

Review

Multispectral nighttime light remote sensing: Data, applications, and challenges

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ABSTRACT

Nighttime light (NTL) remote sensing has made enduring contributions to characterizing human activity and urban evolution. Recently, NTL remote sensing has been undergoing a significant transition from the panchromatic to the multispectral era, evolving from measuring mere brightness to capturing spectral information. This shift creates unprecedented opportunities for understanding the physical composition of artificial lighting, monitoring its spectral evolution, and quantifying the complex interactions between lighting spectra and the natural environment. This paper presents a systematic literature review of 138 research articles published since 1992 to elucidate the data sources, application trends, and key challenges associated with multispectral NTL remote sensing. Based on the current state of the art, we highlight three key research directions for the future: (1) enhancing data acquisition and band processing capabilities by developing narrow-band multispectral sensors and integrating emerging platforms such as Unmanned Aerial Vehicles (UAVs); (2) establishing a quantitative framework tailored for NTL remote sensing to achieve reliable multi-source data fusion through the systematic correction of NTL radiance; and (3) advancing conventional panchromatic NTL applications to spectral-level analysis, thereby facilitating the expansion of NTL applications and information mining across interdisciplinary and multiple domains. Exploring these issues will advance the quantitative understanding and application of future multi/hyperspectral NTL remote sensing, providing novel scientific insights for sustainable urban planning, dark sky protection, and public health policymaking.

1. Introduction

Nighttime lighting sustains human nocturnal activity and serves as a critical proxy for characterizing socioeconomic development and quantifying anthropogenic impacts on the natural environment. For decades, observations of the global nocturnal light environment have predominantly relied on singular intensity measurements. However, contemporary urban lighting is undergoing profound structural and spectral transformations. A quintessential driver of this shift is the globally unfolding fourth lighting revolution: the transition from fire,

gas, and conventional electric lighting (arc and incandescent lamps) to blue-rich light-emitting diodes (LEDs) (Pust et al., 2015). Although these novel light sources demonstrate substantial potential for energy conservation and emission reduction (Cecchina, 2009; Global, E., 2018; Tcg, 2025), their blue-rich emission profiles have triggered a pervasive spectral shift in the global night sky. Consequently, this escalation of light pollution acts as an emerging environmental stressor with profound implications for global ecosystems and human health (Arroyo et al., 2024; Gaston and Sánchez de Miguel, 2022; Yin et al., 2024). This spectral evolution of lighting, typified by the widespread expansion

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of LEDs, underscores the inherent limitations of traditional single-band brightness observations. Given the increasingly complex physical composition of nocturnal light environments, there is a pressing need to investigate the spatiotemporal evolution of global artificial lighting, encompassing its intensity, spatial footprint, and spectral characteristics. Such comprehensive assessment is not only central to understanding the intricate interactions between modern human activities and natural ecosystems, but also a critical prerequisite for effectively advancing the Sustainable Development Goals (SDGs).

Nighttime light (NTL) remote sensing provides a unique means for monitoring nocturnal illumination activities through the capture of radiation emitted from the Earth's surface (Levin, 2025; Li et al., 2017; Li et al., 2024b). Since 1992, conventional single-band (panchromatic) NTL remote sensing has offered long-term technical support for measuring global urban light and has been extensively applied in numerous human activity-related domains, including urban evolution monitoring, economic assessment, and energy consumption estimation (Combs and Miller, 2023; Huang et al., 2014). Monitoring the spectral transition of nocturnal illumination and its corresponding global environmental impacts, however, necessitates NTL remote sensing capabilities featuring multispectral resolution. Panchromatic NTL data (e.g., NPP-VIIRS) inherently lack spectral resolution, and may even lack sensitivity to specific spectral bands (such as blue light). Consequently, this inability to differentiate the spectral properties and spatiotemporal evolution of modern nocturnal illumination (e.g., LEDs) hinders an in-depth analysis of the authentic response relationships between light

sources and the environment (Levin and Duke, 2012; Tuttle et al., 2014; Wu et al., 2013). Compared to panchromatic NTL data, multispectral data (specifically 3-10 bands) supplement the blue light band response and provide richer spectral information (Figure 1). Blue light radiation is more easily scattered by the atmosphere or water mist and is more prone to inducing biological responses, making it critical information for monitoring nighttime light pollution (Cao et al., 2023b). Blue band data recorded by multispectral NTL remote sensing technology will significantly advance the understanding of the impacts of artificial light at night on human health (e.g., epidemiology) and ecology (e.g., species rhythms) (Kyba et al., 2015). Furthermore, advancements in multispectral NTL data extend to the dimension of spatial resolution. For instance, the spatial resolution of SDGSAT-1 data is 40 m while JILIN-1 is even finer than 1 m. These resolutions are far superior to panchromatic data such as NPP-VIIRS and LJ1-01. Multispectral and high-resolution NTL data significantly enhance the mapping potential of land use and urban characteristics (Guk and Levin, 2020; Guo et al., 2023a), enable more effective assessments of socioeconomic development status, and provide a unique perspective in revealing the political, historical, and cultural differences of cities. This capability compensates for the information missing in panchromatic NTL data (Anderson et al., 2010; Levin and Duke, 2012). Therefore, multispectral NTL information not only enables the refined monitoring of nighttime cities such as light source classification but also provides crucial supplementary information for understanding the impact of artificial lighting on the nighttime environment. This holds milestone significance for understanding

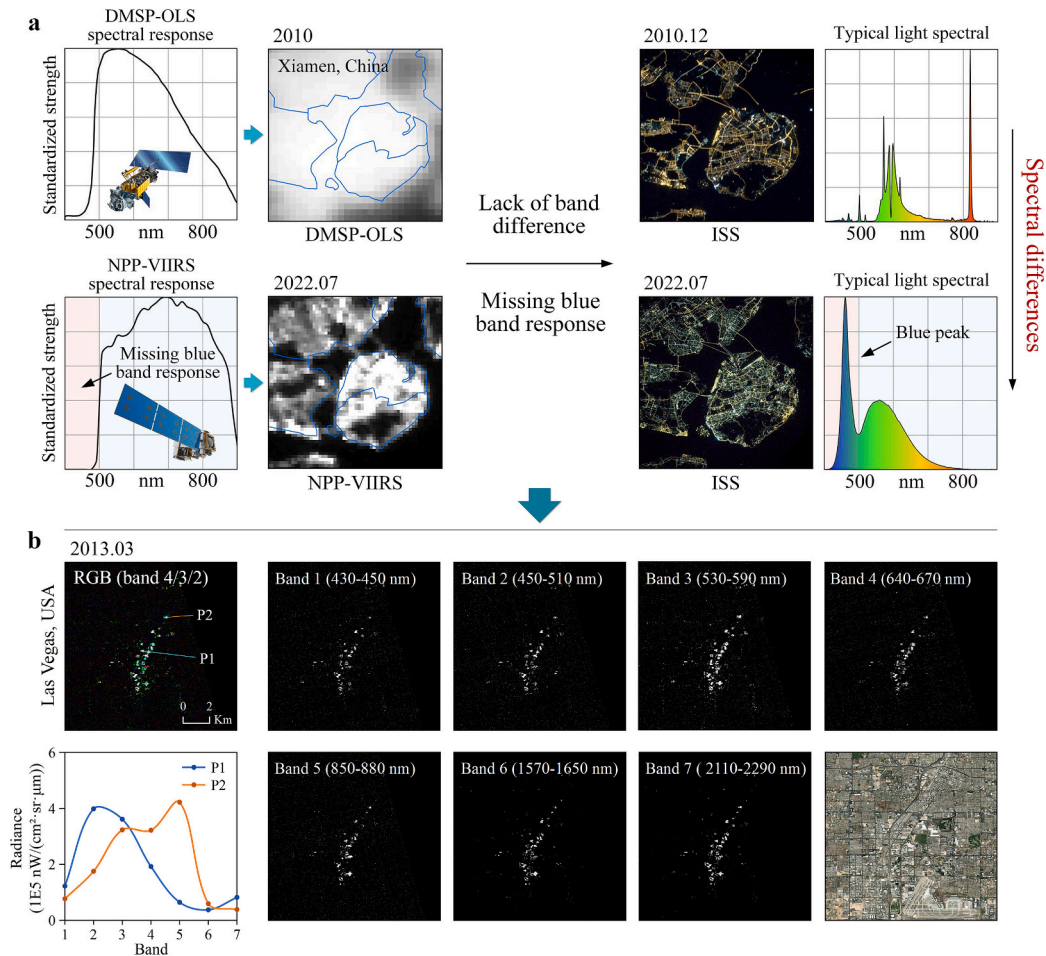


Fig. 1. Spectral evolution of urban lighting and characteristics of multispectral NTL remote sensing imagery. (a) The spectral response of panchromatic sensors fails to capture the spectral evolution of urban lighting. (b) Characteristics of multi-band NTL imagery. This panel includes seven bands of Landsat 8 and daytime imagery. A statistical plot displays radiance curves for two light source locations. Comparisons among DMSP-OLS, NPP-VIIRS panchromatic data, and ISS RGB images are shown, highlighting the significant differences in the blue light band before and after the widespread adoption of LED light sources.

nighttime human activities, their interactions with the natural environment, and the SDGs.

To overcome the limitations inherent in panchromatic data, (Elvidge et al., 2007; Levin et al., 2020) advocated for the development of multispectral sensors with higher spatial resolution and spectral coverage spanning the blue to near-infrared range. The central objective is to enhance the accuracy of light source identification and environmental monitoring through spectral analysis. In recent years, multispectral NTL remote sensing, primarily based on RGB channels, has progressively advanced. The concomitant emergence and deployment of multispectral sensors (including digital cameras) and multi-source acquisition platforms (such as airborne and vehicle-borne systems) have established a multi-scale, multi-angle NTL measurement framework (Zheng et al., 2021). This progress has further stimulated applications such as light source classification, urban environment analysis, and dynamic light pollution monitoring (Bobkowska et al., 2024; Rybnikova et al., 2021a), simultaneously providing new data support for ecological studies, human health assessment, and the SDGs.

NTL remote sensing data have been archived for approximately 30 years since the 1990s, during which the spatial, radiometric, and spectral resolutions of long-term NTL datasets have progressively improved. Coupled with the rapid spectral evolution of urban lighting (e.g., spectral shifts) (Levin et al., 2020), this transition has intensified the urgent demand for advanced data, techniques, and methodologies in multispectral NTL remote sensing. Despite the significant advantages of multispectral NTL remote sensing technology, the following information and challenges remain unclear:

- (1) What is the current status of platforms, sensors, and data sources?
- (2) What is the progression of multispectral NTL data applications?
- (3) What key challenges persist in current research?

Given the surge in NTL remote sensing applications and the immense potential of multispectral NTL, a systematic review of published literature is necessary. Currently, no review systematically reports on the progress of multi/hyperspectral NTL remote sensing. This paper provides a systematic review of the data technologies, application trends, and key challenges of multispectral NTL remote sensing, and proposes potential directions for future development. The overarching goal is to inspire the quantitative application of multispectral NTL remote sensing in urban monitoring, environmental assessment, and sustainable development goals by overcoming current bottlenecks through the advancement of multispectral NTL remote sensing, improved data acquisition techniques, and the construction of multi-source data fusion models. The subsequent structure of this review is as follows: Section 2 provides a statistical analysis of the literature; Section 3 introduces various multispectral data sources; Section 4 showcases the application progress of multispectral NTL remote sensing; Section 5 comprehensively discusses the advantages, challenges, and future research directions of multispectral NTL; and Section 6 summarizes the conclusions.

2. Literature statistics

2.1. Statistical criteria

A systematic literature review on multispectral NTL remote sensing was conducted. To ensure the transparency and reproducibility of our literature search, we performed a systematic retrieval within the Web of Science (WoS) Core Collection database (specifically the SCI-EXPANDED and SSCI indices). The language of the retrieved literature was restricted to English, and document types were primarily limited to research articles and reviews. The search time span was from January 1992 to December 2025. In the first stage, the search field was defined as 'Topic' (TS, encompassing Title, Abstract, and Keywords). We conducted three independent combinatorial searches: (1) TS=("night light" OR "nighttime light" OR "night") AND TS=("remote sensing"); (2) TS=("night light" OR "nighttime light" OR "night") AND TS=("multiband" OR

"multispectral" OR "hyperspectral" OR "spectrum" OR "spectral"); and (3) TS=("night light" OR "nighttime light" OR "night") AND TS=("remote sensing") AND TS=("RGB"). This initial retrieval stage yielded a total of 4,656 records, including cross-duplicates. In the second stage, we performed a supplementary search guided by data sources, utilizing specific spaceborne and airborne platform names (e.g., ISS, SDGSAT-1, UAV) as Topic terms. To ensure comprehensiveness, we relaxed the document type restrictions during this stage to incorporate a broader range of database resources, such as conference papers and institutional reports, resulting in an additional 215 records.

Subsequently, the 4,871 retrieved documents were screened and classified. Studies relying exclusively on single-band (panchromatic) NTL data, duplicate records, and research unrelated to NTL remote sensing were excluded. Ultimately, a collection comprising 138 documents was finalized. To facilitate bibliometric analysis, the selected articles were reclassified according to title, publication year, journal, collaborator country, data source, multi/hyperspectral category, and application type (Figure 2).

2.2. Global landscape of multispectral NTL remote sensing research

Literature statistics indicate that the application of multispectral NTL remote sensing data has expanded since 2010 and has exhibited a sharp upward trend in recent years (Figure 3a). The significant growth observed after 2015 was primarily driven by the widespread adoption of LED lighting in global cities and the subsequent demand for research on light pollution and source detection. In terms of data sources, studies utilizing International Space Station (ISS) imagery occupied a dominant position prior to 2021 with a share of 36.8%. This landscape changed after 2022 as the Sustainable Development Science Satellite 1 (SDGSAT-1) became the leading data source (51.6%) (Figure 3b). This shift is attributed to the advantages of SDGSAT-1 in providing radiometrically calibrated and georeferenced data with more stable spatial resolution and revisit cycles compared to other sensors. Geographically, research is primarily concentrated in China (57 papers), the United States (31 papers), and Spain (20 papers). Notably, Africa remains the only continent without participating national collaborators in these published cases (Figure 3c). Furthermore, research priorities diverge significantly across nations. Studies in China mainly focus on urban evolution while those in the United States prioritize light source detection. In contrast, researchers in Australia, Canada, and European nations concentrate predominantly on light pollution issues.

3. Data sources

Large-scale measurements in multispectral NTL remote sensing date back to the 2000s. NTL photography captured by astronauts aboard the ISS revealed the earliest color NTL information, with formal concentrated acquisition commencing in January 2003 (Figure 4a). Subsequently, the first research paper concerning ISS nighttime imagery was published in 2010, characterizing the relationship between population density and multispectral nighttime imagery (Anderson et al., 2010). Although some ground-based nocturnal imaging, including rooftop cameras, provided localized multispectral NTL data, their utility and research scope were largely restricted. The concept of systematic spaceborne multispectral NTL remote sensing (Nightsat) was proposed by (Elvidge et al., 2007) in 2007, highlighting the significant advantages of multispectral NTL imaging for observing variables related to the environment, human activity, and the economy. Meanwhile, hyperspectral NTL imagery was acquired via airborne platforms in 2009, with subsequent research on light source identification published in 2011 (Kruse and Elvidge, 2011). Since the 2010s, the measurement of multi/hyperspectral NTL data has been progressively explored across various platforms. Categorized by platform type into spaceborne platforms, airborne platforms, and other devices, information regarding the first publication date, spatial resolution, data continuity, and sources of

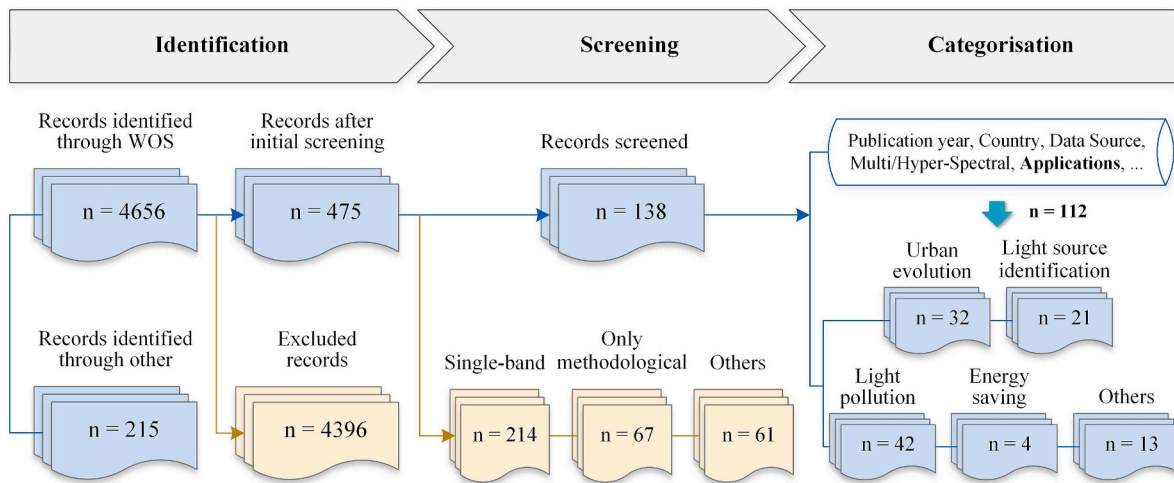


Fig. 2. Literature screening and classification process.

multi/hyperspectral NTL data is presented (Figure 4 and Table 1).

3.1. Spaceborne platforms

Multispectral NTL data are primarily provided by spaceborne and airborne platforms. Based on chronological order, four major spaceborne platform data sources are highlighted: ISS, Landsat, JILIN-1, and SDGSAT-1.

3.1.1. International Space Station (ISS)

The ISS was officially established in 1998, and since 2003, Digital Single-Lens Reflex (DSLR) cameras have been used to formally capture NTL images, providing the longest continuous record of color NTL data to date. The ISS orbits at an average altitude of approximately 400 km, typically fluctuating between 330 and 435 km, with an orbital period of about 90 minutes, completing approximately 16 orbits around the Earth daily (Sánchez de Miguel et al., 2021b). The orbital inclination of the ISS is approximately 51.6°. NTL photographs are typically captured at oblique angles rather than at the nadir, with swath widths ranging from several kilometers to hundreds of kilometers, capable of covering approximately 90% of the Earth's inhabited areas. Data are provided by The Gateway to Astronaut Photography of Earth (GAPE) (<https://eol.jsc.nasa.gov/SearchPhotos/>). Figure 5 illustrates the nighttime imaging density of the ISS nadir points provided by the website. Notably, because it is difficult to completely distinguish whether these are high-quality NTL images or other types of observations (e.g., atmospheric or horizon imaging), the actual number of valid NTL images may be limited, despite the total number of these mixed images reaching one million. Some open-source projects provide considerable references for curated images (Sánchez de Miguel et al., 2014; Stoken and Fisher, 2023), such as the Cities at Night project (<https://citiesatnight.org/about-cities-at-night/>). Figure 6 illustrates the global distribution of the high-resolution, cloud-free NTL images selected in this study, covering approximately 200 major cities worldwide from 2008 to 2023.

The primary DSLR camera models mounted on the ISS for acquiring NTL data include the D2 Xs, D3, D3s, D4, D5, and Z9 (Gape, 2024), with focal lengths ranging from 10 to 800 mm. CMOS sensors have been employed starting with the D2 Xs model. All the aforementioned cameras are equipped with Bayer filters, enabling the provision of simultaneous red, green, and blue (RGB) images (Sánchez de Miguel et al., 2021b). The spatial resolution of these images predominantly falls within the 5–100 m range, and they lack georeferencing and radiometric calibration. Due to the ISS orbit and inconsistent flight times, the images captured by astronauts lack a fixed periodicity, and the database is updated irregularly (Kyba et al., 2015). Recently, the ISS image

georeferencing project developed by (Stoken and Fisher, 2023) has provided geographical references (<https://eol.jsc.nasa.gov/ExplorePhotos/>). ISS data are provided in two formats consisting of Raw files (such as .NEF) and compressed 8-bit .JPG data. For remote sensing applications, it is required to download the data in Raw format (which may be unavailable for some early images) and employ a decoding method devoid of any digital processing (such as white balance or gamma correction). This process is necessary to obtain primitive Top of Atmosphere (TOA) observations and output them as 16-bit TIFF images, which constitute multispectral NTL imagery in the traditional sense. The recommended decoding parameters are “-o 0 -H 1 -r 1 1 1 -4 -T”, and the decoding software can be referenced at LibRaw (<https://www.libraw.org/>). Nevertheless, the decoded ISS data is only a relative digital signal (DN), and its systematic use still requires solving the problems of radiometric inversion and quantification. Compared to satellite sensors specifically designed for NTL imaging, the radiometric quantification of ISS NTL images is significantly more complex (Sánchez de Miguel et al., 2021b). Figure 7 shows the schematic diagram of the imaging process and radiometric correction for ISS data. Some studies have made key attempts, and partially corrected images have been made commercially available (Nocatosat, 2025).

3.1.2. Landsat

Within the Landsat program, the acquisition and application of NTL data commenced with the Landsat 8 satellite (Levin and Phinn, 2016). Landsat 8 was launched in 2013, initiating its data collection mission. It operates in a near-polar Sun-Synchronous Orbit (SSO) at an altitude of approximately 705 km, with an orbital inclination of 98.2° and an orbital period of roughly 99 minutes. The satellite acquires over 700 scenes daily, featuring a revisit period of 16 days for the same location. Equipped with the Operational Land Imager (OLI) sensor, it collects image data across 9 bands within a 185 km × 185 km swath, covering common NTL spectra. The spatial resolution is 30 m (Wu et al., 2024a). The Landsat 8 sensor was not designed for nighttime imaging and exhibits very low sensitivity to NTL, limiting it to recording only high-intensity light sources ($> 40,000 \text{ nW}/(\text{cm}^2 \cdot \text{sr} \cdot \mu\text{m})$) (Levin and Phinn, 2016). Landsat 9, launched in 2021, primarily serves to sustain the observational capabilities of Landsat 8. Landsat nighttime imagery is currently one of the few data sources providing radiometrically calibrated narrowband NTL radiance values, and may serve as validation or comparison data for bright light sources in multi-source remote sensing, thus holding development potential (Figure 8). Currently, all nighttime scene images captured by Landsat satellites are publicly accessible via the USGS Earth Explorer platform (www.usgs.gov/landsat).

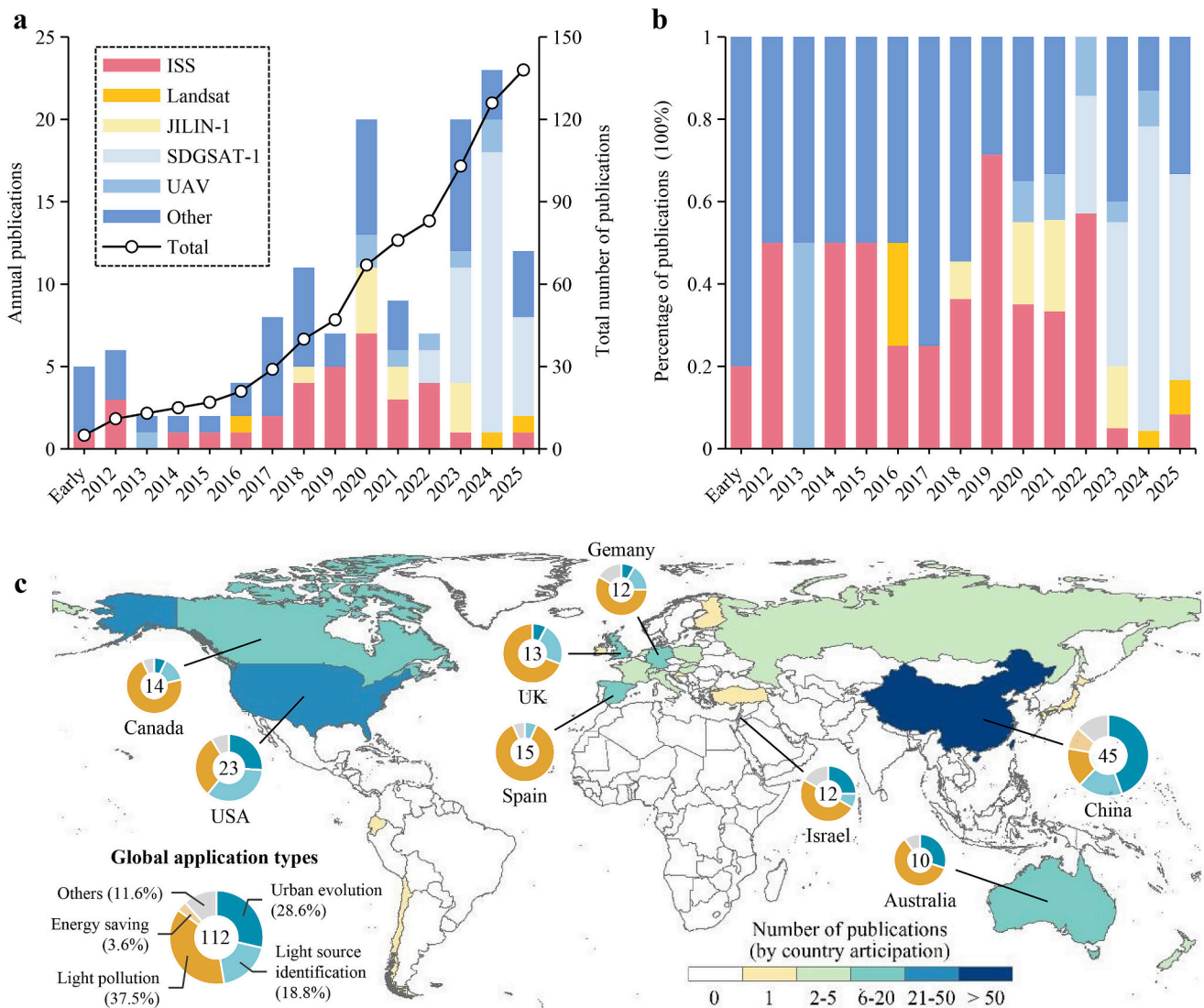


Fig. 3. Literature statistics and analysis. (a) Number of articles published using different NTL data sources. (b) Percentage distribution of published articles by data source. (c) Frequency of countries participating as collaborators in published articles. The fill color of the map represents the total number of papers authored by each country (e.g., 57 papers for China), and the donut chart represents the subset of these papers classified as application-oriented papers (corresponding to Section 4) (e.g., 45 papers for China). Application types are classified into five categories, and a single paper may involve multiple collaborative countries and multiple application categories.

3.1.3. JILIN-1

The JILIN-1 series of multispectral nighttime satellites comprises commercial satellites, including the JILIN-1 03B/C and Video 07/08 satellites (Zhao et al., 2019). JL1-03B, launched in 2017, serves as a representative of this NTL remote sensing satellite series. It operates in a SSO at an altitude of 535 km, utilizing area array staring imaging. The satellite has an orbital period of approximately 95 minutes, with a minimum revisit period of 3 days for the same location. JL1-03B possesses synergistic observation capabilities featuring a panchromatic resolution of 0.98 m and a multispectral resolution better than 4 m, with a swath width of approximately 17 km. The visible light imaging system covers three spectral channels (RGB), with a Signal-to-Noise Ratio (SNR) exceeding 62 (Zheng et al., 2018) and a dynamic range reaching 120 dB; it also provides on-board calibration. The data needs to be obtained through a commercial platform (<https://www.jl1mall.com/store/ResourceCenter>).

3.1.4. SDGSAT-1

SDGSAT-1 was launched in 2021 and successfully acquired NTL data.

The satellite operates in an SSO at an orbital altitude of 505 km, with an orbital inclination of 97.5° and a ground target revisit period of approximately 11 days (Cbas, 2021). The low-light imager of SDGSAT-1 is designed with one panchromatic band P (PL/PH) and three color bands (RGB). The onboard Glimmer Imager Unit (GIU) utilizes a push-broom mode to acquire multispectral NTL data (Liu et al., 2023b), with a spatial resolution of 40 m for color NTL data (Guo et al., 2023a) and a swath width reaching 300 km. The SNR of the GIU exceeds 50 for urban main road lighting, and the dynamic range within the same scene can exceed 60 dB (Li et al., 2024a). Multispectral NTL data can be requested via the public platform (<https://www.sdgsat.ac.cn/>) (Figure 9).

3.1.5. Other spaceborne platforms

Beyond the aforementioned platforms, certain CubeSats or optical satellites also provide limited amounts of multispectral NTL data. For instance, the US AeroCube small commercial CubeSats (AC-4/5/8) began recording NTL imagery in 2014. Covering RGB imaging spectral bands, they possess a spatial resolution exceeding 100 m and an

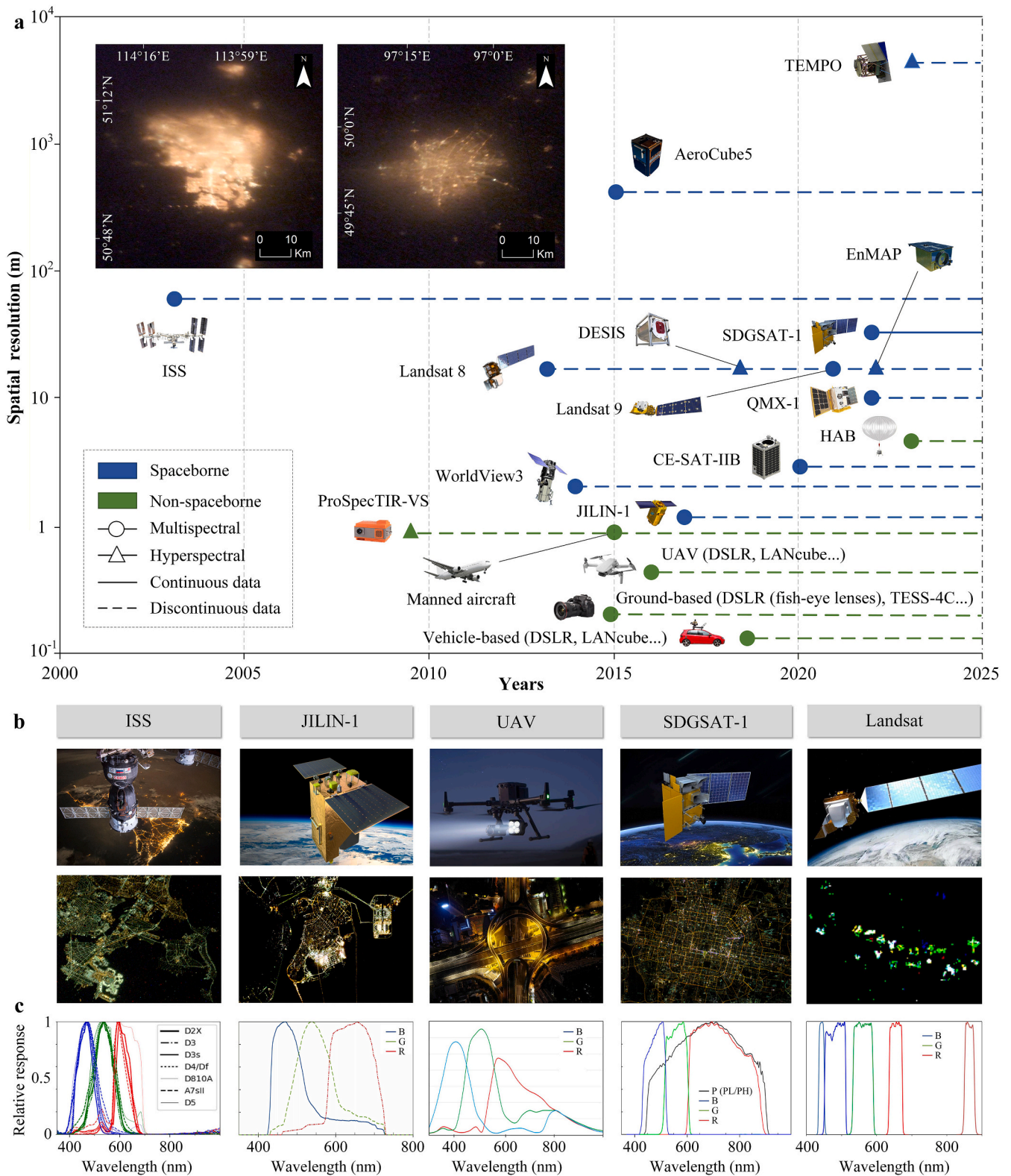


Fig. 4. Multispectral NTL remote sensing data source platforms with publicly data records. (a) Parameters of data source platforms. The images display the first batch of NTL photographs captured by the ISS on January 25, 2003; the left panel shows Calgary (ISS006E21458), and the right panel shows Winnipeg (ISS006E21460). The scattering and occlusion of urban lights by the atmosphere and clouds above the cities during acquisition are evident. (b) Examples of major multispectral NTL data sources, and corresponding sensor spectral response curves (c).

Table 1
Parameters of spaceborne multispectral NTL remote sensing sensors.

Sensor	Start date	Spatial resolution (m)	Revisit period	Imaging time (Local time)	Data source	Spectral bands	Key references
Astronauts' photos from ISS	2003.01	6-100	Irregular	Variable	https://eol.jsc.nasa.gov/	RGB (Bayer) B: 400-550 nm G: 460-610 nm R: 580-690 nm	(Kyba et al., 2015; Sánchez de Miguel et al., 2019)
AeroCube 4/5/8	2012.09	124	Irregular	Variable	https://aerospace.org/	RGB (Bayer) B: 400-520 nm G: 480-600 nm R: 580-700 nm	(Pack and Hardy, 2016; Pack et al., 2017)
Landsat 8/9	2013.02/2021.09	30	16 days	22:00 (Ascending node)	https://earthexplorer.usgs.gov/	7 bands within 430-2290 nm Band 1: 430-450 nm Band 2: 450-510 nm Band 3: 530-590 nm Band 4: 640-670 nm Band 5: 880-880 nm Band 6: 1570-1650 nm Band 7: 2110-2290 nm	(Levin and Phinn, 2016)
WorldView-3	2014.08	1-2	Irregular	21:30-23:30 (Ascending node)	https://earth.esa.int/eogateway/missions/worldview-3#data-section	8 bands within 400-1040 nm Band 1: 400-450 nm Band 2: 450-510 nm Band 3: 510-580 nm Band 4: 585-625 nm Band 5: 630-690 nm Band 6: 705-745 nm Band 7: 770-895 nm Band 8: 860-1040 nm	(Barentine et al., 2021)
JILIN-1 (JL1-3B/C, JL1-07/08)	2017.01	~ 0.9	3 days	21:00-23:00 (Ascending node)	https://www.jl1mall.com/	RGB (Bayer) B: 437-512 nm G: 489-585 nm R: 580-723 nm	(Guk and Levin, 2020; Watson et al., 2023; Zheng et al., 2018)
DEGIS	2018.06	30	Irregular (same as ISS)	Variable	https://teledyne.tcloudhost.com/	Hyperspectral, 235 bands within 400-1000 nm	(Dlr, 2018; Ryan et al., 2024)
CE-SAT-IIB	2020.10	5	5 days	22:00-23:00 (Ascending node)	https://www.restec.or.jp/en/index.html	RGB (Bayer) B: 450-510 nm G: 510-580 nm R: 630-690 nm	(Matsuzawa et al., 2021; Murata et al., 2023)
SDGSAT-1	2021.11	40	11 days	21:00-22:00 (Ascending node)	https://www.sdgsat.ac.cn/	3 bands within 430-900 nm B: 430-520 nm G: 520-615 nm R: 615-900 nm	(Guo et al., 2023a; Guo et al., 2025; Yin et al., 2024)
QMX-1	2022.02	21	11 days	22:00-23:00 (Ascending node)	https://qmx.whu.edu.cn/	9 bands within 400-1000 nm and RGB (Bayer)	(Zhong et al., 2023)
EnMap	2022.04	30	4 or 27 days (depending on viewing angle)	22:30-23:30 (Ascending node)	https://www.enmap.org/	Hyperspectral, 242 bands within 420-2450 nm	(Bachmann and Storch, 2023; Guanter et al., 2015)
TEMPO	2023.08	3250	Irregular (Geostationary orbit)	Variable	https://search.earthdata.nasa.gov/	Hyperspectral, 1000 bands within 540-740 nm	(Carr et al., 2017; Carr et al., 2024)

irregular imaging cycle. The detection threshold is approximately 20 nW/(cm²·sr), with an SNR reaching 4 dB (Pack and Hardy, 2016; Pack et al., 2017). The Qimingxing-1 (QMX-1) satellite, developed by Wuhan University, features nighttime visible light imaging capabilities. It is designed with 9 NTL imaging bands, covering a swath of 107 km with a resolution of 21 m (Zhong et al., 2023). However, multispectral NTL data from this source have not yet been publicly released. CE-SAT-IIB is a microsatellite developed by Canon, launched in October 2020. Its sensor is an ultra-high-sensitivity camera capturing nighttime imagery containing RGB bands, with a resolution of up to 5 m (Murata et al., 2023; Tellus, 2021). Certain high-resolution commercial optical satellites also possess multispectral NTL acquisition capabilities, such as the commercial high-resolution remote sensing satellite WorldView-3, launched in 2014. It features eight bands and achieves a resolution of

1-2 m (Barentine et al., 2021; Esa, 2015). It should be noted that satellite sensors with daytime imaging as their primary objective (such as WorldView and Landsat), although capable of nighttime imaging, are insensitive to low-light NTL and can only image high-intensity light sources.

In addition to multispectral data, three cases of hyperspectral NTL observation spaceborne platforms have been reported (Table 1). The German Aerospace Center (DLR) Earth Sensing Imaging Spectrometer (DEGIS), launched in 2018, operates within the Multi-User System for Earth Sensing (MUSES) platform on the ISS. The DEGIS sensor features 235 bands covering a wavelength range of 400–1000 nm, with a spatial resolution of 30 m (Dlr, 2018, 2019). The Environmental Mapping and Analysis Program (EnMAP) is a German hyperspectral satellite mission that commenced operations in April 2022. It carries a dedicated push-

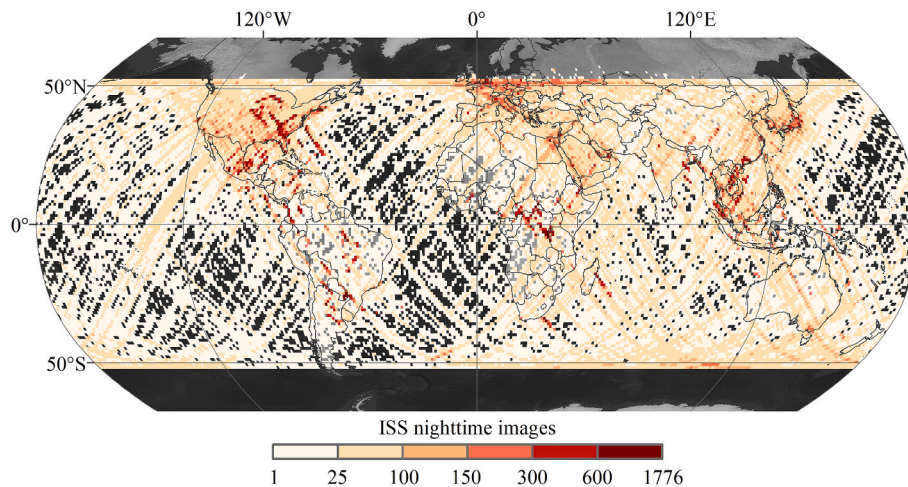


Fig. 5. Global distribution of ISS nighttime imagery from 2002.02-2025.12, showing the locations of images that are “Cataloged with Center Point” and “No Center Point” ($n = 9,698$), as well as those that are “Not Cataloged” or were “Cataloged by Machine Learning” ($n = 1,212,730$). It should be noted that these datasets contain a mixture of NTL images and other types of imagery, which have not yet been fully classified or definitively quantified.

broom hyperspectral imager with a spectral range of 420-1000 nm, a swath width of 30 km, and a spatial resolution of 30 m (Bachmann and Storch, 2023; Guanter et al., 2015). Tropospheric Emissions: Monitoring of Pollution (TEMPO), equipped with a visible-light-sensitive spectrometer, is the first geostationary NTL observation satellite (Carr et al., 2024). Launched in 2023 to begin data acquisition, it is primarily used for air quality monitoring. Its spectral range is 293-741 nm, with a spatial resolution of 2 km in the north-south direction and 4.75 km in the east-west direction (Carr et al., 2017; Tempo, 2015).

3.2. Airborne platforms

3.2.1. UAV

The acquisition of multispectral NTL remote sensing data using Unmanned Aerial Vehicle (UAV) systems represents an emerging technology that synergizes the high flexibility of UAVs with the unique advantages of NTL remote sensing (Colomina and Molina, 2014; Tate et al., 2020). UAVs typically operate at flight altitudes of 50-500 m and are generally equipped with digital or professional multispectral cameras, such as the Sony $\alpha 7$ series, Canon EOSR series, Nikon Z series, and MicaSense RedEdge series. Most are outfitted with CCD or CMOS sensors, achieving centimeter-level resolution (Fiorentin et al., 2018).

3.2.2. Manned aircraft

Conducting multispectral NTL remote sensing via manned aircraft constitutes a large-scale, highly efficient method of surface observation, which is particularly suitable for regional nocturnal light environment monitoring (Hale et al., 2013). The cruising altitude of such aircraft typically ranges from 0.5 to 3 km. When employing wide-angle lenses, the swath width can reach 1-5 km, with a spatial resolution of approximately 1-5 m. Manned aircraft are also capable of carrying hyperspectral imaging equipment for nocturnal imaging (Kruse and Elvidge, 2011). For instance, the ProSpecTIR-VS airborne hyperspectral system integrates Specim's Airborne Imaging Spectrometer for Applications (AISA) and the Eagle (VNIR) imaging spectrometer, enabling the simultaneous acquisition of hyperspectral data covering the 0.4-0.9 μm spectral range (Kruse et al., 2012).

3.2.3. High-altitude balloons (HAB)

Utilizing High-Altitude Balloons (HAB) for NTL remote sensing constitutes a unique approach to Earth observation. By mounting digital cameras on balloons, imagery analogous to ISS data can be acquired. Small-scale HABs (such as latex balloons) represent an effective method for transporting lightweight payloads (Walczak et al., 2023). HABs can

reach flight altitudes of up to 20 km (stratospheric levels), achieving swath widths of 20-40 km while maintaining high spatial resolution (1-10 m). During ascent or transit, they are capable of imaging light sources from varying altitudes and angles (Aubé et al., 2023). However, controlling the flight trajectory is typically challenging.

3.3. Other devices

Vehicle-based platforms represent a flexible and efficient ground-based observation method in NTL remote sensing, primarily employed for acquiring high-precision nocturnal light environment data of localized areas and for conducting spaceborne in situ measurements (Levin, 2023a). Cameras are typically mounted on vehicle roofs or dedicated brackets at heights of 2-5 m. When employing wide-angle lenses, the swath width can reach 10-50 m, with a resolution of 1-10 cm. Vehicle-based platforms are also frequently equipped with Sky Quality Meters (SQM) or multispectral ground-based photometers to conjointly conduct NTL data measurement missions (Sánchez de Miguel et al., 2017; Xu et al., 2018). For instance, the LANcube is an open-source and low-cost multi-angle and multispectral photometer developed by (Aubé et al., 2020a, 2020b). It is typically integrated with vehicle-based platforms to simultaneously measure light radiance from five to six faces (Levin, 2023a). The SQM does not directly provide spatial resolution but rather measures the integrated brightness in a specific direction (Cinzano, 2007). However, when equipped with RGB color filters, the SQM can be transformed into a low-cost multispectral observation instrument, and multiple units can be combined to form a multispectral observation array (Kyba et al., 2012). The TESS-4C is a four-channel version of the TESS-W photometer covering the 380 to 750 nm spectral range and is frequently used for stationary observations (Labrousse et al., 2025). Furthermore, NTL remote sensing via rooftop or web cameras provides a method for continuous observation at fixed locations, serving as supplementary data for ground measurements (Baur et al., 2018). Rooftop platforms are often equipped with various high-performance digital cameras or professional multispectral cameras. By utilizing DSLR cameras with fish-eye lenses, they can track and capture sky brightness over a large field of view (Jechow et al., 2018). At installation heights of 30-100 m, resolutions down to the centimeter level can be achieved, with swath widths reaching up to a kilometer. While ensuring stability and appropriate shooting angles, considerations must also be made regarding camera vibration and pointing drift (Dobler et al., 2015).

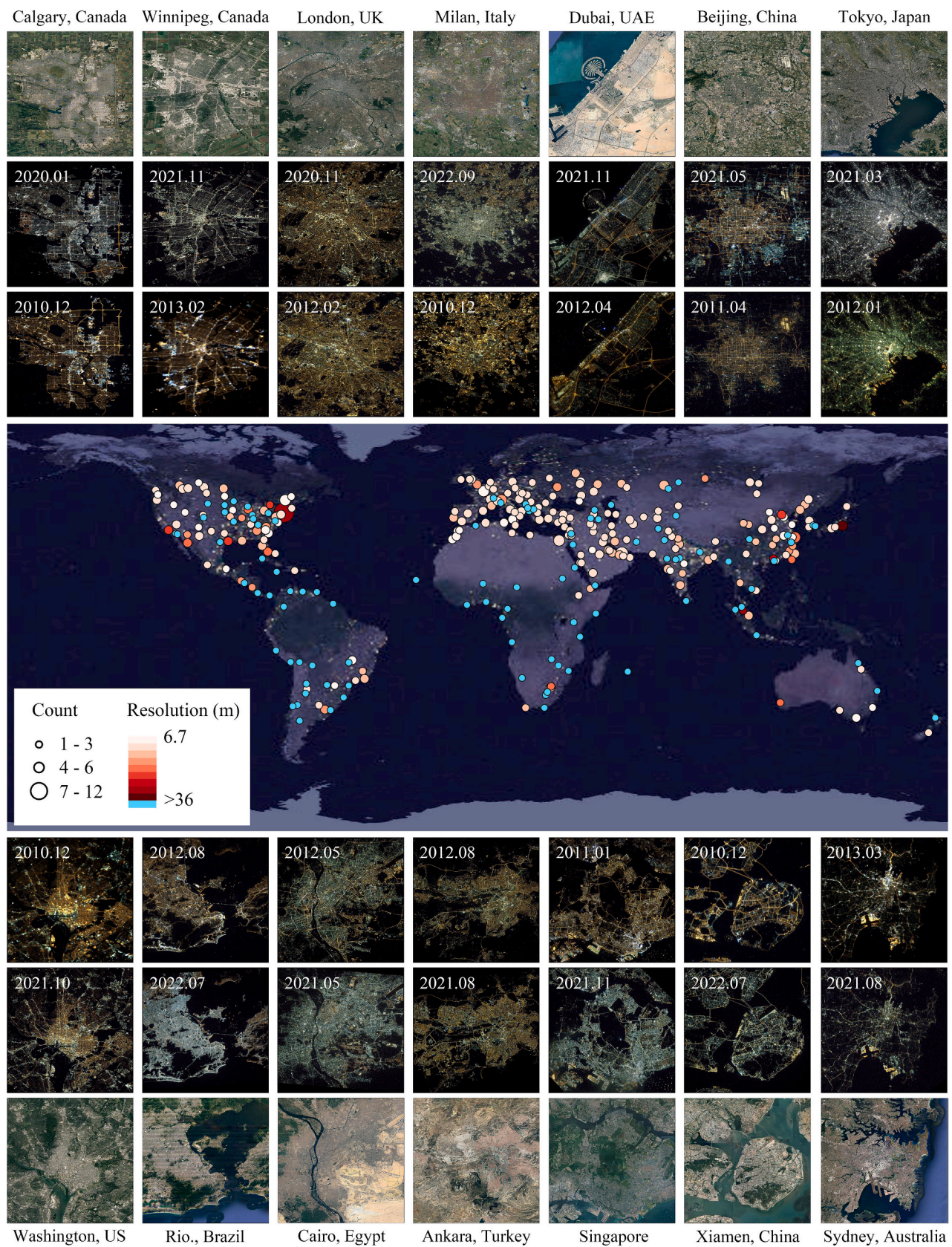


Fig. 6. Global distribution of high-resolution (average 11.7 m), cloud-free ISS NTL images of 200 major cities from 2008 to 2023 (n = 681).

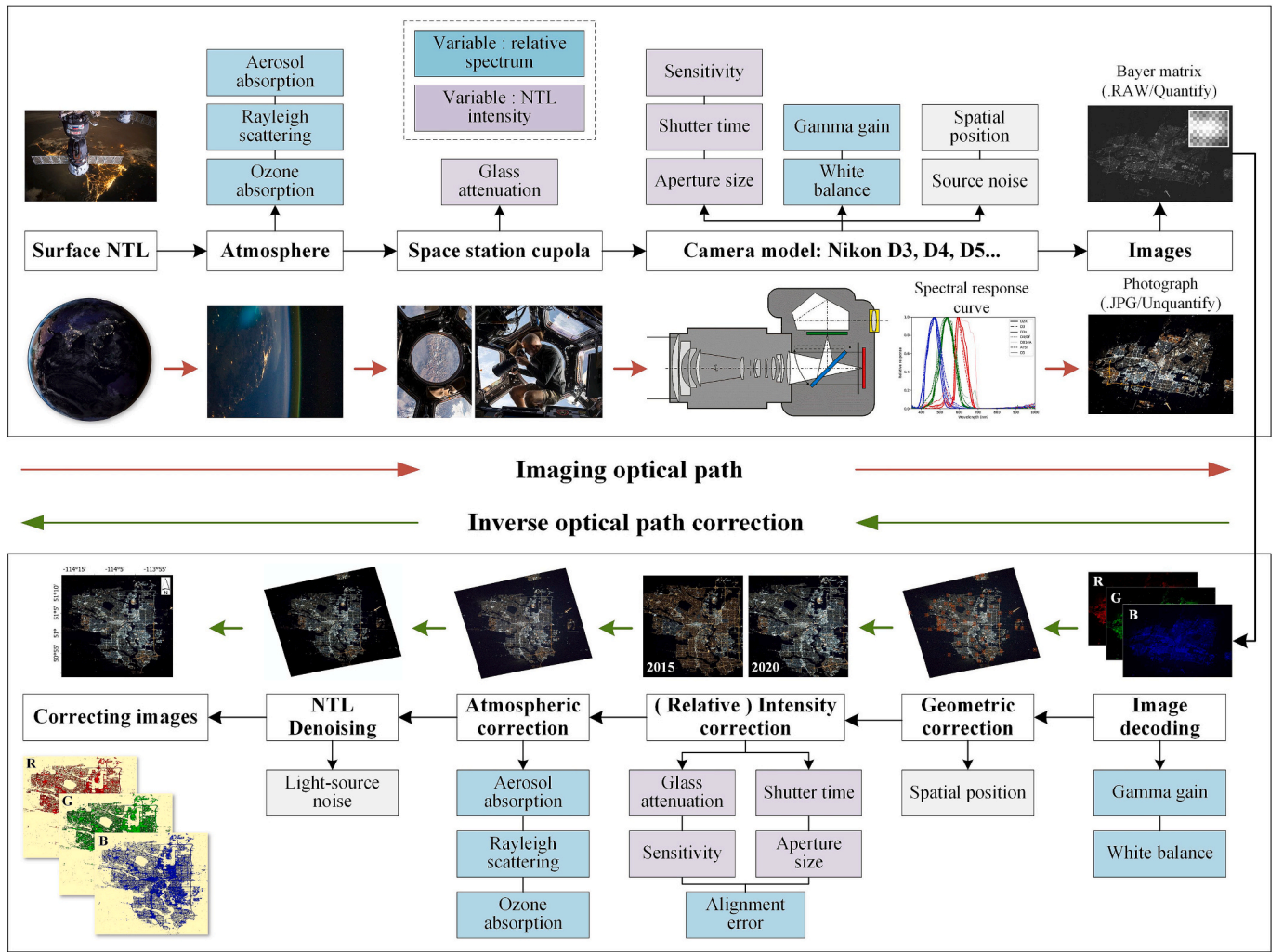


Fig. 7. Schematic diagram of the ISS NTL imaging, decoding, and radiometric correction processes.

4. Applications of multispectral NTL remote sensing

This section systematically outlines the core application scenarios of multispectral NTL remote sensing. These applications are categorized into four themes, including identifying urban lighting sources, assessing energy conservation and emission reduction in urban lighting, quantifying light pollution disparities, and analyzing urban and social evolution. A small number of studies are classified under other application scenarios (Figure 10). For each theme, the current progress achieved in multispectral NTL remote sensing is reviewed, methodological advancements are discussed, and prospects and challenges are highlighted.

4.1. Identifying urban lighting sources

Milan, Italy, is considered one of the earliest cities globally to widely adopt LED lighting, having completed the LED retrofit of its main urban area in 2015 (Iau, 2015). LED fixtures are mandated for sale in some nations, such as the United States. Certain sectors predict that global urban lighting sources will progressively transition to LEDs by 2030 (Kyba et al., 2017; Pr, 2023; Tcg, 2015). However, the dynamics of widespread light source renewal at the global level remain unclear. This has prompted light source monitoring to become a primary application of multi/hyperspectral NTL remote sensing (accounting for approximately 19% of the application literature). Its primary objective is to identify and distinguish different types of light sources to further evaluate the information on urban evolution implicit in light source updates

and their multiple impacts on the nocturnal environment. Urban interiors contain various light sources, such as LEDs (of multiple color temperatures), High-Pressure Sodium (HPS), fluorescent lamps, and halogen lamps (Mohurd, 2008). These sources differ in classification methods, spectral characteristics, and spatiotemporal distribution (Table 2).

Spectral characteristics serve as a crucial basis for light source identification, as different light sources exhibit significant differences in radiometric properties across the visible and near-infrared bands (Elvidge et al., 2010; Jia et al., 2024). Panchromatic NTL data lack the ability to discern spectral differences and are therefore unable to distinguish light source types, whereas multispectral data (such as R/G/B bands) demonstrate a significant leap forward in identifying various artificial light sources within urban areas. Currently, almost all applications of multi/hyperspectral NTL remote sensing data are conducted based on broad-band RGB imagery. Despite the immense potential of light source monitoring, classifying light sources using limited NTL spectral information remains highly challenging. Methods using spectral indices (Jia et al., 2024) have identified and distinguished red LEDs, white LEDs, and other light sources in cities of China's coastal provinces. Compared to index thresholds, machine learning methods employing supervised classification have demonstrated relatively broader application potential. For instance, approaches combining ISODATA clustering, manual class merging, and decision tree classifiers, as well as neural networks, maximum likelihood, and Support Vector Machines (SVM), have been implemented to identify LEDs and other light sources

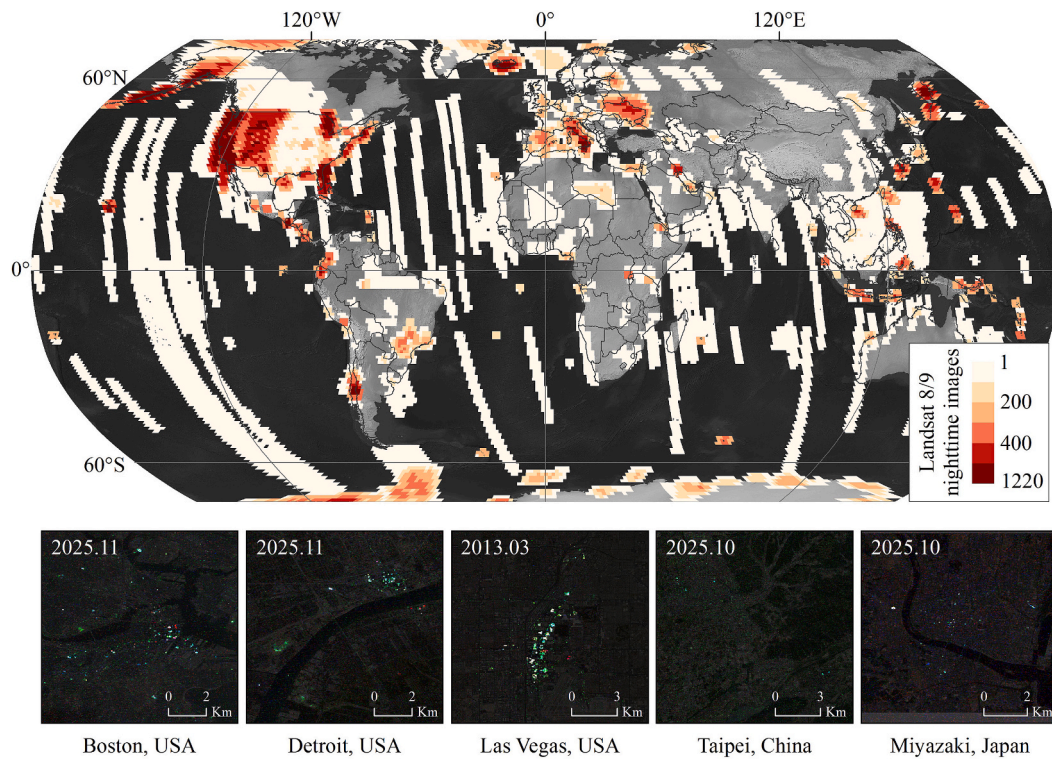


Fig. 8. Global distribution of Landsat 8/9 nighttime imagery from 2013 to 2025 ($n = 106,878$), alongside selected city NTL images (bands 4, 3, and 2) overlaid on daytime imagery. The displayed NTL imagery represents radiometrically calibrated Top of Atmosphere (TOA) radiance, expressed in units of $nW/(cm^2 \cdot sr \cdot \mu m)$.

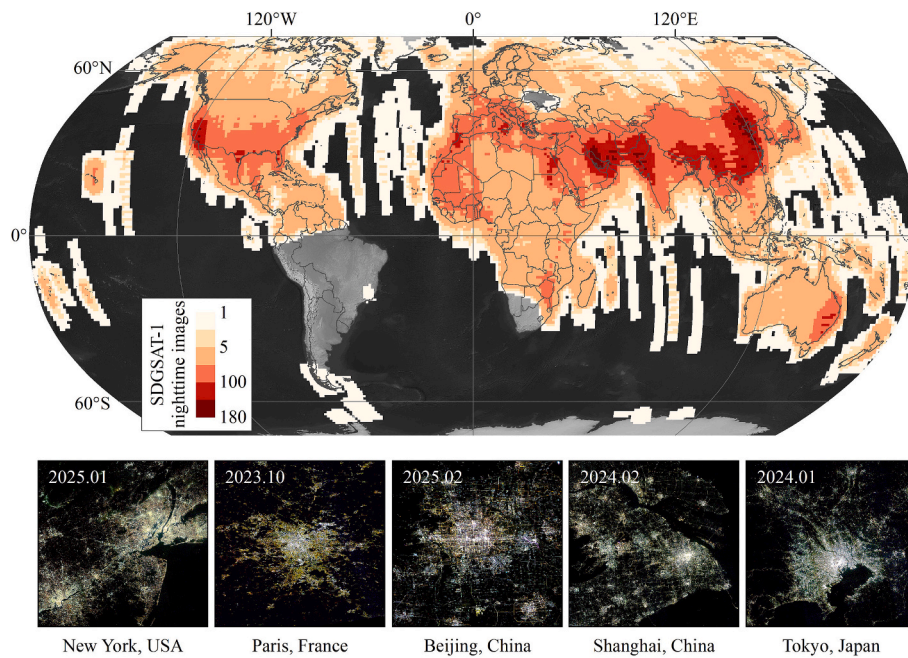


Fig. 9. Global distribution of SDGSAT-1 NTL imagery from 2021 to 2025, along with selected city images ($n = 36,157$).

(Cheng et al., 2020; Liu et al., 2024a; Zheng et al., 2018). Furthermore, Random Forest and its extensions have exhibited wide applicability, such as achieving LED light source classification in specific scenarios like the road level or urban scale (Watson et al., 2023; Yin et al., 2024; Zou et al., 2025).

While progress has been made in identifying and distinguishing light source types using RGB NTL remote sensing data, analyses targeting specific regions or scenarios may lack generalization, and the types of

distinguishable light sources remain limited. A few cases utilizing ground-based hyperspectral imaging equipment to acquire NTL remote sensing imagery have classified lighting sources, identifying at least 6-7 types and revealing over 40 distinct spectral clusters (Dobler et al., 2016). This indicates that classifying light sources using broad-band RGB NTL imagery may involve significant uncertainty. Some studies have raised similar concerns; (Sánchez de Miguel et al., 2019) conducted a preliminary exploration of urban light source classification using NTL

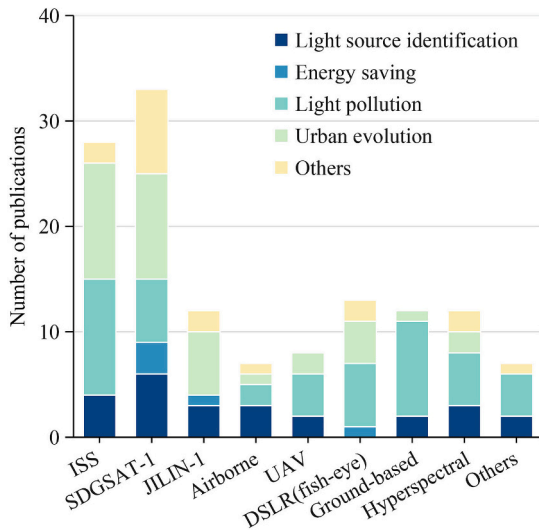


Fig. 10. Number of application studies categorized by data source (a single paper may include multiple application scenarios).

remote sensing technology. By simulating ISS imagery and displaying laboratory-measured spectra of approximately 10 major categories of common lighting sources in a panel format, they found it difficult to

precisely distinguish between the various sources. Moreover, similar conclusions were drawn through comparisons with light source classification results from RGB and low-altitude hyperspectral data (Kruse and Elvidge, 2011; Metcalf, 2012). Consequently, relying solely on RGB NTL imagery presents severe limitations. Specifically, while broad RGB bands can relatively easily separate HPS lamps from LEDs, they cannot distinguish among spectrally similar white light sources, such as Compact Fluorescent Lamps (CFL), MH lamps, and white LEDs. Such fine-grained discrimination necessitates hyperspectral data or multispectral sensors with more narrow visible bands (Yu et al., 2026). Furthermore, differentiating among Correlated Color Temperatures (CCT, e.g., 2000K, 3000K, and 4000K) within the LED category itself introduces an additional challenge, strictly requiring high spectral resolution to accurately capture subtle shifts in the blue emission peak. Moreover, in practical applications, classification accuracy varies across different environments due to the effects of environmental spectral mixing, which encompasses both direct light emissions and surface reflections.

High spatial resolution multispectral NTL data will provide greater detail regarding spectral differences between light sources for monitoring purposes. Simultaneously, machine learning and deep learning have demonstrated immense potential in image processing, presenting significant room for exploration in light source monitoring within the NTL remote sensing field. By training on specific target samples (such as LED sources) and integrating other data sources (such as urban renewal data and ground samples), there is considerable potential for exploring

Table 2
Summary of light source identification and classification

Method	Light Source Type	Accuracy	Data Source	Study Area	Reference
Index-based thresholding	WLED, RLED and other	86%-90%	SDGSAT-1	Coastal areas of China	(Jia et al., 2024)
Index-based thresholding	LED and HPS	Distinguish only color differences	CE-SAT-IIB	Port of Tokyo, Japan	(Murata et al., 2023)
Index-based thresholding	LED and HPS	~90%	JILIN-1	Shanghai, China	(Cheng et al., 2020)
Machine learning (RF)	LED and HPS	72%-83%	JILIN-1	Quito, Ecuador	(Watson et al., 2023)
Machine learning (RF)	HPS, LED and FL	92%	SDGSAT-1	Beijing, China	(Yin et al., 2024)
Machine learning (RF)	HPS, warm LED, cool LED, and color LED	95.7%	UAV	Part of the campus of Fuzhou University (China) and its surrounding commercial area, approximately 53,285 m ²	(Zou et al., 2025)
Machine learning (RF)	LED and HPS	80.3%	SDGSAT-1	Beijing (China), Shanghai (China), Guangzhou (China), Shenzhen (China)	(Lv et al., 2024)
Machine learning (RF)	Window light, neon light, road reflection, building reflection, and background light	95.8%	UAV	Changsha, China	(Zhang et al., 2023)
Machine learning (RF)	HPS and MH	87%	ISS	Haifa, Israel	(Rybnikova et al., 2021a)
Machine learning (NN, SVM, LDA)	Incandescent, LED, HPS, and MH	83.3%, 92.3%, 100%, and 100% respectively	UAV	Oak Ridge National Laboratory (ORNL), USA	(Tate et al., 2020)
Machine learning (ISODAT, Decision Tree)	LED and HPS	83.8%	JILIN-1	Hangzhou, China	(Zheng et al., 2018)
Supervised classification	HPS, MH, red and blue neon, red and blue LED, and fluorescent	~60%	ProSpecTIR-VS (Hyperspectral) and ISS	Las Vegas, USA	(Metcalf, 2012)
Supervised classification	LED and HPS	89.9%	SDGSAT-1	Shanghai (China), Mumbai (India), Damascus (Syria), Kigali (Rwanda), Ouagadougou (Burkina Faso)	(Liu et al., 2024a)
Unsupervised clustering	LED and non-LED	> 80%	SDGSAT-1	Beijing-Tianjin-Hebei region, Yangtze River Delta, Guangdong-Hong Kong-Macao Greater Bay Area, Chengdu-Chongqing Economic Circle, and Hainan Island	(Chen et al., 2024)
Unsupervised clustering	~40 types	> 85%	Hyperspectral single-slit scanner	New York, USA	(Dobler et al., 2016)
Spectral matching	Blue and red neon lights, HPS, and MH		ProSpecTIR-VS	Las Vegas, USA	(Kruse and Elvidge, 2011)
Spectral matching	LED, HPS, LPS, and MH	~90%	Enmap	Las Vegas, USA	(Bachmann and Storch, 2023)

the detection and classification of light source targets in urban-scale imagery (Figure 11).

4.2. Assessing energy conservation and emission reduction in urban lighting

Compared to traditional sources such as HPS streetlamps, LED fixtures possess higher luminous efficacy, thereby reducing baseline energy consumption under equivalent illumination requirements (Djuretic and Kostic, 2018). Panchromatic NTL data typically consider only the overall

intensity without distinguishing between light sources when modeling urban energy consumption (Zhong et al., 2024). In contrast, by differentiating light source types and incorporating relevant energy consumption models or assumptions, multispectral NTL data can evaluate relative energy consumption differences before and after lighting upgrades to assess energy conservation and emission reduction (Chen et al., 2024). Studies indicate that the widespread adoption of LED lamps can result in energy savings and reduce carbon emissions from lighting by 40%–60% (Cheng et al., 2020; Pardo-Bosch et al., 2022; Yoomak et al., 2018). Building upon light source classification via NTL

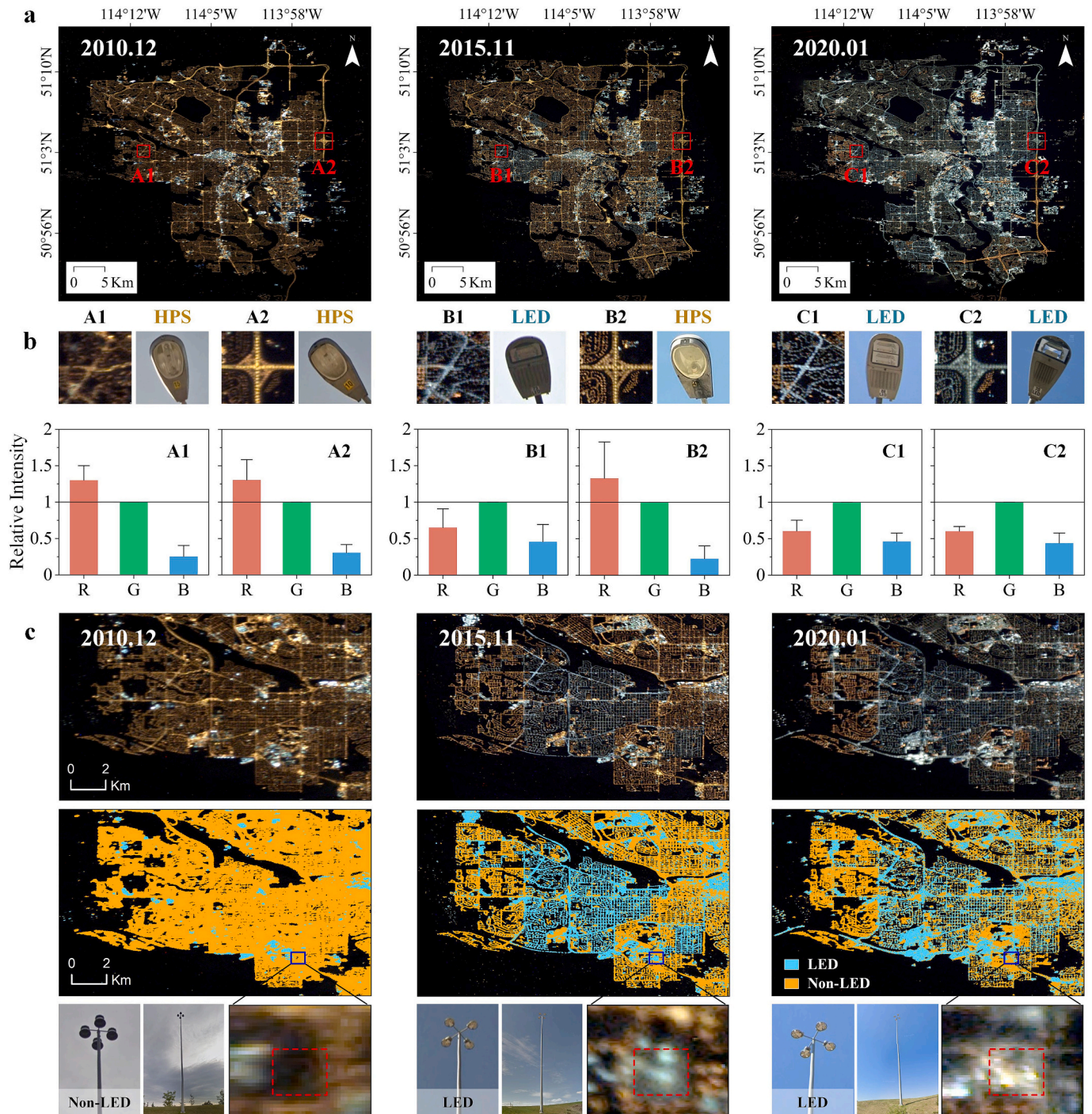


Fig. 11. NTL remote sensing lighting source detection. (a) ISS NTL imagery of Calgary in 2010, 2015, and 2020 (ISS026E12438, ISS045E155032, and ISS061E120642). (b) Local light sources and their relative spectral (RGB) intensities. (c) LED light source detection results using a Random Forest model. Fixture images are derived from open-source street view imagery.

remote sensing, quantifying the energy consumption differences between LED and traditional sources (primarily HPS) demonstrates significant application potential for assessing the impact of large-scale lighting upgrades on urban nocturnal energy conservation and emission reduction. Currently, directly utilizing multispectral bands to categorize streetlamp types into LED and HPS lamps can achieve an overall accuracy of 89.9% in specific cities (Liu et al., 2024a). The electricity savings from public and road network lighting upgrades were estimated by establishing a classification model to distinguish between LED and HPS lamps and by building a model utilizing light intensity and lamp density per unit area. (Chen et al., 2024; Lv et al., 2024). (Cheng et al., 2020) utilized JL1-03B multispectral NTL data to classify light sources and estimated that replacing a single HPS lamp with an LED solar streetlamp could save 1.85×10^4 kWh of electricity and reduce CO₂ emissions by 18.47 tons over its lifecycle (~20 years).

Multispectral NTL remote sensing technology provides a crucial basis for evaluating the implementation effects of urban energy conservation and emission reduction policies, playing a key role specifically in monitoring carbon emissions from streetlamp system upgrades (Ahmed et al., 2022). However, the effectiveness of energy saving and emission reduction from lighting sources remains unclear at the global scale, particularly in rural or economically underdeveloped regions. These disparities will significantly impact the feedback information regarding the energy-saving and emission-reducing effectiveness of global LED updates and hinder urban sustainability assessments. Furthermore, in current research, estimating the carbon reduction benefits of LED sources by establishing conversion relationships among light source quantity, type, power consumption, and carbon emissions has yielded favorable results, yet it remains limited to statistical methods based on light source counts. A possible approach involves constructing fitting models between the illumination range and intensity (spectrum) of light sources and estimation parameters, thereby transforming the “light source quantity” problem into a “unit area” multispectral radiance level, to subsequently estimate the spatial distribution of corresponding parameters (Jia et al., 2026; Zhang et al., 2023; Zhong et al., 2022).

4.3. Quantifying light pollution disparities

Statistics indicate that over 80% of the global population resides under light-polluted skies (Falchi et al., 2016). The recent spectral shift in nocturnal lighting caused by LED updates has exacerbated the socio-environmental burden and aroused widespread concern within both academia and the public (Côté-Lussier et al., 2020; Hoelker et al., 2010; Sánchez de Miguel et al., 2021a). The significant blue light emission from LEDs exerts negative impacts on animal behavior, plant phenology, and human health. In terms of human health, examples include the suppression of melatonin production (Aubé et al., 2013) and correlations with the incidence rates of various cancers (Garcia-Saenz et al., 2020; Garcia-Saenz et al., 2018). Regarding biological impacts, effects include the disruption of bat nocturnal activity (Pauwels et al., 2019) and alterations in nocturnal insect abundance (Bolliger et al., 2020). Currently, no single device can simultaneously satisfy all light pollution measurement requirements (Mander et al., 2023). To mitigate the light pollution impact of LED sources, several approaches have been adopted. For instance, employing warm-temperature amber LEDs (< 2200 K) or utilizing smart lighting systems to dynamically adjust LED intensity based on usage scenarios. However, regardless of color temperature, LED lighting contributes to an increased socio-environmental impact of light pollution, particularly regarding blue light (Gaston and Sánchez de Miguel, 2022; Pawson and Bader, 2014).

Studies based on panchromatic NTL data have provided extensive insights into light pollution monitoring. However, relying solely on a single physical quantity of total brightness or radiance, they fail to characterize the differential response characteristics of humans and ecological environments to light spectral energy. In reality, in addition to blue light, the stress effects of blue-violet light (e.g., on insects), red

light (e.g., on birds), and infrared light (e.g., on vegetation) exhibit significant differences within ecological environments (Kong and Nemali, 2021; Owens et al., 2020; Syposz et al., 2021; Wiltshko et al., 1993). Multispectral NTL remote sensing provides a novel perspective for light pollution assessment (Ling et al., 2025; Zheng et al., 2018). Research utilizing multispectral NTL for light pollution assessment is the most prevalent, accounting for 37.5% of the total application literature. Initial studies employed ground-based and ISS imagery to investigate light pollution in localized areas, revealing that light pollution is concentrated in densely populated commercial and residential zones (Pun and So, 2012; Wu et al., 2025a). Compared with panchromatic data, multispectral data provides more robust evidence of light pollution, particularly the potential effects of blue and red light on humans and plants (Wu et al., 2023). Nocturnal aerial photography further identified street-related lighting as the primary source of zenith light pollution and highlighted the impact of manufacturing industries (Hale et al., 2013; Kuechly et al., 2012). To achieve more specialized monitoring, the integration of spaceborne remote sensing and ground monitoring networks (such as NITESat and GONet) has provided extensive and continuous multispectral light pollution assessments (Barentine et al., 2021; Walczak et al., 2021; Walczak et al., 2017). Recently, the application of emerging platforms such as UAVs and hyperspectral technology has enhanced the granularity of light pollution analysis (Alamús et al., 2017). Furthermore, the integration with SQMs and ground-based (rooftop) spectrometers effectively accommodates fine-scale research on light pollution over small areas. For instance, a hyperspectral NTL measurement dataset spanning ten years revealed the spectral evolution of urban night sky lighting (Bobkowska et al., 2024; Massetti et al., 2022; So et al., 2025).

With advancements in multi/hyperspectral NTL remote sensing technology, the focus of light pollution research has also deepened to include ecological and health risk assessments triggered by spectral characteristics themselves (Côté-Lussier et al., 2020). Compared to panchromatic data, multispectral NTL data are more suitable for epidemiological studies, revealing associations between outdoor nighttime light exposure and various cancers (Garcia-Saenz et al., 2020; Garcia-Saenz et al., 2018; Kyba et al., 2015). A study based on ISS imagery of Milan found that LED source updates resulted in a significant enhancement of light pollution indicators such as the Melatonin Suppression Index (MSI) (Kyba et al., 2017). Utilizing the same methodology, the assessment results presented in this paper reveal a pervasive MSI growth effect across different cities (Figure 12). Additionally, light pollution assessment using multispectral NTL remote sensing extends to urban peripheries. For instance, light source monitoring and identification are conducted in nature reserves to assess the impact of LED sources (Yan et al., 2025), and ground-based and spaceborne multispectral NTL measurements are utilized to monitor light pollution impacts on coastal ecosystems (Levin et al., 2024; Vandersteen et al., 2020).

As previously analyzed, the dual opposing impacts of LED light sources involving positive aspects (such as energy conservation and emission reduction) and negative aspects (such as light pollution) have sparked intense controversy between fields such as energy and climate, and those such as ecology and life sciences (Schulte-Römer et al., 2019; Weber et al., 2025). A critical issue is that the risk of spatiotemporal scale imbalance between these two impacts has not yet been analyzed, which poses a significant challenge to sustainable nocturnal urban development (Figure 13). Against the backdrop of current climate goals and urban expansion, global urban lighting sources will gradually transition to LEDs, which will exacerbate the opposing landscape of their dual environmental impacts. Future efforts require a coordinated assessment of these dual impacts to promote low-carbon decision-making for urban lighting and the sustainable development of nocturnal ecology.

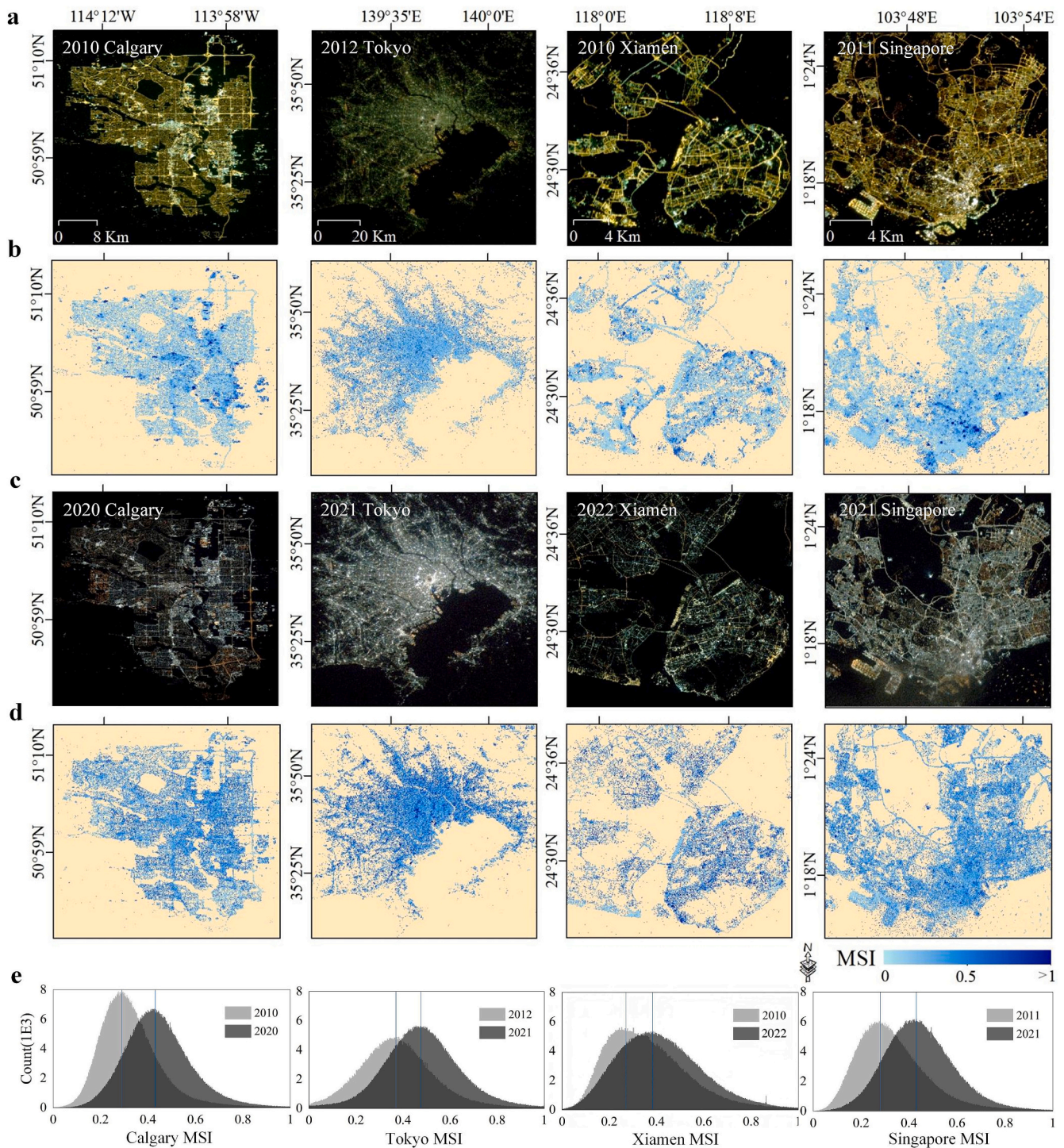


Fig. 12. Trends in the Melatonin Suppression Index (MSI) for selected cities. (a) and (c) show the ISS NTL images with a resampled spatial resolution of 30 m, including Calgary (ISS026E12438, ISS061E120642), Tokyo (ISS030E82777, ISS064E43286), Xiamen (ISS026E12263, ISS067E184108), and Singapore (ISS026E14696, ISS066E66873). (b) and (d) spatial distribution of MSI. (e) statistical distribution of MSI, displaying the statistically significant shift in MSI indicated by black (recent) and gray (early). The model used to calculate $MSI = 1.09 \cdot (B/G) - 0.053$ is cited from (Sánchez de Miguel et al., 2019).

4.4. Analyzing urban and social evolution

Panchromatic NTL data have been extensively explored in analyzing urban structure, encompassing aspects such as monitoring urban boundary expansion, assessing two-dimensional morphological characteristics, and modeling total population and economic aggregates. However, limitations exist regarding the analysis of urban and social evolution, particularly the differences in internal social attributes within

cities. Multispectral NTL imagery, primarily satellite-based, leveraging its high spatial resolution and spectral information, has become a significant instrument for the fine-scale interpretation of urban spatial structure and dynamic evolution. Beyond providing the light distribution structure available from panchromatic data, multispectral NTL data further differentiates lighting spectra. While these spectral signals ostensibly represent mere physical information resulting from the coupling of light types, surface environments, and urban structures, they

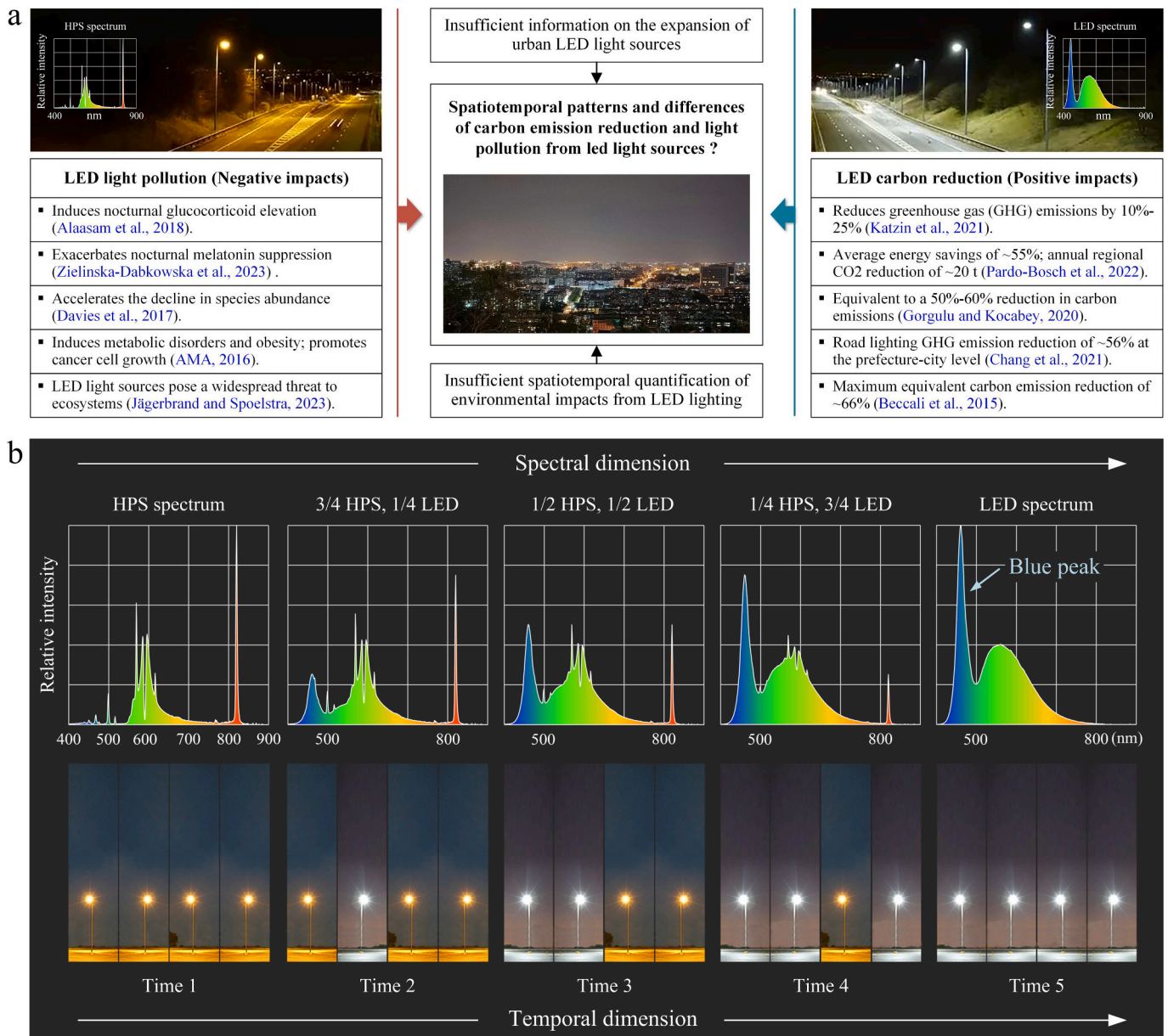


Fig. 13. Dual environmental impacts of lighting spectral evolution. (a) Controversy regarding the opposing spatiotemporal landscape of light pollution versus energy conservation and emission reduction. (b) conceptual diagram of spectral evolution during light source updates. The spectra used represent HPS and LED (~6000K) streetlights.

embody significant imprints of urban and social evolution (Figure 14). Research integrating multispectral NTL for the analysis of urban and social evolution accounts for 28.6% of the total application literature.

In terms of monitoring urban physical morphology, studies have found that utilizing RGB-band NTL imagery yields higher accuracy in extracting urban main roads compared to panchromatic data (Wu et al., 2024b). Similar significant advantages have been observed in impervious surface extraction (Chen et al., 2019; Kotarba and Aleksandrowicz, 2016), built-up area identification (Li et al., 2023; Wicht and Kuffer, 2019), urban expansion monitoring (Yin et al., 2020), and functional zone delineation and nighttime vitality characteristic identification (Huang et al., 2021). By integrating ground measurements, corresponding progress has been achieved in analyzing urban environmental interactions using multispectral NTL data. Examples include the visual comfort and color rendering capability of public space lighting, as well as the relationships between building structures, land features (vegetation), and illumination (Huang et al., 2021).

Nocturnal spectral characteristics also serve as proxy indicators for perceiving urban socioeconomic patterns, revolutionizing the perception of human well-being and population distribution (Wang et al., 2025b). While panchromatic NTL data, as a common economic proxy, reflect a strong correlation between light brightness and economic vitality, studies utilizing multispectral NTL imagery have revealed that higher levels of socioeconomic development are correlated with a higher proportion of LED lighting and road network density (Watson et al., 2023). Conversely, by coupling light brightness with spectral variations (e.g., average spectra), superior accuracy compared to panchromatic data has been demonstrated in identifying impoverished areas and assessing poverty levels (Kuffer et al., 2018; Wang and Li, 2024). Furthermore, by aggregating multispectral NTL data (e.g., averaging) or utilizing them as auxiliary information in conjunction with land use, Point of Interest (POI), and social media data, explorations have been conducted into population mapping and anthropogenic heat flux at high spatial resolutions (e.g., 10 m) significantly superior to historical

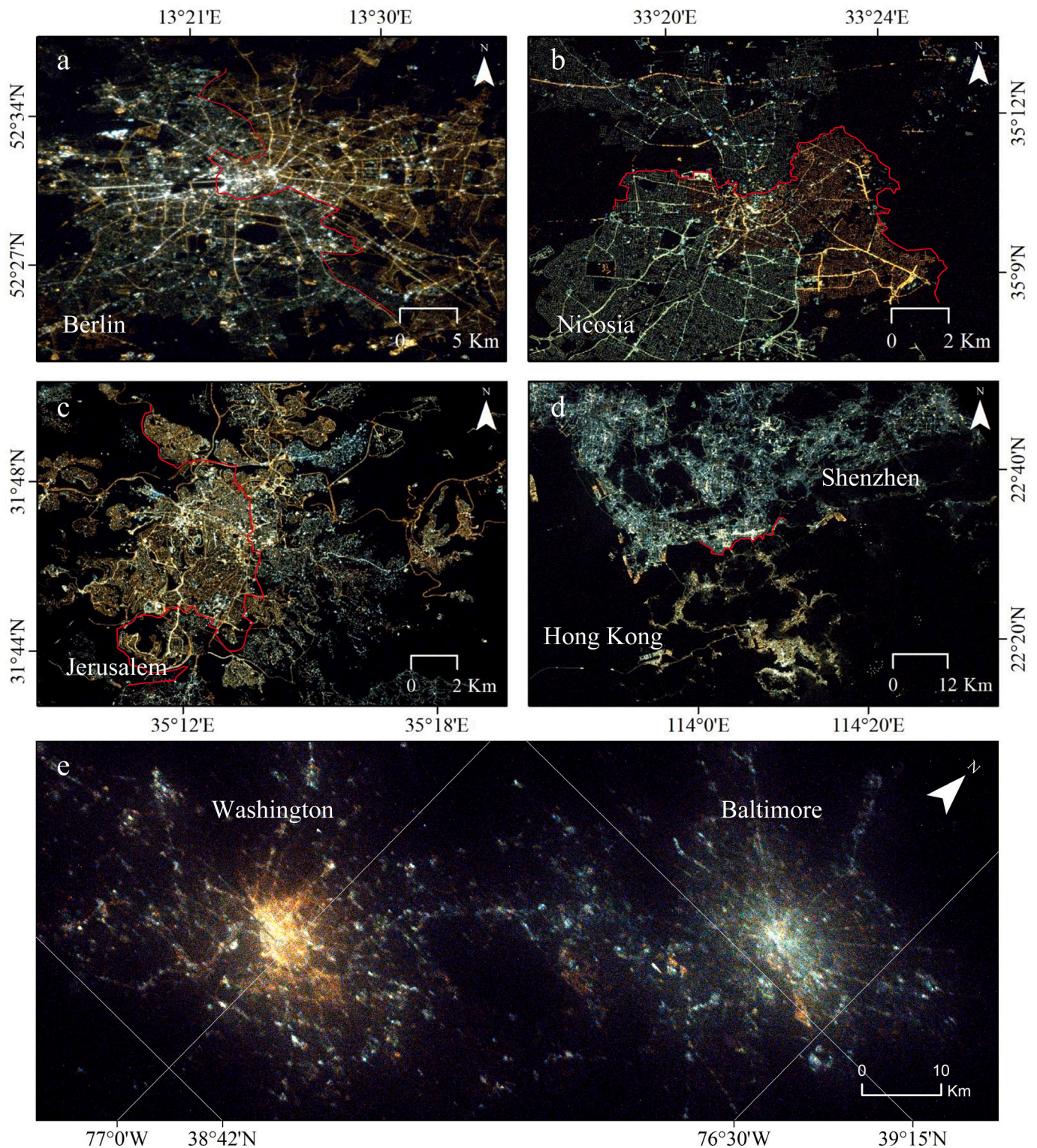


Fig. 14. Lighting characteristics within and between cities. (a) Lighting differences within Berlin (ISS035E17366). The red line roughly indicates the location of the Berlin Wall. (b) Nicosia in Cyprus (ISS065E57135). The red line roughly represents the administrative boundary of Nicosia. (c) Jerusalem (ISS067E177370), the red line roughly represents the 1949 Armistice Line (Green Line) of Jerusalem. (d) Shenzhen and Hong Kong (ISS073E8954). The red line roughly shows the border between Shenzhen and Hong Kong.

capabilities (Guo et al., 2023b; Li et al., 2018; Liu et al., 2023a; Wang et al., 2019).

The integration of platforms such as rooftop cameras, airborne systems, and high-altitude balloons with hyperspectral technology provides dynamic and fine-scale supplementary data for urban research. For

instance, (Dobler et al., 2021; Dobler et al., 2015) utilized rooftop cameras to capture the illumination dynamics of over 4,000 urban light sources every 10 seconds over a three-week period, revealing the characteristics and patterns of human activity within the urban pulse. Another study measured hyperspectral urban lightscape dynamics over

25 consecutive summer nights with a temporal resolution of 6 minutes (Baur et al., 2018). Additionally, multispectral NTL imaging mounted on high-altitude balloon platforms offers a more flexible approach for assessing lighting variations across urban functional zones (Walczak et al., 2023).

4.5. Other applications

The application potential of multispectral NTL remote sensing far exceeds that of traditional data, and the uniqueness of its spectral information is increasingly permeating broader interdisciplinary fields. Explorations are also gradually underway in numerous emerging domains such as education, oceanography, agriculture, and disaster management. For instance, laboratory experiments use hyperspectral imaging systems to measure the reflectance of artificial light sources to evaluate crop nutrition and fertilization methods (Nguyen et al., 2020). This reveals important potential for assessing the impacts of nighttime lighting intensity and spectral features on urban vegetation growth at larger airborne or spaceborne remote sensing scales. This demonstrates significant application potential for assessing the impact of nighttime lighting intensity and spectral characteristics on urban vegetation growth at broader airborne or spaceborne remote sensing scales. In the field of atmospheric chemistry, airborne hyperspectral NTL measurements have been attempted to evaluate the photolytic effects of different lighting sources on the atmosphere (NO_x) (Stark et al., 2010). In marine scenarios, multispectral NTL data have been piloted for the detection of marine vessels and oil and gas platforms (Qiu et al., 2024; Zhao et al., 2023). This application has also extended to evaluating the potential impacts of nighttime light pollution on the marine environment through underwater multispectral measurements (Tamir et al., 2017). With the continuous development and application of spectral information, particularly the transition from panchromatic to multispectral technology, NTL remote sensing is expected to experience a new wave of vigorous development, becoming a tool for human and Earth system observation equal in importance to daytime remote sensing.

5. Challenges, insights, and application prospects of multispectral NTL remote sensing

Having undergone over 30 years of development, NTL remote sensing is currently transitioning from the panchromatic to the multispectral era. The future advancement of multispectral NTL remote sensing necessitates multifaceted exploration across data acquisition, processing, and application dimensions to further elevate its scientific value and application potential. Based on the review of existing literature and building upon the progress of panchromatic NTL remote sensing, three key challenges of multispectral NTL remote sensing are summarized from a theoretical perspective, and highlight potential future research advances and application prospects (Figure 15).

5.1. Challenges in data acquisition

The performance of sensor platforms determines the availability, information richness, and quality of raw data. Daytime multi/hyperspectral remote sensing technology is relatively mature. However, due to the low radiance intensity of artificial light sources at night, multispectral sensor technologies suitable for low-light environments are limited (Longcore et al., 2018). Most multispectral NTL sensors utilize the Bayer-encoded RGB mode, such as ISS, Jilin-1, AeroCube, and UAVs (Liu et al., 2021b). Such imaging sensors exhibit out-of-band response, namely spectral crosstalk (or overlap) (Liu et al., 2021b). For example, the potential well of the Red band in a Bayer filter has a certain responsiveness to light sources in the Green or even Blue bands. Furthermore, due to Bayer filter characteristics, decoding (interpolation) is required to obtain full-pixel imagery of the three RGB bands. Nevertheless, Bayer-format multispectral NTL sensors suffer from a loss of

pixel resolution precision and may introduce systematic errors regarding the accuracy of radiance across multiple bands. Consequently, such precision may prove insufficient for NTL research scenarios necessitating high spatial resolution and accurate radiometric quantification.

Given the limitations of broadband multispectral NTL sensors in acquiring data, the development of narrowband multispectral NTL sensors is crucial (Elvidge et al., 2010). The development of the SDGSAT-1 sensor represents a successful endeavor (Guo et al., 2023), adopting narrow-band RGB bands (430–900 nm) with reduced spectral crosstalk effects and featuring a high spatial resolution of 40 m. The high-power emission spectra of common lighting sources are primarily concentrated in the 400–900 nm range (e.g., LED sources), while a few sources extend to 1200 nm, such as HPS and metal halide (MH) lamps (Guaix, 2015; Lspdd, 2025; NOAA, 2010). Given light spectrum types and environmental factors, such as the responses of vegetation and organisms to specific bands (Figure 15a), as well as imaging efficiency requirements, future multispectral NTL sensors should feature high radiometric sensitivity and signal-to-noise ratios. It is recommended that the spatial resolution be superior to $60 \text{ m} \times 60 \text{ m}$, with a spectral band (narrowband) set containing 4–8 bands. Furthermore, this set should include at least four bands consisting of blue (central wavelength $\sim 480 \text{ nm}$), green ($\sim 560 \text{ nm}$), red ($\sim 660 \text{ nm}$), and NIR ($\sim 820 \text{ nm}$) (Barentine et al., 2021; Elvidge et al., 2007; Elvidge et al., 2010; Levin et al., 2020; Price, 1997). To strengthen the correlation between application requirements and future sensors, it is necessary to establish a mapping relationship between specific bands and specific physical and biological characteristics. Specifically, the blue band ($\sim 480 \text{ nm}$) is designed not only to accurately capture the typical emission peak of modern white LEDs but also to serve as a key element for quantifying the effects of nighttime light pollution on public health and the ecology of nocturnal animals, owing to its high overlap with the peak of the human melatonin suppression curve. The red ($\sim 660 \text{ nm}$) and green ($\sim 560 \text{ nm}$) bands not only provide the basis for calculating light source color temperature and extracting spectral gradients, but their specific wavelengths can also be utilized to evaluate the potential interference of artificial light at night on plant photosynthesis (e.g., chlorophyll absorption). Furthermore, the near-infrared ($\sim 820 \text{ nm}$) band is crucial for the fine-grained identification of traditional light sources (e.g., HPS), as well as for quantifying the ecological interference with plant phytochrome responses (e.g., flowering cycles) and nocturnal animals (e.g., birds). Therefore, configuring 4 to 8 multispectral bands ranging from the blue to the near-infrared spectrum can closely integrate the hardware design of the sensor with the specific application requirements of urban energy monitoring, ecological environmental protection, and public health assessment. Furthermore, For longer-term development, establishing an NTL remote sensing satellite constellation is necessary to compensate for the lack of globally seamless and periodically stable coverage in NTL data.

The limited number of bands in multispectral sensors makes it difficult to precisely distinguish the spectral characteristics of different light source types, creating limitations for a refined understanding of the social and environmental impacts of NTL. Hyperspectral NTL remote sensing has recently been progressively explored, and its spatial and spectral resolution represents immense progress. According to literature records, hyperspectral NTL data were acquired via airborne methods ($\sim 1.8 \text{ km}$ altitude) as early as 2009, revealing their significant potential in characterizing urban development (Kruse and Elvidge, 2011; Metcalf, 2012). The satellite sensor dedicated to hyperspectral NTL (DESI) was mounted on the ISS in 2018 for imaging, enabling the characterization of more distinct spectral features between High-Intensity Discharge (HID) sources and LED lamps (Ryan et al., 2024). Currently, the quantity of research conducting hyperspectral NTL remote sensing remains very limited (Dobler et al., 2021). It is worth noting that as the number of spectral bands increases, the radiance received by each individual band gradually decreases. Furthermore, once the true NTL radiance is partitioned into individual bands, the influence of interference factors is

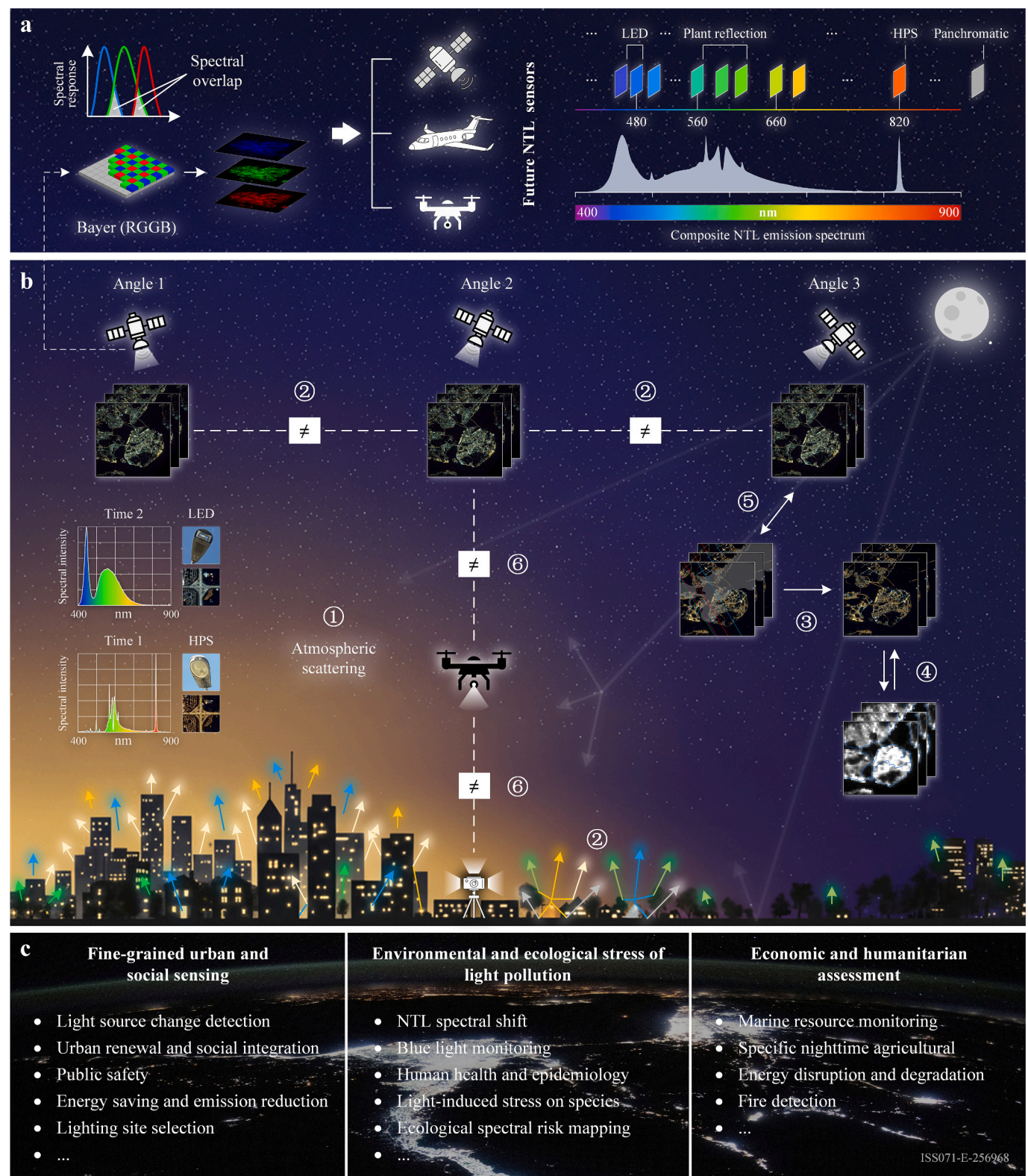


Fig. 15. Key challenges and application prospects of multispectral NTL remote sensing. (a) Data acquisition challenges. Displays the limitations of platform and sensor spectral responses, as well as concepts for future platform modalities and sensor band designs. (b) Challenges in radiometric quantification of multispectral NTL. Illustrates six primary factors, including: 1) atmospheric effects, 2) anisotropy of spectral reflection, 3) image quality optimization, 4) comparison between panchromatic and multispectral data, 5) fusion of multi-source multispectral data, and 6) matching with in situ measurements. (c) Directions for future application development. Displays three major potential application directions.

relatively amplified. Therefore, the core future challenge in advancing the application of hyperspectral NTL sensors lies in enhancing radiometric sensitivity and spectral identification capabilities in low-light environments.

Furthermore, the update periodicity of spaceborne multispectral NTL data is unstable, particularly in regions outside major urban agglomerations. Recently, UAVs have been widely explored as a supplementary means to acquire nighttime color NTL imagery (Zou et al., 2025). Given the advantages of low cost and high efficiency, UAV technology represents one of the key approaches for the future acquisition of multi/hyperspectral NTL imagery. However, the radiance intensity of artificial light sources at night is very weak, falling far below that of sunlight. Airborne low-cost sensor technologies suitable for low-light environments are limited, especially under conditions of spectral dispersion where the radiance intensity of each band is significantly reduced. This results in extremely weak signals in certain bands of narrow-band multi/hyperspectral imagery acquired by UAVs, leading to a lack of feature matching points. Consequently, currently common software and methods may struggle to complete large-scale image stitching (Bobkowska et al., 2024). Therefore, future research directions for developing multi/hyperspectral data acquisition equipment and technologies primarily include narrow-band multi/hyperspectral imagers, and UAV multispectral NTL image processing methods.

5.2. Challenges in radiometric retrieval and quantification

Future progress in multi/hyperspectral NTL remote sensing requires clarifying the key issue of which physical quantity should be adopted to obtain a quantified and unified NTL standard. Daytime remote sensing achieves a unified physical standard by measuring surface reflectance. For instance, daytime multi/hyperspectral remote sensing imagery uses sunlight as a calibration reference, allowing for the acquisition of unified and comparable spectral information (i.e., reflectance) across different times, angles, and sensors. In contrast, NTL remote sensing captures multiple artificial light sources. The criterion for judging light is the spectral curve, and common units include radiance ($\text{nW}/(\text{cm}^2 \cdot \text{sr} \cdot \mu\text{m})$ or $\text{nW}/(\text{cm}^2 \cdot \text{sr})$), radiant flux, and relative intensity. NTL remote sensing measurements utilize multiple common units, such as brightness ($\text{mag}/\text{arcsec}^2$ or cd/m^2), illuminance (lm/m^2 or lx), radiance ($\text{nW}/(\text{cm}^2 \cdot \text{sr})$), and the recently proposed radiant flux (W) (Katz and Levin, 2016; Unihedron, 2005; Zeng et al., 2025). Radiance is the most commonly used physical unit and is the fundamental physical quantity in remote sensing measurement. However, a critical drawback is that it is an apparent physical quantity rather than an intrinsic physical property. The sources and transmission paths of radiance signals under different observation geometries and surface environments are extremely complex, making direct comparison impossible. Radiant flux (Zeng et al., 2025) can eliminate the influence of projection differences across different latitudes, thereby obtaining more globally comparable light intensities. However, radiant flux measured at the same location by spaceborne, UAV, and ground-based platforms is completely incomparable due to the immense differences in the geometric diffusion distances of light sources, preventing the matching of data from multiple imaging systems and serving merely as a data optimization method.

Therefore, although these physical quantities play increasingly important roles in their respective application scenarios (such as socioeconomic simulation and ecological light pollution assessment), NTL lacks the concept of light source reflectance (or it is inapplicable), and the physical quantity currently adopted for NTL remains ununified. In other words, while the standard emission spectrum of a light source is known, it is impossible to determine whether the NTL imaged by sensors represents direct light, reflection from complex surface features, or a spectrum resulting from the mixture of multiple light sources. These mixed spectra may be completely inconsistent with the spectra emitted by the in situ light sources. How to construct or define physical models to obtain “pure” and unified surface light radiance or physical quantities

is one of the primary issues requiring consideration in multi/hyperspectral NTL quantification. In terms of current progress, the precise retrieval and quantification of multispectral NTL radiance still pose significant challenges. Fundamentally, the core of obtaining a unified physical quantity lies in establishing a physical link for the inverse retrieval of intrinsic surface radiance from satellite observation signals (TOA radiance). However, the radiative transfer process of the nighttime light environment is far more complex than that of daytime remote sensing. While daytime remote sensing primarily addresses reflected signals from a single passive light source (the Sun), NTL remote sensing faces a complex scenario involving a mixture of active emissions and passive reflections. The signals received by satellite sensors not only contain light directly emitted from the surface but also incorporate atmospheric path radiance, background environmental reflected light (such as moonlight), and complex coupling effects between surface features and light sources. Therefore, obtaining pristine and consistent NTL physical quantities necessitates the systematic decoupling of the aforementioned interfering factors. This demands a deep understanding and quantification of the key factors influencing multi/hyperspectral NTL radiative transfer, which constituting the primary challenges in current radiometric retrieval and quantification research:

5.2.1. Atmospheric effects

Quantifying atmospheric effects is one of the critical challenges facing multispectral NTL remote sensing. NTL imagery exhibits an inherent blooming effect that is closely related to atmospheric scattering (Wang et al., 2025c). Currently, almost all studies based on multispectral NTL remote sensing data still fail to account for atmospheric effects, relying solely on parameters such as Top of Atmosphere (TOA) apparent radiance for analysis (Jia et al., 2024). Atmospheric correction is relatively well-established in daytime remote sensing data processing (e.g., MODIS/Landsat), where relatively comprehensive correction models and methods have been developed. However, significant differences exist in light propagation paths between NTL and daytime remote sensing. The optical path in daylight remote sensing generally involves the process of entering the atmosphere (downwelling), reflecting off the surface, and exiting the atmosphere (upwelling) into the sensor. In contrast, NTL remote sensing consists of direct emission from multiple light sources or reflection from the surface exiting the atmosphere (upwelling) into the sensor (Román et al., 2018). Furthermore, the mixed spectra from different types of nocturnal light sources and multi-path reflection/direct emission are discontinuous, discrete, and highly heterogeneous (non-blackbody radiation) (Kocifaj, 2018). These differences dictate that traditional atmospheric correction physical models and input parameters cannot be applied to the correction of multi/hyperspectral NTL imagery. Despite the differences in optical paths compared to daytime remote sensing, NTL remote sensing shares similar aspects regarding atmospheric attenuation processes such as aerosol absorption, Rayleigh scattering, and ozone absorption (Sánchez de Miguel et al., 2021b). Among these, the Rayleigh scattering effect is particularly pronounced for the attenuation of short-wave blue light in LED sources, reaching up to 1.5 times that of red light (Otas et al., 2012). As LED sources expand globally, the mixed spectrum of nocturnal lighting is gradually shifting towards blue light, meaning that atmospheric processes will exert a greater impact on spaceborne NTL remote sensing imagery.

To date, no unified model has been established for the atmospheric correction of multispectral NTL remote sensing data (Levin et al., 2020; Román et al., 2018). Several methods have been attempted to mitigate the impact of atmospheric effects on panchromatic or multispectral NTL images. For example, approaches combining ground weather station observation data with parameter simulation methods have been used, considering atmospheric effects such as lunar irradiance correction which are not involved in daytime remote sensing (Román et al., 2018; Rybníková et al., 2021a). If the characteristics of “one-way atmospheric processes” and “multiple light sources” are considered exclusively, NTL

remote sensing appears analogous to ground-based stellar measurements in astronomy. Drawing upon astronomical observation methods, the use of stellar spectra as a reference for NTL calibration has also been employed (Sánchez de Miguel et al., 2021b). This method requires the prerequisite of using sensors with identical spectral responses for the synchronous observation of stellar imagery by ground and spaceborne platforms, and it necessitates avoiding the influence of ground-based light pollution. Additionally, certain relative correction methods are utilized to circumvent atmospheric effects, but these can only correct for consistency between images and are unable to recover the intensity differences between distinct bands within the same image (Gong et al., 2025; Wei et al., 2020).

Given the attenuation impact of the atmosphere on short-wave spectra, it is necessary to establish dark-sky protected multi/hyperspectral NTL radiometric calibration sites in the future, similar to astronomical observation sites within dark sky reserves (Aubé and Roby, 2014; Silver and Hickey, 2020; Wei et al., 2019), to satisfy the verification and correction of temporal, atmospheric, and angular effects. For instance, precisely radiometrically calibrated LED lamp arrays could be deployed in flat, open field areas free of urban light pollution to provide stable, controllable NTL radiation sources of known intensity. Regarding reference pure light arrays for historical data correction, records may exist in imagery containing dragon fruit farmlands (Wen and Liu, 2024; Zhan et al., 2025). By precisely measuring the radiance, spectral characteristics, and synchronous atmospheric parameters emitted by these lamp arrays, the atmospheric effects of spaceborne imaging data can be corrected. A recent study evaluated the effectiveness of point sources for multispectral NTL radiometric calibration (Sánchez de Miguel et al., 2021b). Similar methods have also been tried in certain small-scale scenarios (Cui et al., 2023; Liu et al., 2021b).

5.2.2. Anisotropy of spectral reflection

Elucidating the directional reflection characteristics of multispectral NTL is crucial. Previous research has revealed that satellite-imaged NTL intensity varies across different zenith and azimuth angles due to urban structures, a phenomenon termed the angular effect of NTL remote sensing (Li et al., 2019; Li et al., 2022; Tan et al., 2022). The correction of angular effects has enhanced the accuracy of panchromatic NTL quantitative analysis. In NASA's Black Marble product suite, the Bidirectional Reflectance Distribution Function (BRDF) has been applied to the correction of NPP-VIIRS data (Román et al., 2018). Currently, NTL anisotropy has solely been verified in panchromatic remote sensing imagery. However, correcting angular effects for multispectral NTL remote sensing is likely to be significantly more complex. BRDF modeling in daytime remote sensing is based on a light source (the sun) with a known and relatively stable spectrum. Its BRDF variation with wavelength primarily reflects changes in the spectral reflectance of surface features, aiming to eliminate reflectance differences caused by variations in observation and solar angles to yield a standardized spectral reflectance product known as Nadir BRDF-Adjusted Reflectance (NBAR), which represents the intrinsic properties of surface features. However, the concept of "light source reflectance" is inapplicable to NTL.

For multi/hyperspectral NTL remote sensing, the emission spectra, intensity, and direction of light sources within each pixel are unknown, variable, and highly coupled with surface reflection. In other words, the quantity of light reflected by surface features versus direct emission, as well as the directional distribution of their respective spectral energies, remains unclear. Even with the aid of existing daytime BRDF models, isolating the influence of mixed lighting remains impossible. Therefore, one of the complexities regarding the anisotropy of spectral reflection lies in quantifying the coupling physical mechanisms between light source spectra and surface reflection. Panchromatic imagery amalgamates these complex effects without distinction. In contrast, the ultimate goal of anisotropy correction for multi/hyperspectral NTL imagery may be to decouple this complex interaction between light sources and the

surface. For instance, a study based on hyperspectral NTL assumed 90% direct light and 10% reflected light, along with corresponding surface absorption/reflection coefficients, to assess the impact of mixed spectral shifts (Bachmann and Storch, 2023). A recent intriguing study provided statistical evidence regarding the proportions of upwardly escaping light and other light (e.g., shielding lights) (Nachtlichter et al., 2025). Furthermore, the impact of the seasonal rhythms of urban vegetation on NTL anisotropy cannot be overlooked (Li et al., 2025; Román et al., 2018). For example, in high-latitude cities (especially those with high greening rates), deciduous street tree species may cause BRDF variations in the green band between winter and summer to be more significant than in other bands. This implies that the spectral variation mechanisms influencing the seasonal and angular effects of NTL necessitate a deeper understanding.

Airborne NTL remote sensing technology offers a potential means to address the aforementioned issues. Panchromatic NTL imagers possess extremely large Fields of View (FOV), such as the NPP-VIIRS with a swath width exceeding 3,000 km, enabling the provision of sufficient multi-angular observational data for analyzing multi-angular effects. However, multispectral spaceborne NTL sensors typically exhibit narrow FOVs. Although sensor imaging angles can be altered for customized imaging, the quantity of multi-angular observations for the same location remains limited. The flexibility of airborne platforms and the future development of multi/hyperspectral imagers will provide effective observational data for analyzing the anisotropy patterns of multispectral NTL (Aubé et al., 2023). Recently, certain studies have attempted multi-angular NTL analysis using UAV remote sensing (Wu et al., 2025b), revealing significant differences in spectral intensity across multi-angular and temporal observations (Levin, 2025; Levin et al., 2020). Furthermore, UAV NTL has been utilized to distinguish the structural sources of urban nocturnal light sources (Hale et al., 2013). Based on the preceding analysis, and considering the heterogeneity of multi-angular imaging arising from urban structures, reflective surfaces, and spectral differences, the questions of whether it is necessary to construct an orthoimage for multispectral NTL remote sensing and how to achieve this constitute a significant topic for enhancing the consistency of future NTL research.

5.2.3. Image quality optimization

In addition to the aforementioned factors, multispectral NTL data are subject to influences including spectral mixing, periodic moonlight, cloud occlusion, and background noise (Kyba et al., 2011; Liu et al., 2021a). Although data quality correction methods for daytime remote sensing imagery have been extensively developed, the feasibility of applying these methods to NTL imagery, particularly multispectral data, remains unclear. Developing data quality correction methods tailored to NTL characteristics remains a challenge, as exemplified by the issue of spectral mixing in NTL imagery (Benhalouche et al., 2022). Spectral mixing in NTL encompasses three aspects: first, mixed spectra from multi-type surface reflections resulting from image pixel resolution, which is similar to daylight remote sensing; second, mixed spectra from multi-source emissions unique to NTL; and third, cross-band response spectra of currently common broadband (Bayer) sensors. The combination of these spectral mixing effects with atmospheric effects leads to the spectral unmixing methods for multispectral NTL data potentially differing from those for daytime remote sensing imagery. It is necessary to test the applicability of daytime remote sensing spectral unmixing methods and develop unmixing models specifically tailored for multi/hyperspectral NTL remote sensing imagery.

Currently, data quality optimization methods for multispectral sensors like the ISS and SDGSAT-1, such as denoising, cloud correction, and pansharpening, are being extensively explored, substantially enhancing both data quality and usability (Li et al., 2024a; Liu et al., 2023b; Wang et al., 2025c; Zhang et al., 2022). To achieve robust multispectral NTL radiometric correction, future efforts under ideal conditions necessitate the development of system correction models dedicated to NTL. Such

models should integrate multi-source auxiliary data, including atmospheric and lunar phase parameters, and simultaneously address correction processes for cloud occlusion, spectral mixing, and background noise while considering temporal and angular effects.

5.2.4. Comparison between panchromatic and multispectral data

Panchromatic NTL data characterized by global coverage and long time series remain in widespread use, having coexisted with multispectral NTL data for decades. Numerous studies have attempted to combine panchromatic and multispectral data for analysis to facilitate the utilization of multi-source data. However, one of the critical deficiencies lies in the ambiguity of NTL blue light radiance intensity. Panchromatic NTL sensors (such as OLS and VIIRS) lack a blue light response, and thus the inability to capture blue radiation from emerging LED light sources causes the radiance observed by the DNB to be lower than the actual value (Figure 16) (Kyba et al., 2017). With the widespread adoption of LED lighting in cities globally, this discrepancy in sensor spectral response not only renders panchromatic and multispectral NTL data incomparable but also risks generating spurious trends in long-term remote sensing radiance records. (Kyba et al., 2017; Levin, 2025). Nevertheless, current studies have not yet adequately accounted for the impact of this factor. Secondly, certain studies fail to account for differences in radiance calculation methods. For instance, NPP-VIIRS employs integrated radiance across the full band ($\text{nW}/(\text{cm}^2\cdot\text{sr})$), whereas multispectral data typically utilize average spectral radiance for each band ($\text{nW}/(\text{cm}^2\cdot\text{sr}\cdot\mu\text{m})$). Furthermore, current methodologies for comparing multispectral and panchromatic data (including at the spectral and spatial resolution levels) remain inconsistent.

In the spectral dimension, multispectral NTL generally involves four dimensionality reduction approaches: (1) Matching human vision. This is the most commonly used method. It employs the photopic cone sensitivity of the human eye as the standard for synthesizing multispectral (RGB) NTL data into panchromatic data, which is analogous to the grayscale conversion process of digital or artistic images. Human vision is sensitive to green light but insensitive to blue light. The weighting parameters are typically R (0.299), G (0.587), and B (0.114) (Cheng et al., 2020; Dobler et al., 2015; Guo et al., 2023a; Liu et al., 2024a; Wu et al., 2024b; Zhang et al., 2024; Zheng et al., 2018). Currently, common multispectral NTL sensors consist of Bayer-encoded RGB components. The initial “RGGB” design of Bayer filters simulated the proportion of human visual response (i.e., R:G:B $\approx$ 1:2:1) to acquire human-eye-like color imagery. However, the decoding process eliminates these characteristics, and the generated multispectral imagery is influenced solely by the intrinsic RGB spectral response. Consequently, in the field of remote sensing, for regions abundant in LED light sources, the radiance values of NTL will be attenuated due to the lower weighting parameter of the Blue band. (2) Mean brightness. Panchromatic brightness is synthesized by calculating the mean value of radiance across multiple bands (Dobler et al., 2015; Levin et al., 2020; Wang et al., 2019; Wang and Li, 2024). (3) Index synthesis. Fundamentally, the first two approaches are both spectral indices constructed based on multispectral data, differing only in the definition of RGB weights. Corresponding derived indices are also utilized for the spectral dimensionality reduction of multispectral NTL (Guk and Levin, 2020; Jia et al., 2024; Labrousse et al., 2025; Wang et al., 2025b). (4) Spectral response/Synthetic photometry. Based on the spectral response curve of the panchromatic data intended for comparison (e.g., NPP-VIIRS), this method maximally fits the multispectral imagery or light source to the radiance values of the panchromatic band (Aubé et al., 2013; Jia et al., 2024). Strictly speaking, there is no standard method for spectral dimensionality reduction, and the choice is contingent upon the objects of comparison and the application scenarios. However, for the analysis of identical panchromatic data, adopting a consistent dimensionality reduction approach is recommended. With the increase in the number of bands in future NTL sensors, synthetic photometry will become more applicable (Cardiel et al., 2021).

Conversely, to compensate for the insufficiency of multispectral NTL data, certain studies consider generating pseudo-color NTL images from panchromatic NTL data to achieve the spectral information augmentation of NTL imagery. For instance, approaches utilizing ISS imagery and machine learning methods convert panchromatic VIIRS/DNB into RGB images (Rybnikova et al., 2021b; Rybnikova et al., 2022). Additionally, methods involving the fusion of panchromatic NTL with Landsat multispectral information to generate pseudo-multispectral NTL data have been explored (Lu et al., 2024; Wang et al., 2025a). However, these methods lack a physical basis for quantitative radiometric conversion. Therefore, they are not recommended for accurate quantitative NTL retrieval. In future research, it is necessary to further verify the consistency between panchromatic and multispectral data and conduct validation in conjunction with ground based or low altitude measurement data.

5.2.5. Consistency fusion of multi-source multispectral data

Considering the consistent fusion of multi-source multispectral data is crucial for global-scale NTL analysis. Recent advancements in data acquisition have been achieved by multispectral NTL sensors, such as the ISS and SDGSAT-1. However, almost all multispectral NTL imagery is fragmented (or striped), primarily concentrated in urban centers, and lacks global data with continuous coverage of rural areas and urban fringes. This imposes limitations on understanding development in underdeveloped regions, urban expansion, and boundary conflicts between cities and nature. Currently, multispectral NTL data with continuous global coverage in both spatial and temporal dimensions are extremely limited. (Sánchez de Miguel et al., 2022) corrected and synthesized ISS data to obtain multispectral NTL imagery with continuous coverage of Europe for two periods around 2013, with the spatial resolution reduced to 1 km. This represents the only currently reported multispectral NTL imagery with continuous coverage at an international scale. Nevertheless, the radiometric consistency of the fused data across urban scales remains unclear in that study. This may lead to systematic biases between different research findings, such as scale effects at the spectral and spatial levels (Weng, 2014; Wu and Li, 2009; Zheng et al., 2023).

Building upon radiometric correction, the critical challenges of multi-source multispectral NTL imagery fusion also encompass three main aspects: (1) Differences in imaging time. Evidence suggests that turning off lights around midnight significantly reduces NTL brightness (Nachlichter et al., 2025). Recently, some cities have developed smart lighting systems where light source intensity varies with time (Jägerbrand and Spoelstra, 2023). Cultural, festival, and political factors can also cause extreme short-term variations in light radiance intensity (Ramírez et al., 2023). (2) Imaging angular effects. This refers to brightness and spectral differences caused by observation angles. (3) Sensor spectral response. Distinct differences exist in the spectral response curves of different multispectral sensors (Figure 3c), resulting in imaging differences in NTL brightness and spectra. The quantitative radiometric impacts on multispectral NTL brought about by the aforementioned factors remain unclear. To achieve consistent fusion among multispectral NTL data, future research needs to quantify the individual contributions and combined radiometric impacts of differences in imaging time, angle, and the spectral response of the sensors themselves.

5.2.6. Matching with In situ measurements

Major aspects contributing to the difficulty of quantifying multispectral NTL remote sensing also include the challenges of acquiring ground-based in situ measurement data and achieving consistency between ground measurements and the radiance values of spaceborne imagery. In daytime optical remote sensing or other electromagnetic remote sensing, in situ observations are typically indispensable as validation or supplementary data (Balsamo et al., 2018; Sharma et al., 2024; Sobrino et al., 2012). However, currently, the vast majority (> 90%) of application studies based on spaceborne multispectral or even panchromatic NTL remote sensing imagery lack documentation of

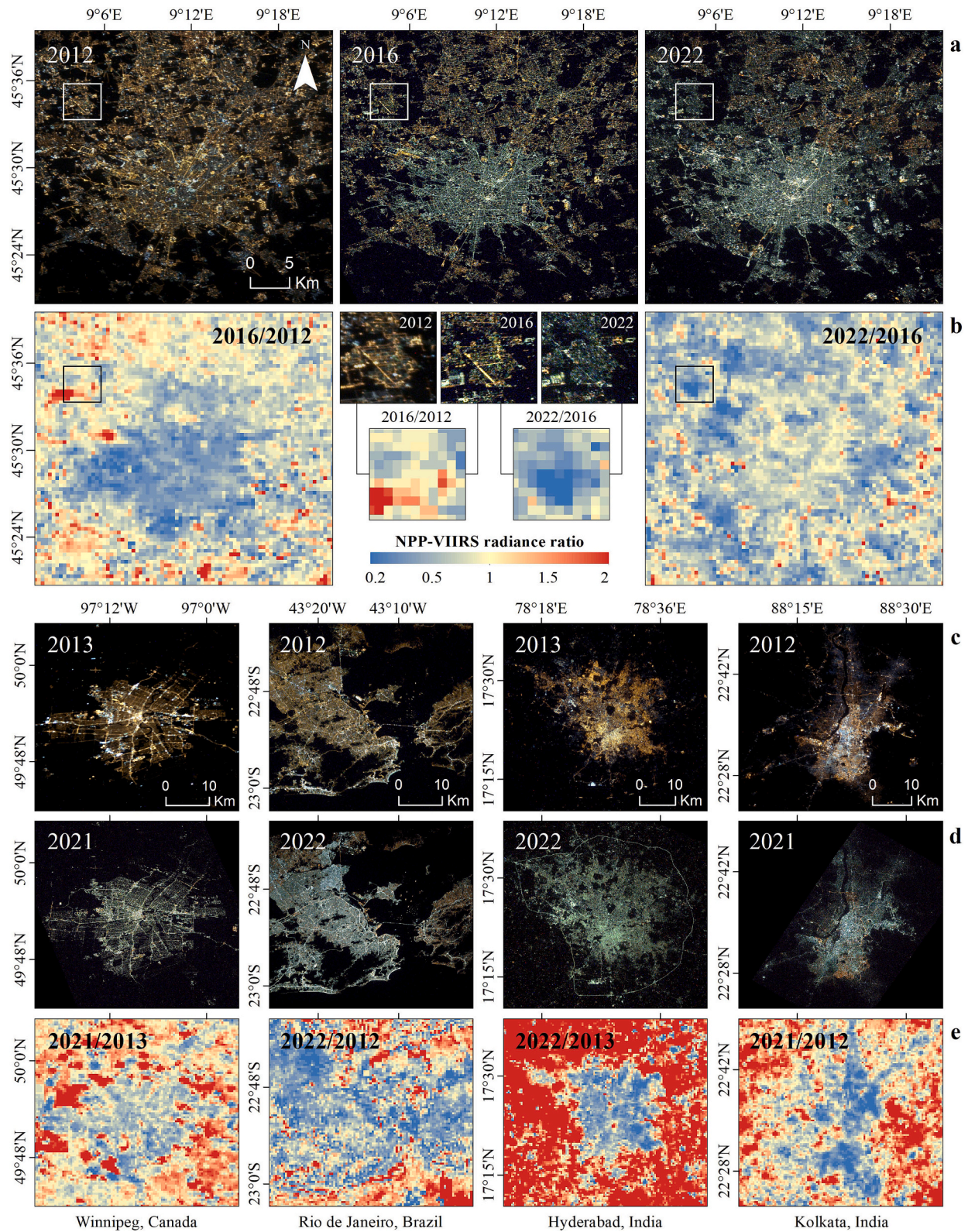


Fig. 16. Observation changes of spaceborne sensors induced by the expansion of LED light sources. (a) Decoded ISS imagery (Refer to [section 3.1.1](#)) of Milan, Italy, in 2012 (ISS026E10974), 2016 (ISS047E127793), and 2022 (ISS067E345065). (b) Radiometric changes observed by the NPP-VIIRS sensor, including the ratio of 2016 to 2012 (2016/2012) and the ratio of 2022 to 2016 (2022/2016). (c) and (d) show the ISS images of the four case cities, including Winnipeg (ISS034E44274, ISS066E47253), Rio de Janeiro (ISS027E30659, ISS067E176819), Hyderabad (ISS034E44363, ISS066E123360), and Kolkata (ISS034E5977, ISS066E46153). (e) Radiance changes observed by NPP-VIIRS. The ratio of recent to early observations (Recent/Early) reveals that the expansion of LED lighting results in a general decline in NPP-VIIRS observations.

ground-based in situ measurement data, with such data being tested in only a limited number of cases (Fernandez-Ruiz et al., 2023; Levin, 2023a; Román et al., 2018). For instance, one study involving ground measurements based on hyperspectral NTL spaceborne remote sensing was conducted in a laboratory setting and did not account for the mixing effects of the real-world ground environment on light source spectra (Ryan et al., 2024).

Another more critical issue is that the appropriate methodology for conducting ground-based observations remains unclear. More strictly speaking, based on currently common physical quantities (such as radiance), it is uncertain whether ground measurements of urban multispectral NTL and spaceborne imagery possess strict consistency at a theoretical level. Spaceborne imaging captures the TOA NTL radiance within the sensor's field of view. Compared to ground-based measurements, regardless of the measurement direction, the spectra resulting from the mixing of direct light from multiple sources and surface reflections above cities (excluding the atmosphere) exhibit more complex spectral variations than those measured on the ground. In fact, there is currently no consensus regarding measurement direction (vertical or horizontal) (Cavazzani et al., 2020; Jechow et al., 2019; Labrousse et al., 2025; Levin et al., 2020; Liu et al., 2024b; Walczak et al., 2017). Panchromatic NTL research indicates that downward ground measurements (aligned with the spaceborne sensor imaging direction) exhibit a higher correlation with satellite imagery values compared to other directions (Katz and Levin, 2016). Another experiment revealed the spectral (RGB) correlation measured by different ground-based multispectral photometers in the same direction (upward), finding that the fitting of the blue band was the strongest (Levin, 2025). Currently, the equipment commonly used for ground measurements primarily consists of SQMs and multispectral photometers, with measurement units of $\text{mag}/\text{arcsec}^2$ (or cd/m^2) that are inconsistent with the radiance ($\text{nW}/(\text{cm}^2 \cdot \text{sr} \cdot \mu\text{m})$) of spaceborne NTL remote sensing imagery (Katz and Levin, 2016; Kyba et al., 2013). The method of comparison typically involves performing a regression fit between SQM measurements and low-altitude or spaceborne remote sensing imagery (Katz and Levin, 2016; Kyba et al., 2013; Sánchez de Miguel et al., 2020). Fundamentally, SQM measurements cannot serve as absolute ground validation data for spaceborne NTL remote sensing imagery and require the unification of dimensions. Furthermore, only a very limited number of studies (panchromatic NTL) have explicitly employed ground-based measuring instruments that match or approximate the spectral response curves of satellite sensors for measurement (Fernandez-Ruiz et al., 2023; Román et al., 2018).

To advance toward quantitative multispectral NTL remote sensing, implementing ground measurements in future research is vital. It is advisable to establish and expand multispectral ground in situ measurement datasets at the global level as soon as possible, ensuring the inclusion of key information such as the specific measurement time, sensor type, measurement height, and measurement methodology. For instance, regarding ground measurements for panchromatic NTL remote sensing data, the global ground photometer monitoring networks developed by the European STARS4ALL and EELabs projects provide compelling cases (Eelab, 2025; Fernandez-Ruiz et al., 2023). A multispectral NTL ground-based in-situ measurement network should be established and expanded at the global level as early as possible. Future ground observation protocols must document critical metadata in detail, including measurement timing, cloud cover, observation geometry, sensor parameters, and measurement altitude. First, regarding time synchronization, ground measurements must precisely pinpoint the specific time of nighttime observation to strictly match the overpass imaging time of the target satellite (e.g., the 21:00-22:00 period). Simultaneously, continuous measurements across different time periods are recommended to effectively quantify and eliminate temporal discrepancies caused by the dynamic scheduling of urban lighting (such as midnight dimming or switch-offs). Second, in terms of observation geometry, it is recommended to adopt a unified measurement perspective

(such as downward or omnidirectional measurement) and constrain the measurement tilt angle to within 15 degrees to maximize observation consistency with spaceborne sensors. It is also necessary to evaluate the spectral radiance differences between measurements taken by UAVs at various altitudes and spaceborne remote sensing images, quantifying the FOV and the impacts of occlusion from the urban canopy (trees, high-rise buildings). Regarding instrument matching, the specific models of ground sensors (e.g., LANcube, TESS-4C) should be documented in detail, and their exact spectral response curves in the corresponding spectral channels (e.g., the 430-520 nm) should be provided to ensure the realization of high-precision spectral cross-calibration between the space and ground ends. Furthermore the multiple scattering and reflection of surface lights caused by cloud cover should be considered and avoided (Aubé and Simoneau, 2018; Kocifaj, 2018). Adequate attempts at these advancements will provide a solid data benchmark for the quantitative validation and consistent application of multispectral NTL remote sensing globally.

5.3. Establishing a unified NTL radiative transfer model

NTL remote sensing is of equal importance to daytime remote sensing for the sustainable development of human and Earth systems. To advance toward the era of multispectral NTL remote sensing and elevate its potential to a level comparable to that of daytime remote sensing, it is necessary to establish an NTL Radiative Transfer Model (NRTM) that considers multiple factors, thereby gradually systematizing NTL remote sensing. Based on the preceding analysis, factors interfering with NTL radiometric consistency include the atmosphere (L_{air}), imaging angle (L_{angle}), moonlight (L_{moon}), background noise (L_{bg}), imaging time (L_{time}), and sensor differences (L_{sensor}). According to the characteristics of these interfering factors, we categorize them into signal modulation factors and environmental superposition factors. Signal modulation factors include imaging angle, imaging time, and atmospheric attenuation, while environmental superposition factors consist of moonlight, atmospheric path radiance, and background noise. The radiative transfer process of NTL remote sensing is a complex coupled system involving active emission, passive reflection, and medium scattering. The total spectral radiance ($L_{\text{obs}}(\lambda)$) received by spaceborne multispectral sensors at the TOA can be described by the following unified physical model containing signal modulation terms and environmental superposition terms:

$$L_{\text{obs}}(\lambda) = L_{\text{ir}}(\lambda) \cdot \Omega(\lambda, \theta_v, \phi_v) \cdot \Phi(\lambda, t) \cdot T_1(\lambda) + L_{\text{moon}}(\lambda) + L_{\text{path}}(\lambda) + L_{\text{bg}}(\lambda) \quad (1)$$

The theoretical expansion and parameter definitions of the physical components in this model, arranged in the order of signal generation to transmission, are as follows:

(1) $L_{\text{ir}}(\lambda)$ (Intrinsic surface radiance). This represents the intrinsic spectral radiance of surface light sources at a standard time under the nadir observation direction. Physically, this term is a coupled quantity, encompassing the sum of energy directly emitted by light sources and the upwelling energy reflected by surface structures.

(2) $\Omega(\lambda, \theta_v, \phi_v)$ (Angular modulation function). This serves as a comprehensive factor describing the geometric occlusion of direct light and the BRDF effects of reflected light. It quantifies the ratio of radiant intensity at a specific viewing zenith angle θ_v and azimuth angle ϕ_v relative to the nadir direction. Since the reflection characteristics of light sources with different wavelengths vary within the surface environment, this function exhibits spectral dependence.

(3) $\Phi(\lambda, t)$ (Temporal modulation function). This describes the diurnal variation characteristics of artificial light source intensity. Due to the varying switching schedules of light sources with different spectral types, the variation in nighttime light radiance intensity exhibits significant spectral differences (Levin et al., 2020). This term is used to normalize imagery acquired from non-synchronous orbits or at different overpass times t to a uniform standard time.

(4) $T_1(\lambda)$ (Atmospheric upwelling transmittance). This is the atmo-

spheric attenuation factor during the transmission of light from the surface to the sensor, following the Beer-Lambert law, and is primarily influenced by Aerosol Optical Depth (AOD), Rayleigh scattering, and gas absorption.

(5) $L_{moon}(\lambda)$ (Moonlight reflected radiance). This is the primary additive interference term in the multispectral shortwave bands. Specifically, it manifests as the complete path where lunar irradiance at the TOA penetrates the atmosphere, reflects off the surface, and penetrates the atmosphere again:

$$L_{moon}(\lambda) = \frac{1}{\pi} E_m(\lambda, \Phi_{phase}) \cdot \cos \theta_m \cdot T_1(\lambda, \theta_m) \cdot \rho_s(\lambda) \cdot T_1(\lambda, \theta_v) \quad (2)$$

where E_m is the lunar spectral irradiance at the TOA controlled by the lunar phase Φ_{phase} ; θ_m and θ_v are the lunar zenith angle and the sensor viewing zenith angle, respectively; T_1 and T_1 are the atmospheric downwelling and upwelling transmittances, respectively; and ρ_s is the surface reflectance coupled with BRDF characteristics.

(6) $L_{path}(\lambda)$ (Atmospheric path radiance). This term represents the atmospheric background radiance independent of the intensity of surface artificial light sources. At night, its primary sources include two aspects. First is moonlight scattering. On moonlit nights, moonlight acts as an external light source scattered by atmospheric molecules and aerosols into the sensor (a mechanism identical to daytime path radiance). Second is airglow. On moonless nights, this is the faint luminescence produced by photochemical reactions in the upper atmosphere. Diffuse light generated by the atmospheric scattering of surface artificial light sources is typically categorized as the adjacency effect $L_{bg}(\lambda)$ and is not included in this term. Based on the single scattering approximation, its physical process can be described as:

$$L_{path}(\lambda) = \frac{\omega_0(\lambda) \cdot \tau_{atm}(\lambda) \cdot P(\Theta)}{4\pi \cdot \cos \theta_v} \cdot E_m(\lambda, \Phi_{phase}) \quad (3)$$

where ω_0 is the atmospheric single scattering albedo; τ_{atm} is the total atmospheric optical depth; and $P(\Theta)$ is the scattering phase function, describing the angular distribution probability of light scattering. This term indicates that even if the surface is completely dark, moonlight scattered by the atmosphere will introduce background brightness values.

(7) $L_{bg}(\lambda)$ (Background and adjacency effects). This term encompasses the adjacency effect and sensor noise. Its theoretical model is typically described as the product of the average environmental radiance and the atmospheric diffuse transmittance, superimposed with the sensor's inherent electronic noise:

$$L_{bg}(\lambda) = L_{env}(\lambda) \cdot T_{diff}(\lambda) + N_{sensor}(\lambda) \quad (4)$$

where L_{env} is the weighted average of the background brightness surrounding the target pixel (calculated via convolution with the Point Spread Function (PSF)); T_{diff} is the atmospheric diffuse transmittance; and $N_{sensor}(\lambda)$ is the dark current and noise of the sensor in a specific band.

Based on the aforementioned model, the radiometric inversion and quantification of multispectral NTL is fundamentally a process of component decoupling. The core of this process lies in constructing a standardized nighttime radiometric benchmark system to support the precise derivation of model parameters. Specifically, this procedure involves establishing dark-sky protected radiometric calibration sites to validate atmospheric radiative transfer models, which allows for the precise simulation and deduction of lunar reflection (L_{moon}) and atmospheric path radiance (L_{path}) from observed values. Multi-angular observations (e.g., via UAVs) are integrated with data from ground-based in-situ measurement networks to eliminate the modulation effects derived from the imaging angle ($\Omega(\lambda, \theta_v, \phi_v)$) and imaging time ($\Phi(\lambda, t)$). Furthermore, the PSF is utilized to correct for adjacency effects ($L_{bg}(\lambda)$) inherent in background noise. By elucidating the physical mechanisms of these interference factors and retrieving the pure upwelling surface

light radiance distribution ($L_{ir}(\lambda)$), this framework aims to establish a theoretical benchmark for the consistent integration of future multi-source, multi-temporal, and multi-angular multi/hyperspectral NTL data, thereby driving the transition of multispectral NTL remote sensing from qualitative observation to systematic quantitative radiometric inversion. It is important to point out that this NRTM framework does not include cloud cover as a modulation factor. Ground based night sky brightness models like Illumina consider the impact of clouds because cloud layers reflect artificial light back to the surface and amplify light pollution for upward ground observations (Ait Abdelaali et al., 2025; Aubé and Simoneau, 2018; Aubé et al., 2020a, 2020b). However the mechanism is entirely different for satellite TOA observations (as discussed in Section 5.2). Thick clouds completely block upward-radiating light from the surface, while thin clouds cause severe multiple scattering and spatial blurring. These effects destroy the spatial constraints of light source geometric diffusion. Therefore quantitative NTL remote sensing strictly masks out cloud pixels during satellite data preprocessing (Zheng et al., 2026). The proposed NRTM focuses on clear sky atmospheric conditions to reconstruct accurate intrinsic surface NTL radiance rather than modeling unrecoverable cloud diffusion.

Proposing the unified NRTM aims to provide a long-term theoretical quantitative framework for the quantification of multispectral NTL remote sensing. However, referencing the historical process of radiometric standardization in daytime optical remote sensing, achieving complete physical parameterization for NTL remote sensing may still require long-term technological accumulation (e.g., 20-30 years). Although future technological advancements (such as high-precision 3D urban modeling and sensors with high radiometric sensitivity) are expected to overcome current observation bottlenecks, at the current stage, comprehensively acquiring the nighttime surface BRDF or accurately decoupling direct and reflected radiation from multiple light sources still faces significant challenges. To consider the feasibility of this model under current data conditions, introducing selective simplifying assumptions is appropriate. First, regarding the most challenging observation geometry and 3D radiation decoupling (L_{angle} and L_{bg}), in the absence of fine 3D auxiliary data, the strict requirements for pixel-level physical BRDF can be temporarily relaxed, and complex urban mixed light sources can be approximately assumed as pseudo-Lambertian (Gagne et al., 2025). Simultaneously, empirical angular attenuation curves acquired by UAVs or multi-source high-frequency revisit satellites (e.g., SDGSAT-1, Jilin-1) in typical urban functional zones can be relied upon to construct scene-based look-up tables (LUTs) for statistical compensation, thereby circumventing the complex ray-tracing calculations that are currently difficult to achieve. Second, for the temporal dynamic effect (L_{time}), when real-time scheduling records of urban lighting systems are unavailable, it can be assumed that lighting variations follow typical periodic patterns (e.g., functional zones), utilizing statistical temporal attenuation functions extracted from hourly UAV measurements (Levin et al., 2020) to approximately replace real-time light source fluctuations. Finally, regarding the atmospheric effect (L_{air}), in the absence of synchronous meteorological parameters with high spatiotemporal resolution, the clear-sky assumption can be accepted, utilizing standard atmospheric radiative transfer models (e.g., 6S) combined with the dark object subtraction method for basic correction. Nevertheless, the feasibility assumptions of the aforementioned physical framework and empirical dimensionality reduction still await comprehensive validation by measurement data.

5.4. Application prospects

In addition to investigating the inherent gaps in NTL remote sensing, such as scale effects, angular effects, and imaging time, the development of spectral information in multi/hyperspectral NTL is equally crucial. With advancements in spectral NTL remote sensing, the exploration of additional future application themes will be stimulated. Four perspectives are provided, including but not limited to fine-grained urban

sensing, health and ecological assessment, economics and humanitarianism, and integration with Earth system models.

5.4.1. Fine-grained urban sensing

The core advantage of multispectral NTL remote sensing lies in its ability to distinguish the spectral characteristics of different light sources, thereby providing a novel, physically-based analytical dimension for fine-grained urban research (Figure 17). It enables the mapping of the renewal processes of infrastructure such as urban streetlights. Secondly, the spectral generational shift of urban lighting encapsulates crucial evidence for distinguishing between new and old neighborhoods, serving as a potential proxy indicator to assess wealth disparities and investment imbalances across different communities, such as examining whether affluent or impoverished communities completed energy-saving and eco-friendly LED retrofits earlier. Furthermore, commercial, industrial, and residential zones within cities form distinguishable mixed spectral characteristics at night due to differences in their lighting facility types, densities, and usage patterns (Cao et al., 2023a). Utilizing techniques such as spectral unmixing or supervised classification allows for the separation of these functional zones from the complex urban lighting background, achieving more accurate delineation of urban functional zones and assessment of nighttime economic activity patterns compared to using single brightness information. Further, spectral information provides a perspective for social sensing research that transcends panchromatic brightness. This potentially allows for the analysis of complex associations between different light colors (such as color temperature and color rendering index) and traffic, the sense of public safety, and crime incidents. At meter-level resolution, combining spectral features can also enable the classification, counting, and even failure detection of point light sources such as streetlamps. Moreover, by precisely classifying light source types and integrating the rated power of

various fixtures, it is possible to construct urban lighting energy consumption and carbon emission estimation models that are more refined than traditional methods. Additionally, fine-grained data can provide decision support for urban planning, such as optimizing the spectral types and spatial siting of newly built light sources (Tardieu et al., 2025), and verifying the actual operational effectiveness of smart lighting systems (such as time-based dimming and on-demand lighting) through multi-temporal observation, thereby exploring pathways for community resilience and sustainable development.

5.4.2. Health and ecological assessment

Multispectral NTL remote sensing advances light pollution assessment from the dimension of brightness to the dimension of biological effects, with the key lying in the quantification of radiation across different bands. Currently, a widespread understanding at the global scale regarding how the spectral characteristics of artificial light affect human health and ecosystems remains lacking. Multispectral data enable the mapping of radiance distribution for specific bands, particularly the blue band (Figure 18).

In terms of human health, serving as a potential global environmental health exposure parameter, multispectral NTL remote sensing data will catalyze a series of prospective epidemiological research applications. For instance, integration into large-scale long-term cohort studies (such as the UK Biobank) allows for the construction of dynamic, high-precision nighttime spectral exposure values and the revelation of potential environmental health inequalities, thereby providing decision support for nighttime environmental comfort and public health interventions (Zhang et al., 2026).

Regarding species stress induced by light pollution, first, the interference of light pollution with specific ecological processes can be assessed. For instance, plant photoperiod and flowering time are

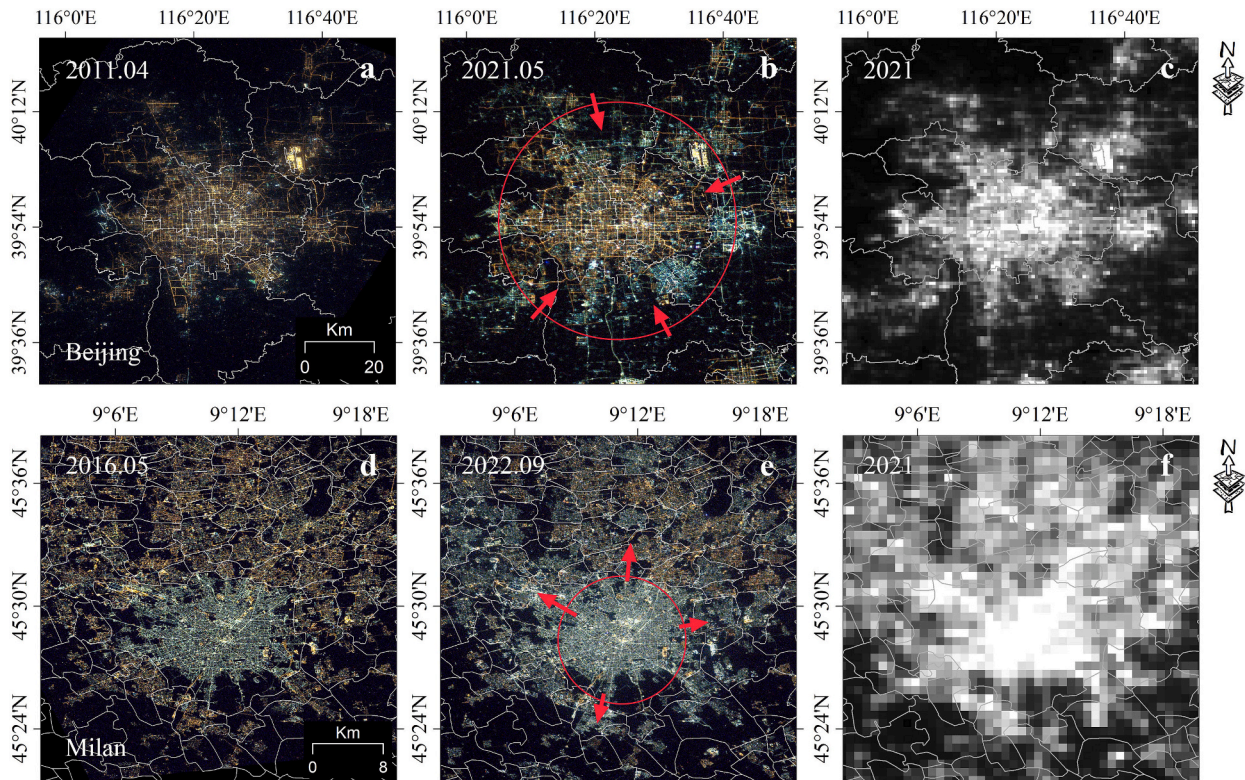


Fig. 17. Multispectral NTL features of urban evolution. (a-c) respectively show the Beijing ISS decoded images (see Section 3.1.1) from 2011.04.19 (ISS027E14758) and 2021.05.01 (ISS065E13031) alongside the 2021 NPP VIIRS image. (d-f) display the Milan ISS images (ISS047E127793 and ISS067E345065) and the NPP VIIRS image. The images highlight the advantage of multispectral night light remote sensing in fine grained urban analysis. Compared to panchromatic data, multispectral NTL data can not only reveal urban expansion, but also discover differences in urban internal evolution through spectral variations. An example is the distinct neighborhood renewal patterns between Beijing (periphery first) and Milan (center first).

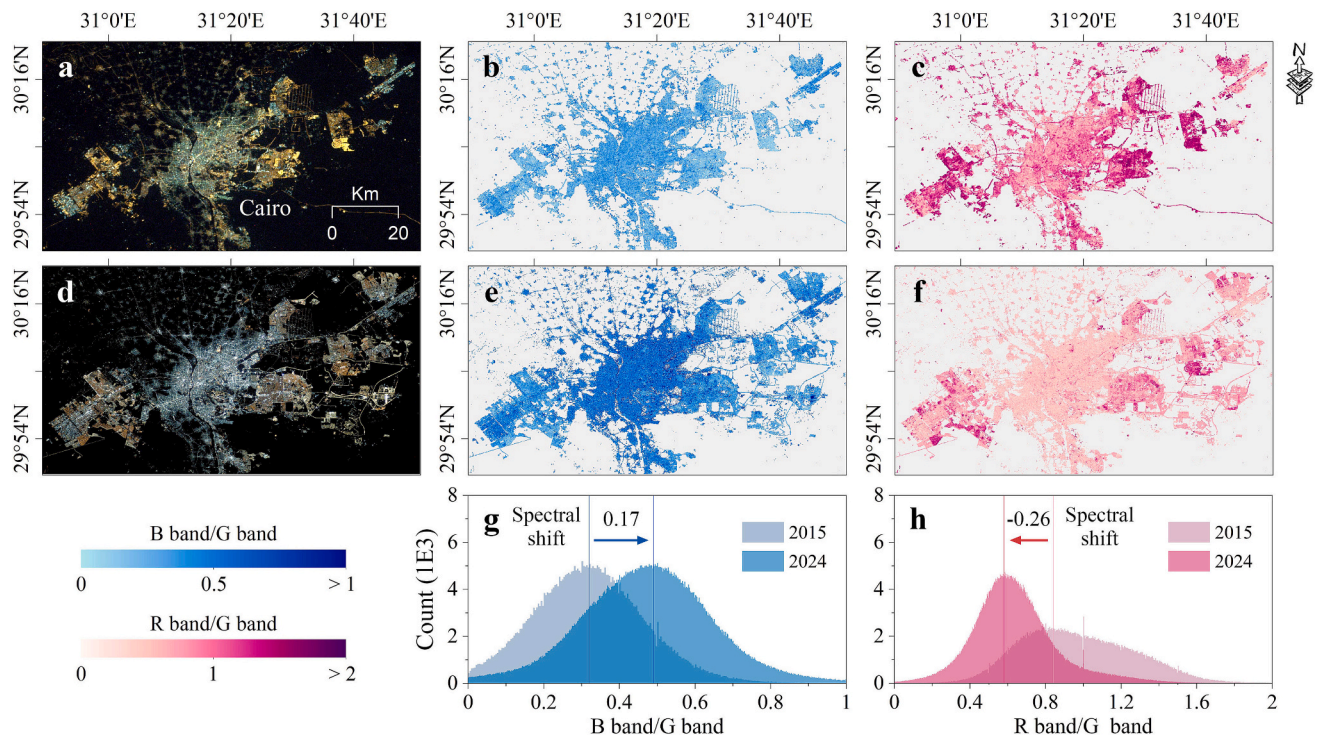


Fig. 18. Risk of light pollution growth associated with urban lighting source evolution. (a-c) Decoded ISS image of Cairo from February 6, 2015 (ISS042E230249), along with calculation results for the B/G and R/G bands, respectively. (d-f) Decoded ISS image of Cairo from January 6, 2024 (ISS070E059321), along with calculation results for the B/G and R/G bands, respectively; (g) and (h) statistical distributions of B/G and R/G. These reveal significant spectral shift characteristics regarding light pollution.

regulated by the ratio of red to far-red light, and by monitoring the spectral composition of nocturnal ambient light, potential alterations in regional plant phenology caused by urban light pollution can be evaluated. Secondly, ecological risk models based on specific spectral threats can be constructed (Sanders et al., 2021; Yan et al., 2025). By mapping

the geographical characteristics of multispectral dark night fragmentation and combining them with the visual characteristics of specific species (such as blue-light-sensitive insects or red-light-sensitive birds), spectral interference risk maps for species can be generated (Smyth et al., 2021). This facilitates the identification of the most threatening

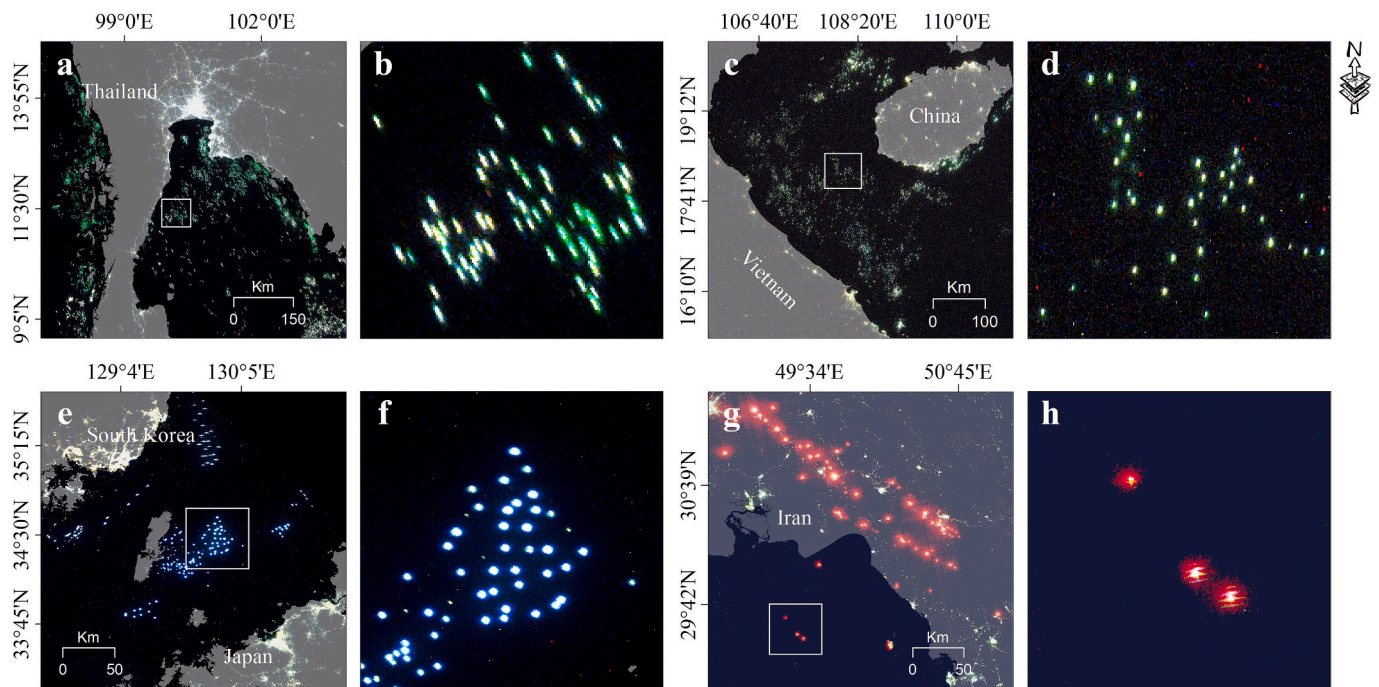


Fig. 19. Offshore oil and gas platforms and fishery lighting sources. (a, b) Marine vessel lights in the waters of Thailand (ISS053E451778), (c, d) China-Vietnam (ISS042E165418), and (e, f) Japan-Korea (ISS037E12066); (g) and (h) oil and gas platform lights in the Persian Gulf (SDGSAT-1: KX10_GIU_20250919). These demonstrate the application potential of multispectral NTL in the marine domain.

light source types and areas, providing a scientific basis for ecological corridor planning and bio-friendly lighting retrofitting.

5.4.3. Economics and humanitarianism

The application of multispectral NTL remote sensing also possesses the potential to extend toward global-scale economic activity monitoring and humanitarian response. Regarding marine economy and regulation, for example, different types of fishing vessels employ fish aggregating lights (catch lights) with unique emission spectra (such as high-intensity blue or green light) to lure specific fish species (e.g., squid and Pacific saury), which distinguishes them from the lighting of offshore oil and gas platforms or cargo ships (Figure 19). Through spectral identification, different types of maritime activities can be precisely distinguished, providing a technical supplement for marine resource management and combating illegal activities (Kanjir et al., 2018). In certain specific agricultural sectors, such as greenhouse supplemental lighting and dragon fruit farming that utilize specific spectra (e.g., combined red and blue light), distinguishable spectral signals are generated at night, providing an effective means for monitoring the spatial distribution and expansion of specific agriculture (Pack et al., 2017; Wen et al., 2026). Furthermore, based on characteristics such as lighting cycles, brightness, and spectra, agricultural (e.g., dragon fruit) yields can be estimated more accurately (Zhan et al., 2025). In humanitarian scenarios such as conflict and disaster monitoring, variations in spectral characteristics can also serve as potential information for analyzing disaster loss and recovery. Besides changes in the area and intensity of light sources, lighting spectral changes induced by disasters are also recorded in multispectral NTL imagery (Levin, 2023b). For instance, the degradation of lighting spectra from LED to HPS or biomass lighting may indicate an interruption or shift in regional energy supply. Regarding fire identification, multispectral NTL remote sensing can also provide a more accurate technical supplement compared to panchromatic NTL data (Cao et al., 2023a; Yu et al., 2024).

5.4.4. Integration with earth system models

Multispectral NTL remote sensing serves not only as a snapshot of human activity patterns but also encapsulates critical information regarding energy and matter fluxes that drive Earth system changes, offering unprecedented opportunities for constructing coupled Earth system models with higher precision. In the long term, a dynamic, spectrally resolved global NTL radiance dataset can be integrated into Earth System Models (ESMs) as a novel Forcing Field, serving to systematically assess the comprehensive impacts of artificial light drivers on global biogeochemical cycles (Cui and Dong, 2025; Johnston et al., 2025). Beyond light pollution stress, in atmospheric chemistry models, for example, nighttime lighting of specific spectra (especially the violet and blue bands) can catalyze photochemical reactions (also known as nighttime photochemistry) of pollutants such as nitrogen oxides (NO_x), influencing the generation of secondary ozone and nitrate aerosols (Brown and Stutz, 2012; Russell et al., 1986; Stark et al., 2010). Multispectral NTL data can address the current deficiencies of atmospheric chemistry models in simulating nocturnal processes. Furthermore, in the field of climate modeling, combining NTL spectral information with refined urban functional modeling can serve as a potential approach for simulating spatiotemporally dynamic, high-resolution anthropogenic emission inventories, thereby enhancing the accuracy of urban canopy models and regional climate simulations.

6. Conclusions

The rapid global transition to LED lighting has triggered a drastic spectral shift in the urban nocturnal light environment, prompting a paradigm shift in NTL remote sensing research from single-intensity monitoring to multidimensional spectral analysis. This paper systematically reviews the research progress of multispectral NTL remote sensing since 1992, confirming that this paradigm shift holds milestone

significance for scientifically assessing light pollution effects and guiding sustainable lighting policies.

Through a review of existing literature, it is evident that multispectral NTL remote sensing has achieved significant evolution in both data and applications. Data sources have developed from early stochastic imaging to global coverage, and are advancing toward the continuous development of specialized, high-resolution satellites (such as SDGSAT-1 and JILIN-1) and near-ground collaborative observation platforms. Application domains have deepened from macro-scale urbanization mapping to fine-grained aspects such as micro-scale light source type identification, precise energy consumption estimation, and the quantification of ecological risks from light pollution. Despite significant progress, current research still faces several core bottlenecks: (1) Absence of data benchmarks. Significant differences exist in spectral responses among different sensors, and a unified absolute radiometric calibration benchmark for nighttime is lacking, making the direct comparison of multi-source data difficult. (2) Unclear physical mechanisms. Existing processing methods largely adopt daytime remote sensing modes, ignoring atmospheric radiative transfer characteristics unique to the night (e.g., the strong Rayleigh scattering effect of blue light) and the complex mixed effects of direct NTL emission and directional reflection, thereby affecting quantitative inversion accuracy. (3) Applications awaiting expansion. High-uncertainty data constrain the majority of applications to the level of qualitative pattern recognition, making it difficult to support a systematized application system.

To overcome the aforementioned limitations, this paper proposes that future research focus on analyses including but not limited to: (1) Enhancing acquisition capabilities. Promoting the research and development of new-generation NTL sensors with narrow-band multi/hyperspectral resolution capabilities, and establishing a “Space-Air-Ground” integrated collaborative observation network to acquire high-quality validation data. (2) Advancing mechanism models. Integrating radiative transfer physical models with advanced artificial intelligence technologies to establish robust correction algorithms for atmospheric and angular effects, thereby achieving the spatiotemporal fusion of multi-source heterogeneous data. (3) Constructing standard products. Building a globally open and shared standardized multi/hyperspectral NTL database to lower barriers to interdisciplinary applications.

Overall, the rise of multispectral NTL remote sensing marks a leap from quantity to quality in this field. Deepening the understanding of the physical properties of data within the multidimensional “spectral-spatial-temporal” framework will serve as a powerful tool for revealing the coupling mechanisms between human activities and the nocturnal environment, providing critical scientific support for realizing the global SDGs.

CRedit authorship contribution statement

Liang Zhong: Writing – original draft, Visualization, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Xinjian Wang:** Writing – original draft, Visualization, Investigation, Data curation, Conceptualization. **Zihao Zheng:** Writing – review & editing, Funding acquisition, Conceptualization. **Qiming Zheng:** Writing – review & editing, Funding acquisition, Conceptualization. **Shaoyang Liu:** Writing – review & editing, Conceptualization, Formal analysis. **Yongpeng Lin:** Writing – review & editing, Visualization. **Zhanghao Chen:** Writing – review & editing, Data curation. **Yuanrong He:** Writing – review & editing, Supervision. **Peng Yang:** Writing – review & editing, Data curation. **Peng Yu:** Writing – review & editing. **Zhiying Xie:** Data curation. **Xiaosheng Liu:** Supervision, 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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.rse.2026.115530>.

Data availability

Data will be made available on request.

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