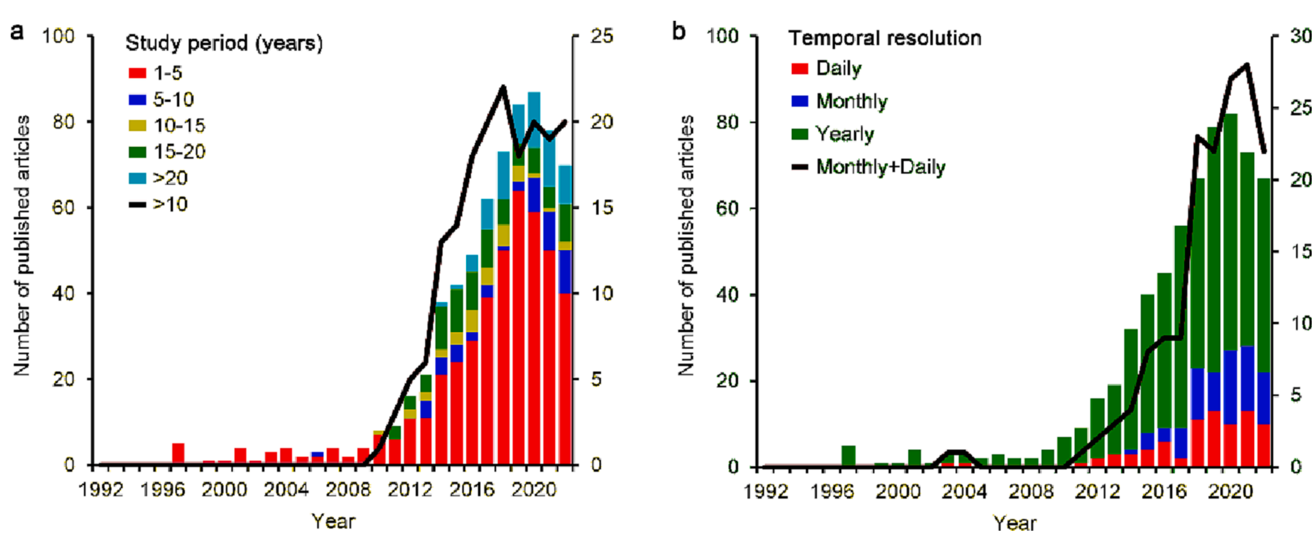

Fig. 4. (a) Number of published articles with different study periods and (b) temporal resolution.

Since 2018, a series of new VIIRS products with increasingly refined image quality have been released, such as NASA's Black Marble VIIRS Product suite (Román et al., 2018), EOG's version 2 VIIRS product (Elvidge et al., 2021), and VIIRS from NOAA-20 satellite (Wang et al., 2021). These new VIIRS products have been increasingly utilized, accounting for 40% of all VIIRS-based studies in 2022 (Fig. 3b). In comparison to the annual DMSP-OLS composite data and Version 1 VIIRS, these new VIIRS products remarkably improve the temporal frequency of NTL observations. In 2022, 15% and 18% of studies were carried out on a daily and monthly basis, respectively (Fig. 4b). These new VIIRS products offer crucial temporal details in understanding urbanization and the associated changes in human activities, motivate new algorithms to be incorporated in NTL image processing (e.g., time series analysis methods), and promote better understanding of NTL data, such as intra-annual seasonality, angular effect, as well as other uncertainties in NTL data.

Concurrently with the development of VIIRS products, several other NTL products with medium or high spatial resolution have emerged, including NTL images from aerial surveys, Luojia-01, EROS-B, and Yangwang-1. Some sensors also offer multispectral information, such as Jilin01 satellite series and SDGSAT-1 (Table 1). These NTL products complement coarse resolution NTL products in such ways as understanding fine-scale spatial variability of NTL data (e.g., relation to urban land-use types), analyzing urban light pollution and its local-scale impacts, and studying urban lighting patterns. The band setting of DMSP-OLS and VIIRS (500–900 nm, panchromatic) makes them prone to underestimating NTL emitted in the blue spectrum (430–500 nm). This issue is worsened in the context of a global scale shift in outdoor illumination sources from High Pressure Sodium lamps (HPS) and Metal Halide lamps (MH) to LEDs, where HPS and MH exhibit strong emission in near-infrared spectrum (800–900 nm) but LEDs emit in blue spectrum (Elvidge et al., 2010; Zheng et al., 2018b). The multispectral NTL imagery opens up opportunities to address this issue. Despite their benefits, the number of studies using medium and high resolution NTL data has been stranded at around 10% of the total studies from 2012 to 2022 (Fig. 3a). This constrained usage could be attributed to several factors, including a narrow image swath, low temporal repeatability, impact of cloud and viewing angle, etc.

3.2. Recent proliferation of urban NTL remote sensing studies

Despite being digitally archived and released in the 1990s, NTL remote sensing gained its popularity after the 2010s. Since then, more than 500 peer-reviewed papers have been published applying NTL remote sensing images as either major or auxiliary input for urban studies. Further inspection into two remote sensing journals with the highest impact factors – *Remote Sensing of Environment* and *ISPRS Journal of Photogrammetry and Remote Sensing* – showed that out of around every 10 articles in the domain of urban remote sensing (i.e., keywords include urban, built-up area, or city) contained at least one article involving NTL imagery. This finding suggests NTL data is becoming one of the key components in urban remote sensing. We expect continuous growth in

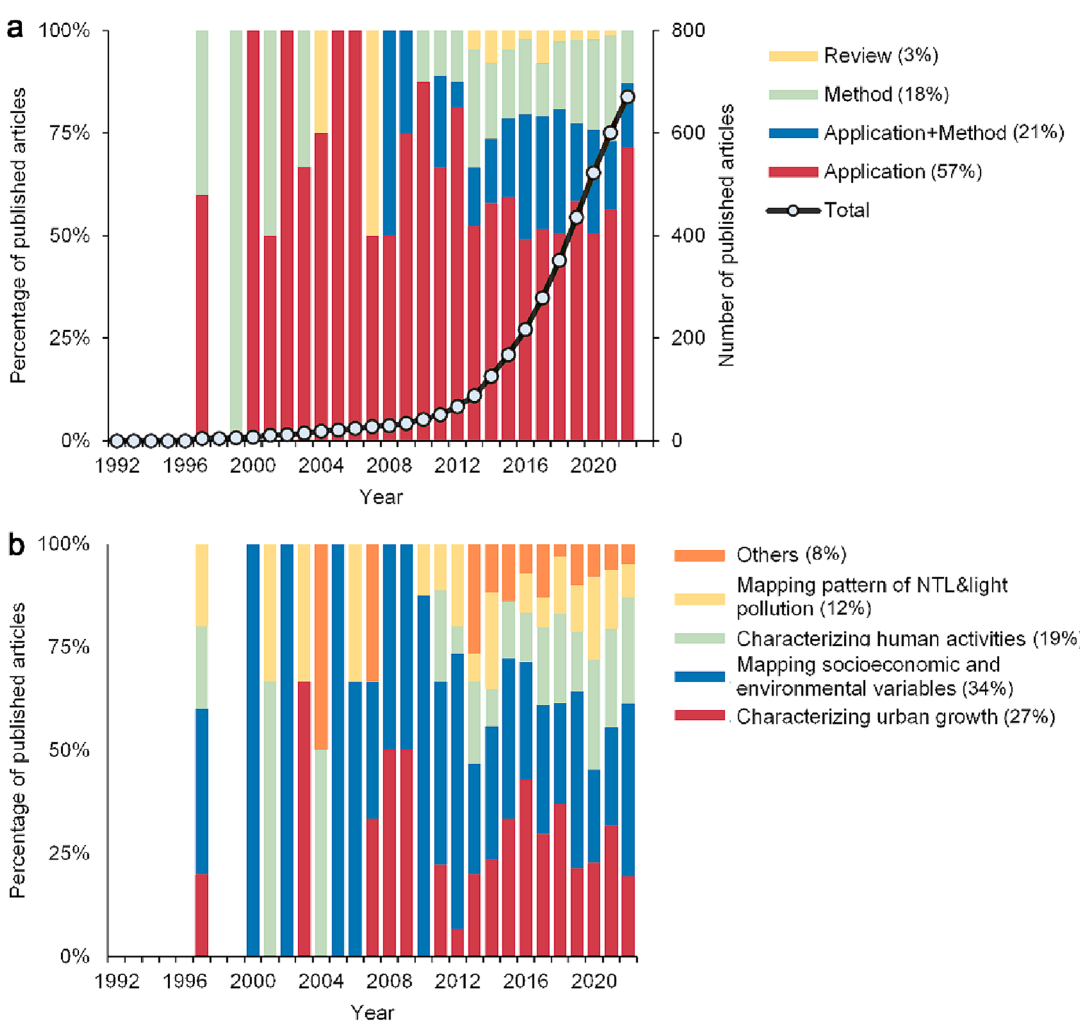

Fig. 5. Percentage composition of article types and the total number of published articles (a). Percentage composition of each topic of NTL-based urban application (b). Values in the brackets indicate the percentage composition of the entire period.

urban NTL studies due to the rapid advancements in NTL platforms and products.

Furthermore, we divided all reviewed articles into four categories (Fig. 5a). The majority of urban NTL remote sensing studies focused on application (60%) or put approximately equal weight on application and method development (21%). Studies that mainly focused on method development accounted for only 19% of all reviewed articles. This trend contracted to the general pattern of urban remote sensing studies, where method development has been the dominant focus identified in a recent review (Zhu et al., 2019). This finding suggests that NTL data is relatively more readily applicable for urban remote sensing than other datasets. Most of the NTL products are pre-processed composite image products, which require little additional processing such as cloud masking, gap filling, geometric and radiometric corrections, etc. However, it does not mean that current NTL data are fully analysis-ready. In the past 10 years, there has been a growing number of studies mainly or partially focusing on method development (Fig. 5a). These methods were built to improve existing methods or to solve newly-identified technical issues in NTL data.

3.3. Spatial pattern of urban NTL remote sensing studies

The spatial pattern of urban NTL studies showed that China and USA contributed to a dominant proportion of studies in the domain of urban NTL remote sensing, followed by the United Kingdom, Germany, and Italy (Fig. 6a). More than three-quarters of the studies either focused on regions in China or USA or examined the entire globe. Around 61% of the articles led by authors from USA centered their study beyond the USA (other countries or globe-wide), while, for studies led by Chinese authors, this figure was less than 15%.

We summarized the statistics on the origin of authors and study area based on the Global South and Global North country division according to the United Nation's definition (UN, 2022). Our analysis revealed a significant spatial inequality in the number of studies led by Global South authors and the number of studies focusing on Global South countries against those of Global North when China was excluded. Only 22% of the studies were led by authors from Global South countries, whilst Global South countries were studied 50% less frequently than Global North countries. Additionally, our findings indicate that the most frequently studied regions were countries that had already undergone significant urbanization. However, hotspots of future urbanization are currently small to medium-sized cities with <1 million population (Reba and Seto, 2020), but these countries on their way to dramatic urbanization received disproportionately lesser attention (Fig. 6b). This phenomenon underscores that the potential of NTL remote sensing in supporting to support the urgent observation demands of societal and

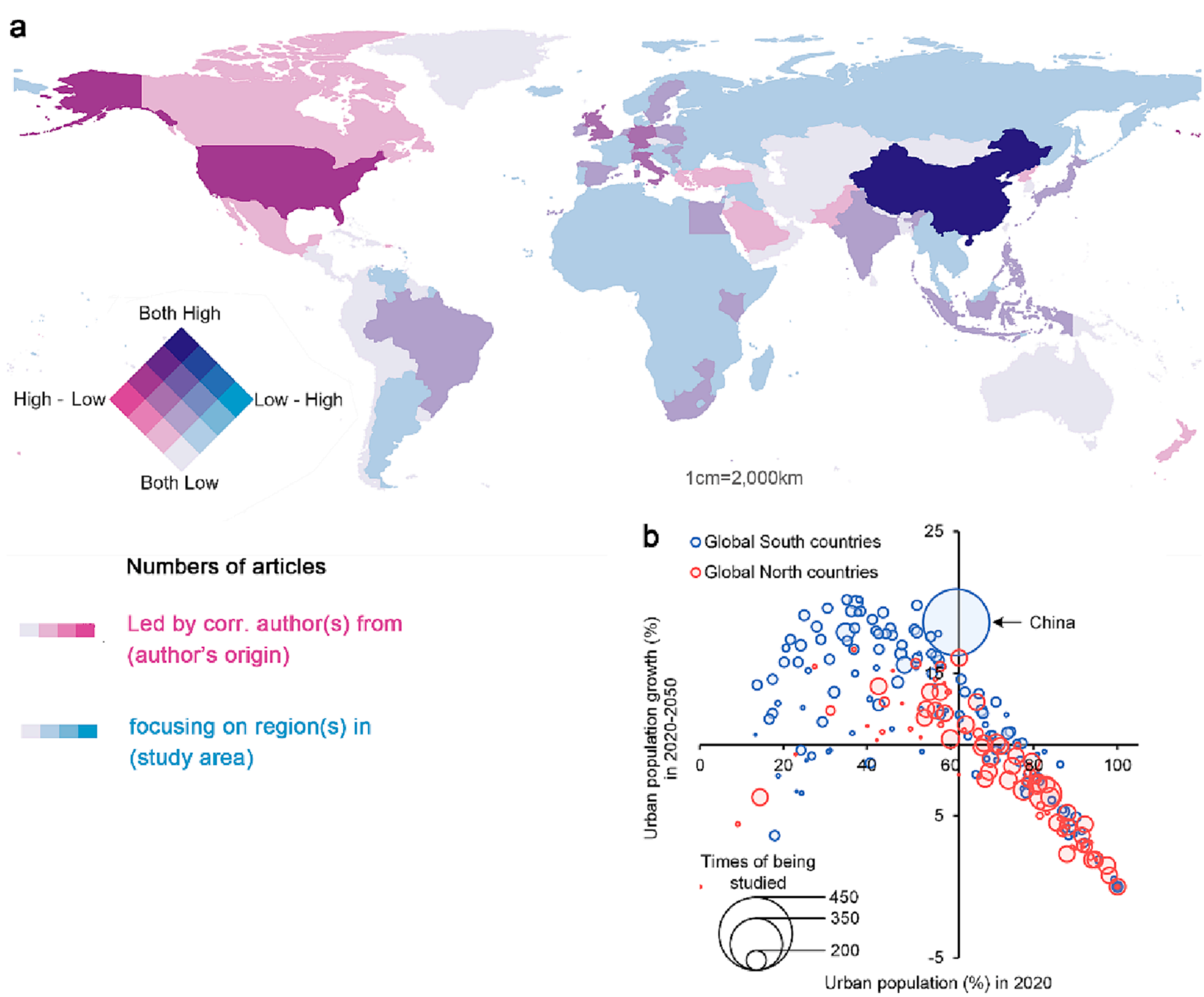

Fig. 6. (a) The total number of published articles accounted by corresponding authors from each country (author's origin) and regions of focus in each country (study area). (b) The number of published articles that focus on study areas of a Global South/Global North country and its corresponding urban population in 2020 (%, out of total population) and urban population (%) growth during 2020–2050 (Data source: World Urbanization Prospects: the 2018 Revision, United Nations).

environmental changes in these fast-urbanizing Global South countries have been overlooked thus far.

4. Key topics of NTL-based urban applications: Progress and challenges

In this section, we provide an overview of the major urban applications of NTL data. We categorize these applications into four topics: (1) characterizing urban growth, (2) mapping socioeconomic and environmental variables, (3) investigating human activities, and (4) mapping light pollution. For each topic, we review the progress made in the past 30 years, discuss algorithmic advancements, and highlight challenges. Topics contributing to less than 10% of total reviewed articles (e.g., analyzing the ecological impact of NTL) were excluded and grouped in the “other topics” category.

4.1. Characterizing urban growth

Remote sensing imagery provides a useful tool to observe urban growth and its impact on ecosystem, climate, and environment (Liang et al., 2016). Compared with other “daytime” images (e.g., Landsat and SPOT), the large contrast between urban and non-urban areas makes NTL imagery preferable in characterizing changes in urban built-up areas. Besides, due to its relatively coarse spatial resolution and large image swath, NTL images are among the earliest datasets for large-scale urban mapping. For example, Croft and Colvocoresses (1979) used six digitized DMSP-OLS images to map major cities in the eastern US. Over the past thirty years, NTL-based studies that map urban extent and urban growth accounted for about 20% of all reviewed articles (Fig. 5b).

Despite the well-acknowledged potentials, accurate urban mapping with NTL data has been hindered by the blooming effect – an effect of enlarging urban areas estimated by NTL data (Small et al., 2005). Addressing this problem has been one of the main focuses of NTL-based urban mapping over time. In the early stage, the percentage of detected NTL out of the total cloud-free observations was used as an indicator. Studies aimed to identify an empirical threshold of this percentage indicator to screen out the blooming effect and retain a coherent urban boundary (Imhoff et al., 1997). The underlining assumption of these studies was that “blooming pixels” were ephemeral and thereby had low detection percentage (Henderson et al., 2001). The resulting urban mapping accuracy was found highly sensitive to threshold selection. Even for the same study area, the selected empirical percentage thresholds differed greatly across studies (Elvidge et al., 1997a; Imhoff et al., 1997). Subsequent efforts turned to selecting a threshold based on NTL intensity. While this approach showed a slight improvement over the percentage threshold, it was found that regions with distinct urban sizes and socioeconomic status required different thresholds to best delineate urban areas. For example, by taking the urban extent identified by Landsat images as a reference, Henderson et al. (2001) found significant differences in the threshold for Beijing (DN $\geq$ 30), Lhasa (DN $\geq$ 19) and San Francisco (DN $\geq$ 51) to best match the reference urban extent. The optimal threshold method was then proposed to address this issue. This method divides the study area into several sub-regions based on their socioeconomic and physical characteristics, and uses a certain approach to determine the threshold for each sub-region (Liu et al., 2012). For instance, Yu et al. (2014) divided China into 10 sub-regions and used the statistical total urban areas as a reference to determine the optimal NTL intensity threshold for each sub-region. While optimal thresholding approaches are similar, they may have minor differences in (i) how to divide the entire study area into sub-regions and/or (2) how to determine the optimal threshold for each sub-region (e.g., using GDP or other statistics as a reference) (Zhang and Li, 2018). The above-mentioned methods have also been applied to other NTL data sources, including VIIRS (Yu et al., 2018; Zhao et al., 2020b), Luojia (Li et al., 2018; Wang, & Shen, 2021) and ISS images (Yin et al., 2020). The thresholding methods are straightforward but subject to several limitations. First, division of the sub-region and determination of the optimal threshold is subjective and time-consuming. Second, the overestimation of urban areas for large cities still prevails, as the extent of NTL is not entirely consistent with the urban extent, albeit with a high correlation. Using NTL data as the only feature to identify urban areas is therefore deemed to incur overestimation.

Machine learning and deep learning methods have been extensively applied to geospatial analysis, including NTL-based urban mapping. These methods usually involve using unstructured data, including NTL images and other features, such as NTL index (e.g., VANUI), NDVI, LST, and kernel density of Point-of-Interests (POIs), with various machine learning models and classification strategies (Cheng et al., 2018; Dou et al., 2017; Jing et al., 2015; Zheng et al., 2021a). Cao et al. (2009) used NTL intensity and NDVI, together with a region-growing SVM method, to iteratively identify urban built-up areas for 25 megacities in China. Goldblatt et al. (2018) deployed a hexagon-pixel-based Random Forest model with Landsat and NTL images on Google Earth Engine and mapped urban built-up areas for India, Mexica, and the United States. Zhang et al. (2022) fed a U-net deep learning network with Luojia-01 NTL images, Baidu migration data, POIs data to map built-up areas in a highly heterogenous urban context. In addition to the supervised methods, unsupervised methods have also been employed (Chen et al., 2020a; Li et al., 2018; Zhang and Seto, 2011). Compared with the thresholding methods, machine learning and deep learning methods yielded a relatively higher accuracy. Incorporating other features (e.g., NDVI) was found effective in avoiding overestimating built-up areas in urban cores, which were vulnerable to the impact of a strong blooming effect and data saturation. Besides, combining coarse resolution NTL images with Landsat and SPOT images improved the spatial details and accuracies in highly heterogeneous urban areas (Liu et al., 2019; Ma et al., 2017).

In addition to the mainstream methods discussed above, several other approaches have shown promise for urban mapping using NTL data. Gradient-based method aims at leveraging the NTL intensity pattern from urban core to non-urban areas to identify a threshold (Li et al., 2022a). Similar strategies have been applied to NTL clusters derived from image segmentation, where the threshold for each cluster is determined by the gradient of NTL intensity quantile (Zhao et al., 2020b; Zhou et al., 2018). Edge-detection algorithms have also been used to enhance the NTL intensity gradient between urban and non-urban areas (Xue et al., 2018; Yu et al., 2018). Besides, Zhou et al. (2014) and Zhou et al. (2015) employed morphological features to determine the threshold of each NTL cluster by the statistical relationship between the mean NTL intensity and the size of each cluster. A few studies extracted temporal features from NTL time series and leveraged temporal information for urban mapping (Xie et al., 2019; Zheng et al., 2021c).

A few challenges are constraining the potential of NTL data for urban mapping. First, almost all NTL-based urban mapping efforts relied on coarse resolution NTL data (88%) or medium resolution NTL data (11%). While recent years have seen the availability of many high-resolution NTL datasets, their potential for urban mapping has not been fully explored. It can be partially ascribed to their accessibility as they are mostly commercial data. The main obstacle to using high-resolution NTL data is the fact that the NTL pattern derived from high-resolution data does not correspond well with the pattern of urban built-up areas (Fig. 7). This discrepancy may be due to a lower NTL detection sensitivity of high resolution NTL data ($\sim 10^{-7}$ W/cm^2/sr) than medium ($\sim 10^{-9}$ W/cm^2/sr) and coarse resolution NTL data ($\sim 10^{-10}$ W/cm^2/sr) (Table 1). Another possible reason is that the NTL pattern aggregated at a mid- or coarse resolution is more suitable for urban mapping. However, high resolution NTL images only reflect the NTL pattern of lighting objects, including main traffic lines and brightly-lit outdoor lighting facilities (Fig. 7). Thus far, only a few urban mapping studies used high resolution NTL images, but they are based on aggregated NTL at parcel-level rather than at a pixel basis (Huang et al., 2021;

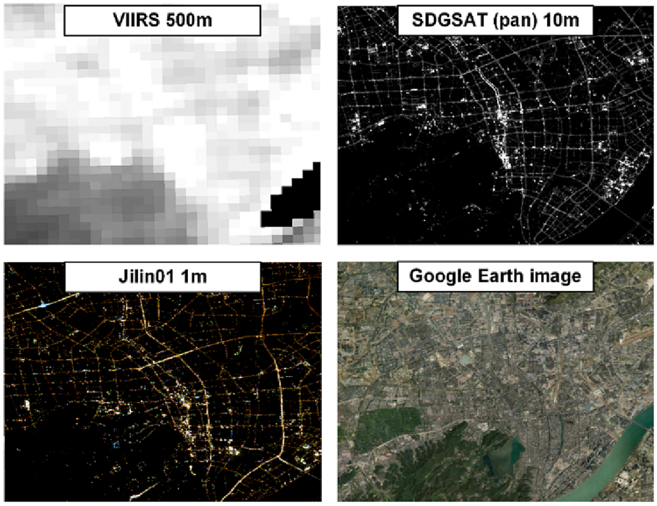

Fig. 7. NTL images collected from VIIRS (500 m), SDGSAT-1 (40 m, panchromatic), and Jilin01 (1 m), and the corresponding "daytime" Google Earth image (city: downtown Hangzhou, China).

Zheng et al., 2018b).

To improve the accuracy, consistency, and temporal details of NTL-based urban mapping, it is important to better leverage temporal information from NTL time series. While long-term NTL observations are available via DMSP-OLS (1992–2013) and cross-sensor calibrated products of DMSP-OLS and VIIRS (1992-present), temporal information has been underutilized in urban mapping studies (Chen et al., 2021; Li et al., 2020b). The majority of the thresholding and classification-based methods only utilized NTL intensity ("spectral" feature). Even for multi-year urban mapping, only the NTL intensity of the target year was used. In daytime remote sensing studies, it has been well demonstrated that utilizing information extracted from the temporal profile, spatial context, or object shapes can be beneficial to urban mapping. Despite some recent efforts, the utilization of information other than NTL intensity is still at an early stage in NTL-based urban mapping.

Leveraging fine-resolution temporal information of daily NTL products to support near real-time urban mapping remains challenging. Obtaining fine temporal scale urban change details is key to meeting the observation demand for contemporary urbanization (Zhu et al., 2019). While daily NTL data have been released by EOG and NASA, the majority of urban mapping studies, around 85%, were carried out on an annual basis, and only 8% on a monthly basis, with scarce efforts on a daily basis The spatial and temporal variations of daily NTL data are significantly higher than those of monthly averaged and yearly averaged composite NTL data, leading to substantial uncertainties and variations in daily NTL observations that impact NTL-based applications, including urban mapping (Wang et al., 2021; Zheng et al., 2022).

NTL data have also been used to characterize features of urban growth from different perspectives, especially intra-urban changes. NTL data was applied, either solely or together with other special indices (e.g., NDVI and NDWI), to estimate impervious surface fraction by linear regression models (Liu et al., 2015) or machine learning models (Chen et al., 2019a). Moreover, the intra-urban spatial variations of NTL were found a useful tool to study polycentric urbanization, such as identifying polycentric cities (Yang et al., 2022), mapping the extent of sub-centers of a polycentric city (Cai et al., 2017; Chen et al., 2017b; Lou et al., 2019), and analyzing their spatiotemporal dynamics (Zheng et al., 2018a). The differences in NTL pattern by urban land-use type have been leveraged to classify urban function zones (Huang et al., 2021; Liu et al., 2020a), urban infrastructures (Stokes and Seto, 2019), and local climate zones (Qiu et al., 2018). Finally, NTL intensity also showed potential in estimating urban changes in the vertical dimension, including floor areas (Liu et al., 2021) and building volume (Shi et al., 2020).

4.2. Mapping socioeconomic and environmental variables

Another important area of urban application for NTL data is the mapping of socioeconomic and environmental variables, such as GDP, population, and energy consumption (Bennett and Smith, 2017; McCord and Rodriguez-Heredia, 2022; Zhou et al., 2022). These variables are usually recorded based on administrative boundaries (e.g., national, state, and city levels), making them less suitable for spatial analysis. This often results in a 1–2 year lag in collecting and releasing the data by the corresponding government institutes, hindering timely representation (Zhang et al., 2015). For other variables that are collected in situ (e.g., PM2.5 from weather station), the data require spatial extrapolation for wall-to-wall presentation and analysis. Spatial-explicit and timely understanding of urbanization-induced socioeconomic and environmental changes is crucial to studying urbanization. Given the close correlation between these variables and human activities, NTL data have been widely recognized as a useful proxy to estimate these variables and spatialize them into grids.

In remote sensing research communities, the potential of using NTL data for estimating socioeconomic and environmental variables has been discussed in Croft (1978) and tested by several attempts around 2000, such as Elvidge et al. (1997b) and Doll et al. (2000). Nevertheless, it was not until the milestone publications by Henderson et al. (2012a) and Pinkovskiy and Sala-I-Martin (2016) that using the NTL as a proxy of economic activities has been conventionally accepted by economic research communities. It accounted for 34% of reviewed articles over the past three decades. Most studies resembled each other, where a model was developed to link NTL intensity with the variable of interest, and the model was then applied to generate the estimates in other regions or at other scales (Fig. 5b). They differed slightly in some of the following aspects:

(1) Variables. Various socioeconomic and environmental variables, due to their close relation to human activities, have been modelled by NTL images:
   - Socioeconomic variables: GDP (Chen and Nordhaus, 2011; Wang, & Sun, 2022), population (Stathakis and Baltas, 2018), electricity/energy consumption and access (Shi et al., 2016), poverty (Elvidge et al., 2009; Yong et al., 2022), steel stocks (Liang et al., 2016), etc.
   - Environmental variables: PM2.5 (Fu et al., 2018), anthropogenic heat (Yang et al., 2017), GHG emission (Wang and Liu, 2017), etc.

(2) Models. To model the relationship between NTL intensity and studied variables, a range of methods have been applied. The majority of studies used regression models and machine learning, such as linear regression model, panel regression model, geographically weighted regression model, exponential model, and random forest regression (Bennett and Smith, 2017; Doll and Pachauri, 2010; Imran et al., 2019; Wang, & Lu, 2021). Deep learning approaches have been utilized for estimating socioeconomic variables (Sun et al., 2020). For example, Ni et al. (2021) incorporated VIIRS images, Very High Resolution (VHR) multi-spectral images, and demographic and health surveys with four deep learning networks (VGG-Net, Inception-Net, ResNet, and DenseNet) to estimate poverty level in African countries. Some studies only examined the statistical relationship between NTL and studied variables (Chen and Nordhaus, 2015; Gaughan et al., 2019). However, the model selection is sensitive to studied variables and study areas, particularly in cases where the study areas are across different socioeconomic statuses, outdoor lighting regulations, and population density. This issue raises concern about the generalizability of the models, as models that perform

well at a global scale may result in large errors at regional scales (Ma, 2018).

(3) Scales. The most critical difference across these studies lies in the scale issue - that is, the scale at which the model was trained and the scale at which the trained model was applied. Out of 201 reviewed articles on this topic, 43% of the articles built the relationship between NTL and socioeconomic/environmental variables and applied the modelled relationship to predict the variable of interest in areas with no data record at the same spatial scale (Rybnikova and Portnov, 2016; Zhang and Seto, 2011). Many attempts have been made to apply the relationship modelled at one spatial scale to another spatial scale, either from plot scale to pixel scale (upscaling; 5%) or from country/province scale to city/pixel scale (downscaling; 33%). For instance, Shi et al. (2016) employed a linear regression model to capture the relationship between total NTL intensity from DMSP-OLS and electricity power consumption (EPC) statistics at a national scale and applied this model with NTL intensity of each pixel to generate a 1 km × 1 km global EPC map. Conversely, built on a mix-effect model of PM2.5 and NTL intensity of 35 meteorological stations in Beijing, China, Fu et al. (2018) generated a 0.04-deg PM2.5 map of Beijing. Few studies extrapolated the modelled relationship in the temporal dimension. Zhao et al. (2017) demonstrated the capability of using the modelled historical relationship between NTL intensity and GDP time series to project GDP in the near future.

One of the key concerns is how these studies are affected by scale. About 76 out of 201 studies (38%) trained their model at one scale and then applied it to a different spatial scale. The implicit assumption in these studies is that the modelled relationship at one spatial scale (e.g., national) is applicable at another spatial scale (e.g., pixel). The validity of this assumption is questionable. Taking estimating population with NTL data as an example, the estimation model is often built upon the relationship between total NTL intensity and total population aggregated at a national level, and then applied to estimate pixel-level population with the NTL intensity of each pixel. However, this type of approach fails to account for the fact that most of the total NTL intensity comes from brightly-lit urban areas, while dimly-lit or dark rural areas are often under-represented in the model, even though they are inhabited by a considerable amount of population. A rough estimation indicated that approximately 1.5 billion people were living in areas without electricity access, thus making any change in their population undetectable by NTL observations (Doll and Pachauri, 2010). Chen et al. (2020b) found that the NTL-based CO_2 emission modelling performance was largely improved if these dimly lit areas were correctly accounted for. VIIRS NTL data exhibits higher low-light detection limits than DMSP-OLS and thereby can better detect dim lights in rural areas. The strong correlation between NTL intensity obtained from VIIRS and socioeconomic variables has been confirmed by many studies (Bennett and Smith, 2017). Even so, a recent study of population estimation with VIIRS NTL data found a stark difference between the regression R^2 at provincial, city and county scales (0.65–0.76) and that at the pixel scale (0.33) (Ma, 2018). Meanwhile, the resulting slopes exhibited even higher discrepancy across scales, from 0.71 (pixel level model) to 5.07 (provincial level model). The high correlation between NTL and population was primarily attributed to the spatial autocorrelation effect. Discrepancies in modelling results were further amplified when this effect was isolated across all modelling scales.

There is also an ongoing debate about the suitability of NTL time series for modeling temporal changes in socioeconomic variables. While some studies have shown acceptable performance in estimating socioeconomic changes with NTL time series data (Shi et al., 2016; Zhao et al., 2019b), others argued that neither raw DMSP-OLS nor inter-annually calibrated DMSP-OLS are effective in modelling national and subnational population (Chen and Nordhaus, 2015). Archila Bustos et al. (2015) corroborated that the strong correlation between NTL and socioeconomic variables based on single-year cross-sectional analysis may not have fidelity over time. There are also concerns regarding the use of inter-annual calibrated DMSP and cross-sensor calibrated DMSP-OLS and VIIRS data, as some calibration models adopt a non-decreasing assumption (Liu et al., 2012). This could potentially decouple NTL from socioeconomic variables in regions undergoing socioeconomic downturns, such as Zimbabwe and post-Soviet cities (Bennett and Smith, 2017).

4.3. Investigating human activities

Changes in human activity patterns resulting from both long-term societal changes and temporary events have a close relationship with urban energy use, resource supply, and public service demand (Roman et al., 2015; Wang et al., 2017). Its strong correlation to NTL intensity has advocated extensive applications in using NTL as a proxy of human activities, such as monitoring changes in human activity intensity due to urbanization (Chen et al., 2017a; Chen et al., 2019c), public holidays (Cao et al., 2018), regional armed conflict (Li et al., 2013; Olsen et al., 2021), disasters (Qiang et al., 2020), regional conflict (Shah et al., 2022), and public events (e.g., Covid-19) (Stokes and Roman, 2022). For example, Jiang et al. (2017) used time series VIIRS data and demonstrated an over 70% decrease in light intensity during the Yemen crisis in 2015. Xu et al. (2021) used NASA's Black Marble VIIRS product to reveal how human activities of global megacities responded to the lockdowns by Covid-19 and how such responses varied across countries. It should be noted that these studies are different from those in Section 4.2. These studies use NTL intensity directly to reflect human activity and its spatial pattern, while studies in Sections aim at using NTL intensity to estimate the spatial pattern of socioeconomic variables (e.g., population).

Studies have used multi-year or time series NTL data to conduct before-after comparisons to illustrate the impact of certain events on human activities and their recovery patterns. For instance, Elvidge et al. (2020a) compared the NTL intensity between the pre-pandemic period and the first three months during the pandemic in major cities of China, and concluded a sharp decline in human activities by 3%-25%. In addition to simple comparison, statistical and time series analysis techniques have been employed to identify disturbance in human activities with NTL data, such as run-length encoding (Stokes and Roman, 2022) and seasonal and trend decomposition using Loess (STL) (Zhao et al., 2020a). Single-year NTL intensity has also been used as a proxy of human activities to estimate human exposure to environmental threats, such as heat hazards (Hu et al., 2017), flood (Mard et al., 2018), and other natural disasters (Chen et al., 2019b).

However, most of these studies require prior knowledge of the event. Therefore, NTL data may only serve as a post-event tool for quantifying changes. It remains difficult to identify the occurrence of an event without any prior knowledge. Drawing on the recent advancement in change detection algorithms for "daytime" remote sensing data, we anticipate more opportunities for achieving this goal. Another hurdle is how to disentangle NTL changes induced by a target event from ephemeral variations of NTL, which is extremely high and may even reach the magnitude of a target event (Elvidge et al., 2020b; Wang et al., 2021). NTL users thus should take particular caution in selecting the temporal composite scale. NTL users should exercise caution when selecting the temporal composite scale, as using a fine scale (daily) may obscure the target event's NTL change signal, while using a coarse scale (monthly or yearly) may oversmooth it (Zheng et al., 2022).

4.4. Mapping light pollution

Nightlights emitted from human settlements not only shift the nightscape of urban areas but also impact remote natural areas hundreds of kilometers away (Cinzano et al., 2001; Falchi et al., 2011). Different terms have been used to describe these nightlights, such as light pollution (Czarnecka et al., 2021), artificial light at night (ALAN) (Davies and Smyth, 2018; Sánchez de Miguel et al., 2021), or outdoor artificial lighting (Irwin, 2018). These terms describe different objects, but they are often interchangeable in studies.

Studies have been using NTL data from various platforms to map light pollution and its patterns (Jiang et al., 2018). Using VIIRS NTL data, Kyba et al. (2017) revealed that artificially lit outdoor areas increased by 2.2% annually from 2012 to 2016, with an annual radiance growth rate of 1.8%. Small and Elvidge (2013) applied empirical orthogonal function (EOF) analysis on nighttime lights derived from DMSP-OLS data and showed an increase of approximately 270% in artificially lit areas for both China and India. Xiang and Tan (2017) compared two-decade DMSP-OLS data and concluded that light pollution encroachment into protected areas in China had increased by about 179%. Other studies incorporated NTL data with field measurements, e. g., using Sky Quality Meter (SQM) (Hänel et al., 2018; Katz and Levin, 2016). Xu et al. (2018) combined ISS NTL images and field measurements collected from upward, horizontal, and downward-pointing SQM to generate a 50-m light pollution map for the National Capital Region, Canada. Some studies have also correlated NTL data, particularly those from high-resolution NTL sensors, with urban land-use maps to examine the variation of ALAN by land-use type (Levin et al., 2014; Zheng et al., 2018b). A general observation is that high ALAN intensity was observed in commercial and public service areas, and relatively low pollution intensity in industrial and residential zones (Kuechly et al., 2012). In addition, lighting sources that drive the changes in ALAN pattern have also been studied. Cheng et al. (2020c) identified High Pressure Sodium (HPS) lamps in a district of Shanghai with Jilin01 image and discussed the implication on urban lighting energy consumption. Hung et al. (2021) found a reduction in upward NTL obtained from VIIRS due to the retrofit program that replaced HPS lamps with LEDs at Chelan county of Washington State, USA.

However, light pollution intensity obtained from space-borne NTL platforms mainly represents upward light emission. To better portray light pollution, radiance transfer models of light pollution have been developed and applied. The first but simplest model, proposed by Garstang (1986), idealized a city as a circular area of uniform brightness from the center. Built on this model, recent studies have made progress by combining field measurement and remotely sensed NTL images to develop radiance transfer models to map sky brightness. New models include Extended Garstang Models (Cinzano and Falchi, 2012), City Emission Function (Kocifaj et al., 2019), Scattering Density Monte Carlo Radiation Transfer Model (Kolláth et al., 2021), and Illumina V2 model (Aubé et al., 2021). These models significantly improve our understanding of light pollution, such as factors that enhance sky brightness (Kyba et al., 2015) and human exposure possibility of light pollution (Aubé et al., 2021).

Although there are several ways to measure light pollution, challenges remain in many aspects. A major challenge is that monitoring with remotely sensed NTL images is limited by such factors as spectral band settings, the influence of shifting lighting sources, and zenith viewing angles. Given the lamp spectral width, panchromatic NTL sensors may largely underestimate sky brightness due to their weak sensitivity to the blue spectrum (Levin et al., 2020). The global trend toward shifting outdoor lighting lamps to LEDs, which have strong emissions in the blue spectrum, exacerbates this issue. Besides, what NTL sensors captured is mostly upward light emission, but light pollution impacts predominantly in the horizontal dimension. A second challenge is the difficulty in correlating remotely sensed NTL observations with field measurements. The correlation is highly sensitive to how ground measurements are made. Katz and Levin (2016) found that NTL derived from EROS-B images had the lowest correspondence with upward-pointing SQM measurements, but the highest correspondence with downward-pointing SQM measurements. The temporal instability of light pollution for both space-borne NTL observation and ground measurement, mismatch in measurement timing and spectral information, and inconsistency in measurement (radiometry vs. photometry) further complicate the integrative use of both data sources (Hänel et al., 2018; Levin et al., 2020).

4.5. Other applications

NTL images contribute to many other fields of urban studies. These applications included lab experiments and simulation or field measurements but began to incorporate NTL data due to its recent proliferation. One important area of study is the impact of artificial light at night (ALAN) on ecosystems. ALAN is a key threat to urban ecosystems, with studies showing shifts in plant phenology, such as advancing tree budburst (Ffrench-Constant et al., 2016; Zheng et al., 2021b) and delaying leave coloring (Meng et al., 2022). Besides, ALAN alters animal behaviors, such as bird migration (Horton et al., 2019; La Sorte et al., 2017), bird habitats selection (Xue et al., 2020), and bat dispersal (Guido and Kalaw, 2021; Hale et al., 2015). Exposure to ALAN also gives rise to health concerns for urban residents, including increasing breast cancer rate (Bauer et al., 2013; Ritonja et al., 2020), affecting melatonin metabolite (Hurley et al., 2013), and incurring atopic diseases (Tang et al., 2022). Sufficient outdoor lighting can avoid dark edges in streets and thereby reduce urban crime rates (Liu et al., 2020b). With continued advancements in NTL remote sensing, we can expect these applications to thrive and even evolve into new areas of research.

5. Future research directions in NTL-based urban applications

Based on our analysis of the trends in how NTL data have been used to study urbanization over the past thirty years and our review of major NTL-based urban applications, we propose that future applications require advancements in the following four interrelated directions (Fig. 8).

5.1. Direction One: A better understanding of NTL data

While the application potential of NTL data has been well-acknowledged, the characteristics of NTL data remain poorly understood. It has resulted in significant uncertainties in NTL-based urban applications, which has in turn hindered the development of new applications. In particular, the following issues should be addressed with priority in future studies.

5.1.1. Understanding scale effects and sources of variations in NTL data

The scale effect, also known as the grain size effect, is one of the key issues in remote sensing (Sobrino et al., 2012; Weng, 2014; Wu and Li, 2009). Similarly, the scale issue is embedded in almost all NTL-based urban applications. For example, when mapping socioeconomic and environmental variables with NTL data, more than one-third of the reviewed studies assumed that the model obtained at coarse spatial level (provincial/national scale) remained valid and applicable at pixel level (see Section 4.2). A recent inspection indicated such assumption was questionable (Ma, 2018). The correlation between NTL and socioeconomic variable declined and the resulting models varied greatly across scales, especially after spatial autocorrelation effect was removed. In fact, the spatial pattern differs greatly across different spatial resolutions, which might lead to different or even contrasting findings. For example, when comparing urban light pollution across land-use types, using coarse resolution data like DMSP-OLS may suggest that commercial, residential and industrial areas are the main contributors to urban light pollution. Conversely, using high resolution data, like Jilin-1 and SDGSAT-1, would end up with the finding that only commercial areas play a key role in urban light pollution, while industrial and residential areas make minor contributions (Fig. 9). Moreover, scale effect not only causes uncertainties in the spatial domain but also in the temporal dimension. Detecting changes in NTL time series with different temporal composite scales (e.g., yearly, monthly and daily) can generate different

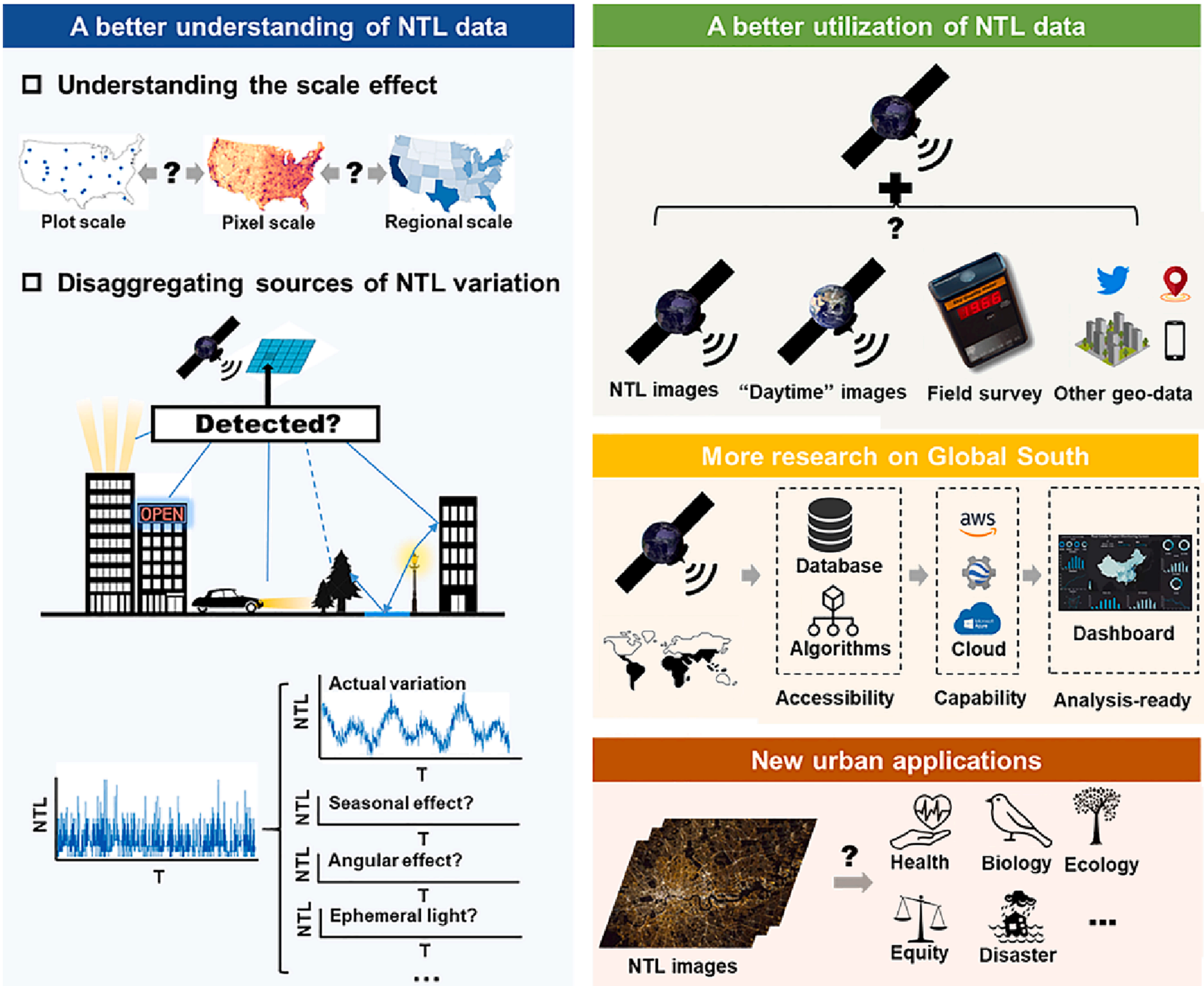

Fig. 8. Four strategic research directions for future urban NTL remote sensing studies.

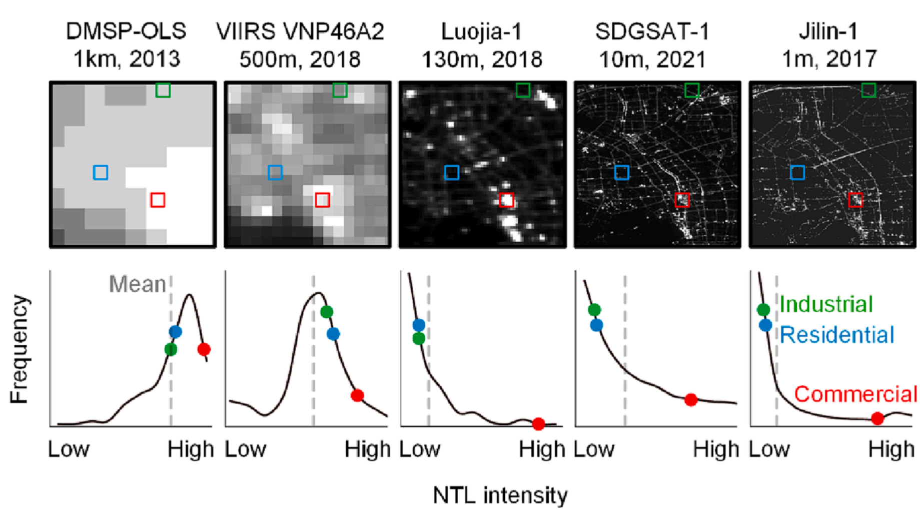

Fig. 9. Illustrative example of the scale effect of NTL data. The upper panel presents NTL images of downtown Hangzhou, China, with different spatial resolutions. The lower panel shows the frequency distribution of NTL intensity and the mean NTL intensity of three typical land-use types, including a commercial block, a residential block, and an industrial block.

NTL patterns and outcomes, such as the detected timing of abrupt NTL changes and the monitored seasonality pattern of NTL time series (Zheng et al., 2022).

The particularly strong scale effect in NTL data is because of its extremely high variations in both spatial and temporal domains. However, spatial and temporal scalability is often assumed in NTL-based urban applications but barely validated. To better understand the scale effect, it is necessary (1) to isolate the impact caused by the differences in NTL data products on scale. However, it remains challenging since NTL data at different spatial or temporal scales are often obtained from different sources with varying sensor performance (e.g., low-light sensitivity). As such, sensor performance can intertwine with the scale effect; (2) to measure the scale effect across both spatial and temporal domains; (3) to analyze the impact of scale effect on NTL-based applications and to quantify the uncertainties incurred by the effect; and (4) to develop algorithms to bridge the difference caused by the scale effect and to make NTL-based models and applications scalable.

Addressing the scale-related issues mentioned above is crucial to improve the robustness of NTL-based applications. First, it will allow users to select the most suitable scale and NTL product for their applications. Second, it will help to better account for the uncertainties in the outcomes of NTL-based applications (e.g., the estimated urban areas and population distribution), as well as those applications using NTL-based products as one of their input layers. Third, it will be beneficial to improve the scalability of algorithms and applications. Moreover, having a clear understanding of the scale effect will provide a solid foundation for future NTL-based studies to combine multiscale NTL datasets (e.g., DMSP-OLS + Luojia-1, or VIIRS + Jilin01) or to integrate NTL data with other geospatial data at different scales.

5.1.2. Disaggregating sources of NTL variations

The lighting sources detected by NTL sensors remain poorly understood. Due to the relatively coarse spatial resolution of NTL images, what each pixel represents is the aggregated NTL intensity rather than the light emission from individual sources. While this aggregated NTL intensity is useful for applications such as distinguishing human settlements from natural areas, it veils what is detected in each pixel. The detected NTL, especially for coarse resolution data, might comprise complicated lighting sources, including outdoor lighting facilities (e.g., flooding lights, decorative lights, and street lamps), lights from indoors, lights reflected from roads, urban lakes and building façade, lights from vehicles, and lights penetrating through trees (middle left panel of Fig. 8).

Disaggregating sources of detected NTL is beneficial to link the detected NTL signals to lighting objects on the ground. This is very pertinent to urban applications looking into certain types or groups of NTL emitters, such as investigating outdoor lighting intensity changes after a streetlamp retrofit program (Cheng et al., 2020c) and estimating traffic-related carbon emission (Shi et al., 2021). It could also provide essential information for establishing complicated city light transfer models, refining outdoor lighting regulations, and reducing lighting-related energy consumption. Quantifying the contributions of lighting sources is also useful for establishing scale effect models, such as downscaling coarse-resolution NTL images into high-resolution images.

Improving our understanding of NTL changes is essential. NTL changes are not only resulted from changes in human activities (e.g., urbanization, traffic patterns and social events) but also from many effects and noises, such as angular effect (Li et al., 2022b), seasonal effect (Levin, 2017), ephemeral lights (Elvidge et al., 2020b), failure of cloud mask (Wang et al., 2021), etc. Unfortunately, these two types of sources of NTL changes are lumped together in NTL time series and to make it even worse, the NTL intensity of these two types of sources can be comparable in many cases.

Disaggregating NTL changes will bring tangible benefits to urban applications relying on NTL time series by separating changes in research object (e.g., human activity intensity) from variations caused by effects and noises. It also helps to prevent NTL changes in research object from being buried in NTL variations caused by effects and noises. For example, decreases in NTL intensity have been used to indicate regional economic downturns (Henderson et al., 2012b). However, such declines in NTL time series can be nothing but due to shifting outdoor lighting from HPS to LED or simply seasonal effect during leave-on times, which area common causes of long-term and short-term NTL declines, respectively (Hung et al., 2021). If sources of NTL variations are properly disaggregated, we will be able to infer the actual cause of such NTL decrease.

To address this research gap, we need to establish quantitative models for each of these confounding effects and noises so that we could separate them from changes in research object. Although some models have been developed for some of the effects and noises, such as seasonal effect (Xie et al., 2019; Zheng et al., 2019) and angular effect (Li et al., 2022b; Tan et al., 2022), they have received criticism for their unsatisfactory performance, such as low R^2 in modelling the seasonal effect. Besides, these models were developed and used separately, and have not been synthesized. Deep learning models have potentials to overcome some of the above-mentioned issues in detecting and disaggregating NTL changes, such as 1-D convolutional neural networks (CNN) and short-term memory neural networks (LSTM). These deep learning models have demonstrated their merits over traditional regression-based change detection with “daytime” time series data (Dou et al., 2021; Masolele et al., 2021).

5.2. Direction Two: Integrating NTL data with other types of geospatial data for improved NTL utilization

Out of 688 articles that we reviewed, 562 articles only utilized one single NTL data product, among which 94% of the articles relied solely on panchromatic NTL data. We need to improve the utilization of NTL data by integrating NTL from different sensors and synergizing NTL data with other geospatial data (e.g., ground surveys, daytime remote sensing data, and OSM data).

5.2.1. Integrating multi-source NTL data

Recent development in NTL platforms has enriched NTL data products with different spatial and temporal resolutions. Future studies should take efforts to integrate multi-source NTL data to improve the attainable spatial, temporal and spectral details in urban applications. For example, fusing coarse spatial resolution but high temporal resolution data (e.g., Black Marble daily VIIRS product, VNP46A2) with medium or high spatial resolution but coarse temporal resolution data (e.g., Luojia-1 or SDGSAT-1) could generate NTL images with high temporal and spatial resolution. Fusing multi-source NTL data would improve the detection of rapid changes in highly heterogeneous urban contexts (Zhu et al., 2010). It would also encourage the usage of mid-/high- resolution NTL data. However, past studies involving medium or high spatial resolution NTL images only contributed to 10% of reviewed articles due to their narrow image swath, high vulnerability to data gaps, and long revisit periods (Fig. 3a). Information from coarse spatial resolution NTL data could be a useful tool to solve these problems in medium or high-resolution NTL data.

Drawing on image/data fusion methods developed in the past two decades for daytime remote sensing images, we deem great potential in NTL image fusion (Zhu et al., 2018). However, a challenging prerequisite of fusing multi-source NTL images lies in how to bridge the NTL intensity differences caused by varied sensor performance across data sources (e.g., spectral range, sensitivity, and overpassing time). For instance, the overpass times of VIIRS, Luojia-1, and SDGSAT-1 are around 01:30 am, 10:30 pm, and 11:00 pm, respectively. City lights generally peak around 8–10 pm and decline sharply after midnight. Local-scale studies using UAV and/or field surveys have both shown that the average outdoor NTL would decline by over 50% between peak hours and after midnight (Li et al., 2020a). As a result, a considerable proportion of outdoor lights could be underestimated by VIIRS. To fuse VIIRS with Luojia-1 or SDGSAT-1, or estimate data gaps in Luojia-1 or SDGSAT with VIIRS, we need to address this pseudo NTL differences caused by varied overpass times. Although there are a few cross-sensor calibration models developed for bridging DMSP-OLS and VIIRS, cross-sensor calibration models for coarse spatial resolution and medium/high spatial resolution NTL data are scarce.

5.2.2. Synergizing NTL data with other geospatial data

While NTL data possesses a unique capability of presenting human activity, the information it can provide is somehow limited. Synergizing NTL data with other geospatial data is imperative. In fact, many geospatial data (e.g., thermal infrared image, spectral indices, and OSM data) have already been used to improve the performance of NTL-based urban applications, such as improving urban mapping accuracy (Xue et al., 2018) and enhancing spatial variation of NTL (Zhang et al., 2013). However, to better portray the complicated urban nightscapes, it is crucial to incorporate additional data sources such as field measurements (e.g., Global at Night campaign), urban 3-D modelling, digital twins, street view images, and daytime geospatial data. With NTL data alone, our capability of characterizing such complicated nightscape NTL data alone is limited in its ability to characterize urban nightscapes, as most of the signals detected by NTL sensors are upward light emissions, and the distribution of nightscape in urban areas is uneven across different directions, and complicated by the street layout and building structures.

Better characterization of the nightscape pattern is essential for enabling many urban applications, such as assessing the impacts of light pollution exposure on human health, reducing urban light pollution encroachment into the surrounding natural ecosystems, and identifying insufficiently illuminated streets for crime prevention. To achieve this goal, future studies should also work on approaches linking photometry from field measurements to radiometry from remote sensing images, as well as developing standardized field measurement protocol, new ground survey devices, better utilization approaches of multi-angle NTL images, and three-dimensional urban models derived from daytime remote sensing data. Integrating NTL light data with ground survey can also help with tracing the emission sources of NTL and improving radiance transfer modeling and city emission function, a key component of night-sky radiance model.

5.3. Direction Three: More research on the Global South

Global South countries are hotspots of future urbanization, but they are also vulnerable to unstable societal conditions such as power outages, regional inequality, and armed conflicts (Li et al., 2013). NTL data can be an invaluable tool for addressing these challenges, yet our review shows that they are underutilized in the Global South. We found that less than one-third of studies on NTL data was led by Global South authors, and less than half of the studies focused on Global South countries (Fig. 7).

Accessibility of NTL data should be improved with less redundant data acquisition procedures, especially for data designed to be publicly available. Moreover, we should take proactive efforts in enhancing application capability in the Global South by producing (near) analysis-ready-data of NTL, robust NTL-based products (e.g., population grid and human activity layers), and scalable and generalizable models with uncertainties accounted for. To further reduce technical barriers to data acquisition, analysis, and visualization for stakeholders from the Global South, we need to deploy these data and models at cloud computing platforms (e.g., Google Earth Engine, Amazon Web Services, and Microsoft Planetary Computer). Thus far, only DMSP-OLS data, EOG's version 1 VIIRS product and NASA's Black Marble VIIRS product (VNP46A1/VNP46A2) are deployed onto these cloud computing platforms, while the latest and high-quality NTL products are still stored and distributed with their own data portal, including EOG's version 2 VIIRS, Luojia-01, SDGSAT-1, etc.

5.4. Direction Four: Developing new urban applications with new NTL data products

The emergence of new NTL products featuring higher spatial, temporal and spectral resolution will open new opportunities for NTL-based applications (e.g., the upcoming version 2 product of NASA's Black Marble VIIRS suite). These new products would enable us to derive new insights into existing urban application topics. For example, NTL products with medium and high spatial resolution can better reveal inner-city NTL variations, previously less capable with VIIRS and DMSP-OLS data. A better representation of NTL variation details inside urban areas is key to applications such as mapping polycentric cities, estimating building volumes, and identifying under-illuminated (e.g., crime-prone areas) and over-illuminated regions (e.g., heavily light-polluted areas) in urban areas. Multispectral NTL time series, such as those obtained from SDGSAT-1, can help to estimate changes in lighting sources and the subsequent changes in lighting-related energy consumption (Guo et al., 2023). This is particularly valuable in the campaign towards sustainable lighting. For example, incandescent and halogen products will be banned in the market of the US since August 2023, while general service lamps (like LEDs) will be enforced.

To fully capitalize on these advances, future studies should also look beyond the existing topics of applications and incorporate NTL data in other perspectives of urban studies, such as urban ecology, climate, disasters, human health, criminology, and environmental justice. Some of these new applications have been explored in the past few decades but they are still at a very early stage in light of the role that NTL data played and how NTL data are used in these applications. Further promoting these new applications would require breakthroughs in NTL remote sensing, such as developing new NTL data sources, addressing the scale effect, and improving the radiance transfer modeling to build a better all-sky city brightness map.

6. Conclusions

The year 2022 marks the 30th anniversary of urban NTL remote sensing since the first generation of NTL data was digitalized and archived in 1992. In this review, we examined the research trends, key progresses and challenges of NTL-based urban applications over the past 30 years and suggested future directions. Despite the recent proliferation of NTL-based applications, our assessment suggested that future urban NTL studies should not only focus on applications but also aim to better understand the characteristics and uncertainties of NTL data, to enhance the capabilities of NTL data by fusing with other datasets, to improve data accessibility and to explore new application areas.

While our paper primarily focused on NTL remote sensing in urban areas, it is worth noting that advancements in NTL studies in other fields, particularly those using other platforms (e.g., lab experiments and ground surveys) and focusing on natural ecosystems can significantly benefit urban NTL studies. For example, a better understanding of ALAN-induced phenology changes in natural ecosystems can complement the understanding of the mechanism of phenology changes in urban areas. Progresses in NTL field measurement equipment, image processing algorithms, urban spatial models, and socioeconomic data can also benefit urban NTL remote sensing. For instance, fine-scale demographic statistics can help to validate population grid estimates from NTL data and to study the effect of spatial scale. Urban 3-D models and digital twins could be useful for developing generalizable radiance transfer models for city lights.

In our bibliometric analysis, we focused on revealing the trends of how NTL data were used, by summarizing statistics in light of publication years, application topics, and NTL products. We highlight that graphic theory-based approaches, such as network analysis and centrality analysis, should be considered in future systematic surveys of NTL literature (Lee, 2006; Van Eck and Waltman, 2010). These methods are found effective in analyzing and visualizing the linkages among research topics, keywords or scholars, and can provide better insights into literature, especially from the perspective of authorship, research diversity and inclusion, and topic biases.

Ultimately, publishing research articles is just the first step. Urban NTL remote sensing scientists must collaborate more with other scientists in allied fields (e.g., urban NTL scientists and light pollution physicists). These scientists possess different knowledge, techniques, and data that can enhance each other to foster urban NTL remote sensing research. Additionally, scientists should work closely with stakeholders in different sectors to bridge the gap between their research focus and the needs of stakeholders. In this way, research can be translated into actionable steps, such as urban light pollution management, urban planning, biodiversity conservation and providing support for people affected by power outages and poverty.

CRediT authorship contribution statement

Qiming Zheng: Conceptualization, Methodology, Data curation, Software, Formal analysis, Visualization, Writing – original draft, Writing – review & editing, Funding acquisition. **Karen C. Seto:** Conceptualization, Writing – review & editing. **Yuyu Zhou:** Conceptualization, Writing – review & editing. **Shixue You:** Resources, Data curation, Visualization. **Qihao Weng:** Conceptualization, Methodology, Formal analysis, Writing – review & editing, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.isprsjprs.2023.05.028.

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