Remote Sensing of Environment 237 (2020) 111443

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Remote sensing of night lights: A review and an outlook for the future

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ARTICLE INFO

Keywords:
Night lights
Light pollution
DMSP/OLS
VIIRS/DNB
ISS
Urban
Human activity

ABSTRACT

Remote sensing of night light emissions in the visible band offers a unique opportunity to directly observe human activity from space. This has allowed a host of applications including mapping urban areas, estimating population and GDP, monitoring disasters and conflicts. More recently, remotely sensed night lights data have found use in understanding the environmental impacts of light emissions (light pollution), including their impacts on human health. In this review, we outline the historical development of night-time optical sensors up to the current state of the art sensors, highlight various applications of night light data, discuss the special challenges associated with remote sensing of night lights with a focus on the limitations of current sensors, and provide an outlook for the future of remote sensing of night lights. While the paper mainly focuses on space borne remote sensing, ground based sensing of night-time brightness for studies on astronomical and ecological light pollution, as well as for calibration and validation of space borne data, are also discussed. Although the development of night light sensors lags behind day-time sensors, we demonstrate that the field is in a stage of rapid development. The worldwide transition to LED lights poses a particular challenge for remote sensing of night lights, and strongly highlights the need for a new generation of space borne night lights instruments. This work shows that future sensors are needed to monitor temporal changes during the night (for example from a geostationary platform or constellation of satellites), and to better understand the angular patterns of light emission (roughly analogous to the BRDF in daylight sensing). Perhaps most importantly, we make the case that higher spatial resolution and multispectral sensors covering the range from blue to NIR are needed to more effectively identify lighting technologies, map urban functions, and monitor energy use.

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https://doi.org/10.1016/j.rse.2019.111443
Received 30 October 2018; Received in revised form 17 September 2019; Accepted 23 September 2019
Available online 04 December 2019
0034-4257/

1. Introduction

Human society has modified the Earth to such an extent, that the present geological era has been termed as the Anthropocene (Crutzen, 2002). Monitoring human activity from space has largely been directed at mapping land cover and land use changes, such as deforestation (Hansen et al., 2013). Remote sensing of artificial lights, on the other hand, provides a direct signature of human activity. Global images of the Earth at night are now iconic, thanks to NASA media releases such as the “Bright Lights, Big City” (published in Oct 23rd, 2000, https://earthobservatory.nasa.gov/Features/Lights) or the “Earth at Night” (published in April 12th, 2017, https://earthobservatory.nasa.gov/Features/NightLights) and other communication channels (Pritchard, 2017).

The availability of artificial lights is often associated with wealth and a modern society (Hölker et al., 2010a; Green et al., 2015). Brighter lights are strongly associated with increased security in the public consciousness, despite little evidence of a causal link. As a result, total installed lighting increased rapidly during the past centuries (Fouquet and Pearson, 2006), and has continued to increase in most countries during recent years (Kyba et al., 2017). An example of recent lighting changes is shown in Fig. 1. Nightscapes change when objects or areas are illuminated for the first time, as in new roads or neighbourhoods, or when lighting technologies change (Fig. 1). As a result, economic development goes in tandem with lighting.

Artificial lights at night can also provide insights on negative impacts, such as disasters (Molthan and Jedlovec, 2013), and armed conflict (Román and Stokes, 2015). The importance of monitoring the Earth at night is also demonstrated by the growing recognition of artificial light as a pollutant (Navara and Nelson, 2007; Hölker et al., 2010b), the development of new lighting sources (such as LEDs, which can increase ecological light pollution; Pawson and Bader, 2014), and the continuing growth in extent and radiance of artificially lit areas (Kyba et al., 2017). Light pollution can be defined as “the alteration of natural light levels in the night environment produced by the introduction of artificial light” (Falchi et al., 2011). Artificial light can alter species abundance or behavior due to changes in their circadian rhythms or due to their attraction to or repulsion from light (ecological light pollution; Longcore and Rich, 2004; Rich and Longcore, 2006), can decrease our ability to observe stars at night (astronomical light pollution), and also leads to negative health impacts to humans through the suppression of melatonin production and insomnia (Hölker et al., 2010b; Falchi et al., 2011; Lunn et al., 2017).

Fig. 1. Lighting changes in Calgary, Alberta (Canada) between 24/12/2010 (top) and 28/11/2015 (bottom). The neighborhood at left has converted from high pressure sodium to white LED lights, while the highway at right is newly illuminated with sodium lamps. The area has a roughly 7.5 × 3 km extent. Images based on astronaut photographs ISS026-E−12438 and ISS045-E−155029.

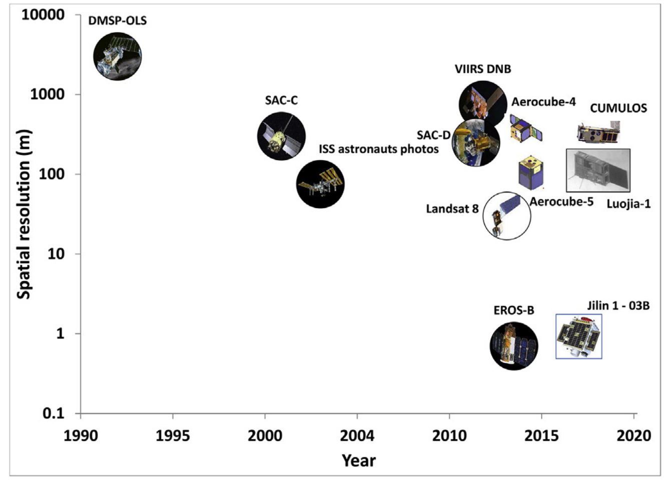

Fig. 2. Space borne sensors with night-time lights capabilities, as a function of the year from which digital night-time images are available, and the spatial resolution of the sensor.

With the development of new space borne, airborne and ground sensors for quantifying light at night, new research opportunities are emerging (Kyba et al., 2015a; Hänel et al., 2018). The first comprehensive review on remote sensing of night lights was published by Doll (2008). Since that time, a variety of new sensors have become available (Fig. 2; Table 1). More recent reviews on remote sensing of night lights have either focused solely on applications of the DMSP/OLS sensor (Elvidge et al., 2009c; Huang et al., 2014; Li and Zhou, 2017), on multitemporal applications using DMSP/OLS and VIIRS/DNB (Bennett and Smith, 2017), on the various applications of night-time imagery (Li et al., 2016) and on the community of researchers active in this field (Hu et al., 2017). Since the recent review of Zhang et al. (2015b), new sensors, algorithms, and applications have emerged (Zhao et al., 2019). In this paper we therefore aim to provide a comprehensive review on the field of remote sensing of night lights, focusing on the visible spectral range, which is mostly related to artificial lights used by people to light the night so as to extend human activity hours. In our review we cover space borne, airborne, and ground based observations (recently reviewed in Hänel et al., 2018). We cover the historical development of this research area, the available sensors, the current state of the art algorithms for routine data processing, key applications, the differences to daytime remote sensing, upcoming space-based night lights missions, and future research challenges.

2. Historical overview

2.1. Earliest observations of night lights

Historically, technological developments in the energy industry (such as the transition from candles to gas, and later on to kerosene and then to electricity) have led over the past centuries to a gradual decrease in the price of lighting services, and were associated with increases in lighting efficiency and in the consumption of light per capita (Nordhaus, 1996; Fouquet and Pearson, 2006). The foundation of the Edison Electric Light Company can mark the modern era of lighting, and since the year 1800, the total consumption of light in the United Kingdom alone has grown by 25,600 times (Fouquet and Pearson, 2006). Walker (1973) reports that already in the 1930s sky illumination has started to preclude astronomical viewing from certain observatories (and see Rosebrugh, 1935), and as Bertrand Russell famously wrote in 1935, “*In the streets of a modern city the night sky is invisible; in rural*

Table 1
Comparison of available space-borne sensors for night-lights mapping, sorted by spatial resolution.

Sensor	Spatial resolution (m)	Operational years	Temporal resolution	Products	Radiometric range	Spectral bands	Main references
DMSP/OLS	3000	Digital archive available for 1992–2013	Global coverage can be obtained every 24 h	Stable lights, Radiance calibrated, Average DN	10^{-6} to 10^{-9} W/cm^2/sr/µm 6 bit Min detectable signal 4 10-5 W/m/sr	Panchromatic 400–1100 nm	Doll (2008); Elvidge et al., (1997b), 2009c
VIIRS/DNB	740	Launched in Oct 2011	Daily images can be downloaded.	Monthly Cloud-free composites available from April 2012 onwards in radiance units of nano-Watts/(cm^2*sr).	14 bit	Panchromatic 505–890 nm	Miller et al., (2012); Elvidge et al., 2013a,b,c, 2017; Román et al., 2018 https://viirsland.gsfc.nasa.gov/
				Daily corrected product, VNP46A1, available since mid-2019 (NASA Black Marble).	Min detectable signal 3 10-5 W/m/sr		https://ladsweb.modaps.eosdis.nasa.gov/search/order/1/VNP46A1–5000
Aerocube 4	500	Experimental cubesat, 2014	Sporadic	N\A	Detection threshold of about 20 nW/cm2/sr to achieve SNR of 4 or more	RGB	Pack and Hardy (2016); Pack et al. (2017)
SAC-C HSTC	300	Launched in Nov 2000	Sporadic	N\A	8 bit	Panchromatic 450–850 nm	Colomb et al. (2003)
SAC-D HSC	200–300	Launched in June 2011	Sporadic	N\A	10 bit	Panchromatic 450–900 nm	Sen et al. (2006)
Astronauts photographs onboard the International Space Station (ISS)	5–200	From 2003 onwards (since mission ISS006)	Photos taken irregularly	Photos can be searched and downloaded from: http://eol.jsc.nasa.gov/	8-14 bit	RGB	Doll (2008); Levin and Duke (2012); Kyba et al., 2015a; Sánchez de Miguel et al. (2014)
CUMULOS	150	Experimental cubesat, 2018	Sporadic	N\A	N\A	Panchromatic	Pack et al. (2018), 2019
LuoJia1-01	130	Launched June 2018	15 day revisit time	Freely available	DN values with lab calibration	Panchromatic, 460–980 nm	Li et al. (2018b), 2019a
Aerocube 5	124	Experimental cubesat, 2015	Sporadic	N\A	Detection threshold of about 20 nW/cm2/sr to achieve SNR of 4 or more	RGB	Pack and Hardy (2016); Pack et al. (2017)
Landsat 8	15–30	Launched in 2013	Night time images acquired irregularly	Freely available	14 bit Only very bright objects are detected	Seven bands	Roy et al. (2014); Levin and Phinn (2016)
Jilin-1 (JL1-3B)	0.9	Launched January 2017	Commercial satellite, acquires images on demand	N\A	8 bit	430–512 nm (blue), 489–585 nm (green) and 580–720 nm (red)	Zheng et al. (2018) https://www.cgsatellite.com/imagery/luminous-imagery/
JL1-07/08	< 1	Launched January 2018	Commercial satellite, acquires images on demand	N\A	N\A	Panchromatic and multi-spectral (blue, green, red, red edge, and near-infrared bands)	Zhao et al. (2019)
EROS-B	0.7	Night lights images offered since mid-2013	Commercial satellite, acquires images on demand	N\A	16 bit	Panchromatic	Levin et al., 2014; Katz and Levin (2016)

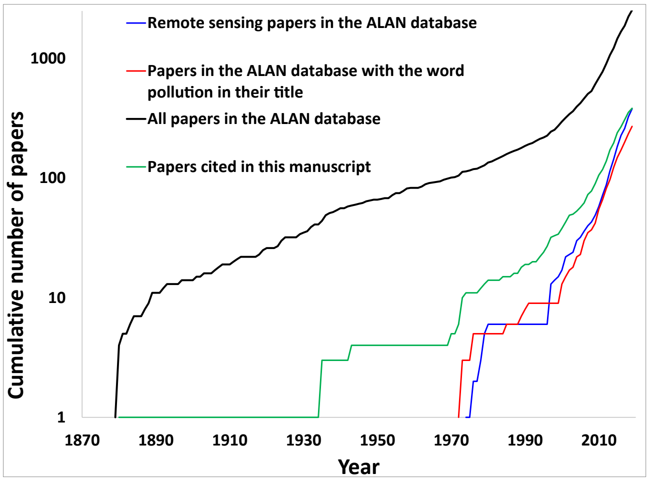

Fig. 3. Cumulative number of papers on artificial lights in the Artificial Light at Night (ALAN) Research Literature Database (n = 2545) (http://alandb.darksky.org/, accessed September 16th, 2019). Also shown are papers where the title of the paper included the word pollution (n = 271), and papers published in remote sensing journals or where either one of the words "remote", "sensing", "satellite", "DMSP", "VIIRS", "Luojia", "SQM" appeared in the title of the paper or that Chris Elvidge was one of the co-authors (n = 380). The green line shows the yearly numbers of papers cited in this manuscript (n = 384). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

districts, we move in cars with bright headlights. We have blotted out the heavens, and only a few scientists remain aware of stars and planets, meteorites and comets." (Russell, 1935).

The Artificial Light at Night (ALAN) Research Literature Database (http://alandb.darksky.org/, accessed September 16th, 2019) which covers 2,545 publications on the topic of light pollution (Fig. 3; note however, that the ALAN database does not include all publications on light pollution or on remote sensing of night lights), has as one of its first papers that of Edison (1880). However, publications on light pollution were scarce until the mid-20th century (Fig. 3; compare with Davies and Smyth, 2018). The first paper mentioning light pollution in its title (within this database) was only published in 1972, and it already suspected possible negative health impacts from exposure to artificial light at night (Burne, 1972). Other papers published in the early 1970s on light pollution were more concerned with the negative impacts that artificial lighting has on the ability of astronomers on view the night sky (e.g., Riegel, 1973), and the front cover of Vol. 179 No 4080 of Science shows the dramatic increase of city lights in Los Angeles between 1911 and 1965, as observed from Mount Wilson.

One of the first famous observations of cities' lights from space is attributed to US astronaut John Glenn, who in his orbit of the Earth in February 20th, 1962, saw Perth as the "City of Lights", thanks to local citizens and businesses who have turned on as many lights as they could as a sign of support for his mission (Biggs et al., 2012). In many ways, the subsequent development of remote sensing of night lights, can be compared to the general development of Earth observation using daytime images for environmental monitoring. However, as will be described below, remote sensing of night lights suffers from a lack of sensors, and consequently there is a temporal lag in the development of algorithms and customer-ready products.

2.2. Space borne sensors for measuring night lights

During nighttime, most passive remote sensing applications have focused on the thermal or microwave spectral regions, measuring radiation related to heat emission (Weng, 2009). In the following sections we detail the various sensors and platforms from which remote sensing of night lights in the visible range has been performed.

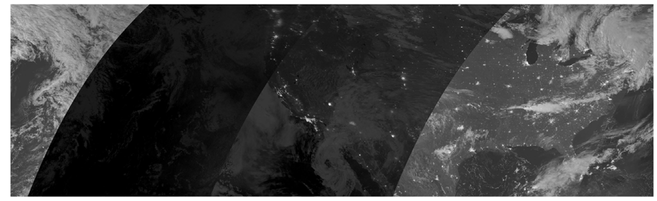

Fig. 4. Lunar eclipse over North America on 2014/10/08, viewed by VIIRS DNB. At far right, the eclipse had not yet begun, and the instrument observed clouds illuminated by full moonlight. The next strip was taken with the moon partially eclipsed, and the dark strip when the moon was near to fully eclipsed. The final strip (at left) was taken one day earlier. Image prepared by Christopher Kyba based on image and data processing by NOAA's National Geophysical Data Center. Image available under a CC BY license at https://tinyurl.com/us-eclipse-20141008.

2.2.1. DMSP/OLS

The first American satellites for Earth observation, launched in the 1960s, were either aimed for weather monitoring (TIROS-1, launched on April 1, 1960; Rao et al., 1990) or for military reconnaissance – the Corona program (McDonald, 1995). The Defense Meteorological Satellite Program (DMSP), started in the mid-1960s as the meteorological program of the US Department of Defense, aiming to collect global cloud cover data day and night. The era of global satellite observation of electric lighting started in 1971 with the launch of the SAP (Sensor Aerospace vehicle electronics Package) instrument flown by the Defense Meteorological Satellite Program. The SAP collected global imaging data in a panchromatic band spanning from 500 nm to 900 nm and a long-wave infrared channel. The signal from the visible band was intensified using a photomultiplier tube. Dickinson et al. (1974) presented a November 1971 SAP image showing nighttime lights of Northern Europe and gas flares in the North Sea. The purpose of the low light imaging was to enable the detection of clouds in the visible using moonlight as the illumination source (see e.g. Fig. 4). The requirement for this came from Air Force meteorologists. A second generation low light imager, known as the Operational Linescan System (OLS) was carried on DMSP Block 5D satellites, with a first launch in 1976. A series of nineteen OLS instruments have been flown and data collection continues to the present (2019). However, the overpass times vary, with some satellites in dawn-dusk orbits and others in day-night orbits (Fig. 5). Only the day-night satellites provide nighttime data in sufficient quantities to produce global nighttime lights products. While the existence of DMSP system was acknowledged in 1972, the use of nighttime images of the Earth within the remote sensing community was very limited until the 1990s (Fig. 3). This is mostly because until 1992 DMSP/OLS images were written to film and were not available in digital form. The University of Colorado, National Snow and Ice Data

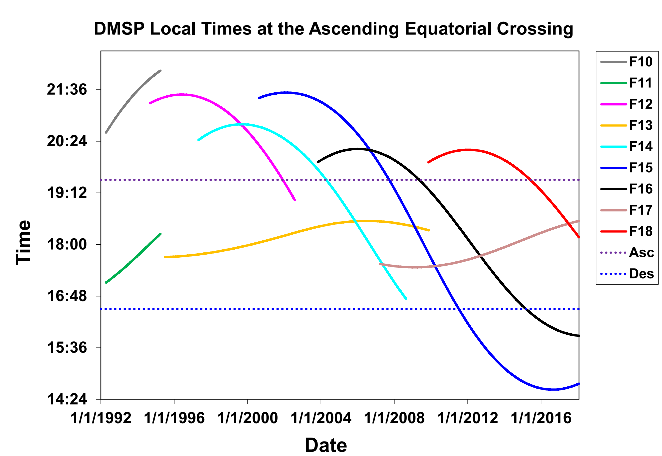

Fig. 5. DMSP local times at the ascending equatorial crossing.

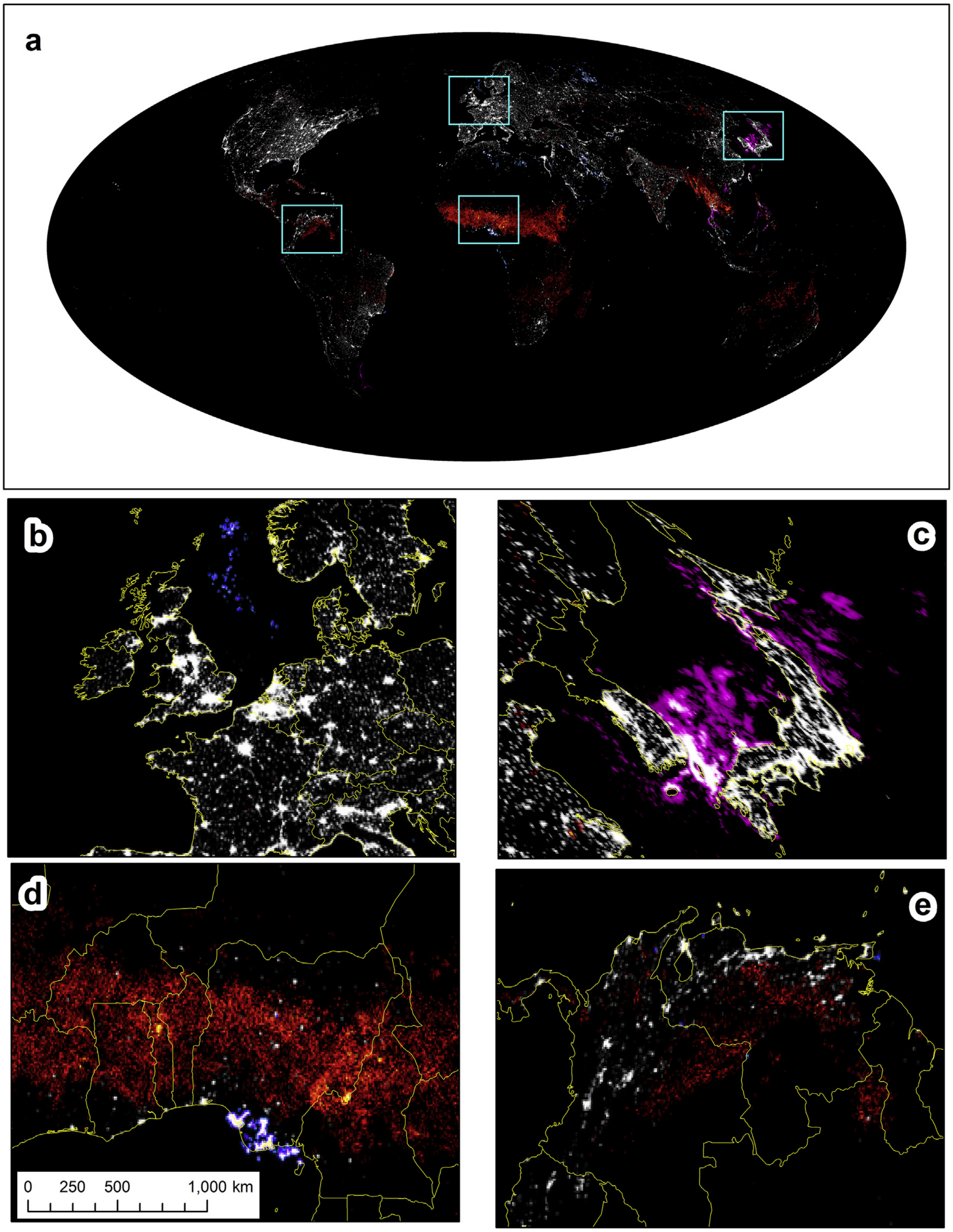

Fig. 6. DMSP colorized night lights. The white represents lights generated from electricity, the red shading shows fires, the pink shading indicates light from squid fishing boats, and the blue spots are gas flares from oil rigs. This dataset was compiled from DMSP data between October 1994 and March 1995. The differentiation of fires, boats, electric lights and gas flares was all done by temporal analysis (do the lights stay constant and do they move). The instrument itself is not able to distinguish between them. Zoomed in areas are shown for northern Europe (b), Japan and Korea (c), western Africa (d), and northern South America (e). Source of dataset: https://sos.noaa.gov/datasets/nighttime-lights-colorized/.(For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Center operated a film archive. Nonetheless, early scientific papers using DMSP/OLS observations of artificial lights from space were already published in the 1970s, with regards to astronomical light pollution (Hoag et al., 1973; Walker, 1973) and concerning the ability to monitor various human activities such as cities' lights, waste gas burning, agricultural fires and fishing fleets who use lights (Croft, 1973, 1978, 1979; Welch, 1980) (Fig. 6). Sullivan (1989) produced the first global map of DMSP nighttime lights by mosaicking hand selected DMSP film segments (Fig. 7). In comparison, the Corona satellite program and its associated photos were declassified much later than the

Fig. 7. Section of the first global map of DMSP nighttime lights, produced by mosaicking film segments by Woody Sullivan, University of Washington.

DMSP program, in 1995, and have since allowed the development of various applications (Dashora et al., 2007).

The launch of NOAA Advanced Very-High-Resolution Radiometer (AVHRR) weather satellites in the late 1970s (on TIROS-N in 1978 and on NOAA-6 in 1979; Rao et al., 1990), enabled the development of global 1 km products for monitoring vegetation, surface temperature and land cover changes, with datasets going back to the early 1980s (Ehrlich et al., 1994). Similarly, a digital archive for DMSP data was established at the NOAA National Geophysical Data Center in 1992. In 1994, Chris Elvidge and Kimberly Baugh embarked on a program to produce global DMSP nighttime lights and fire products from digital DMSP data at NOAA's National Geophysical Data Center (NGDC) in Boulder, Colorado. This team pioneered the development of global satellite observed maps of nighttime lights. Algorithms were developed to geolocate OLS images and screen out sunlit and moonlit data. The first NGDC test product was of the USA and had 29 orbits as input. This product was clearly missing large numbers of lights from known cities and towns (Fig. 8). To address the shortcoming regarding the large numbers of missing lights, the team realized they had no assurance that each area had cloud-free observations. This led to formal tracking of the numbers of observations and cloud-free coverages to ensure a comprehensive and standardized compilation of lighting features. A cloud detection algorithm was developed using the long wave infrared OLS data. The second NGDC product, made with 236 orbits with cloud screening is shown in Fig. 9. For the global products, full years of data are used to ensure that there are multiple observations remaining after filtering out sunlit, moonlit and cloud data. Because fires are so readily detected by both DMSP and VIIRS, NGDC developed an outlier removal process tuned to filter out fires and retain areas with electric lighting (Baugh et al., 2010; Elvidge et al., 2017). One of the major shortcomings of the operational DMSP data collections is signal saturation in

Fig. 8. NGDC's first map of DMSP nighttime lights, produced from 29 orbits and no cloud screening.

Fig. 9. NGDC's second generation DMSP nighttime lights product produced with cloud-screening from 236 orbits acquired in a six month period in 1995.

bright urban cores. In part, this is due to the fact that the visible band gain is gradually turned up as lunar illuminance declines. To produce a global nighttime lights product free of saturation, NOAA worked with the Air Force to schedule reduced gain OLS data (Elvidge et al., 1999). Global nighttime lights products were generated for seven years between 1996 and 2010 based on the preflight OLS calibration (Hsu et al., 2015). A sample of this data is shown in Fig. 10. Another shortcoming of the DMSP data is that its images are blurred, a phenomena termed as “blurring”, “blooming” or “overglow”. This is caused by scattering in the atmosphere (Sánchez de Miguel et al., 2019a), and discussed further in section 2.4.2. Abrahams et al. (2018) demonstrated that this blurring follows a Gaussian point-spread function, and developed an approach to deblur DMSP data. Other approaches for reducing and correcting the “blooming” effect on DMSP data were suggested by Townsend and Bruce (2010), Hao et al. (2015) and Cao et al. (2019). An additional limitation of DMSP imagery is that data acquired in different years in not directly comparable due to differences in atmospheric conditions, variations in sensor settings and sensor degradation; various approaches have been suggested to overcome these issues, amongst them, is the use of Pseudo Invariant Features (PIFs) to normalize DMSP imagery (Wei et al., 2014).

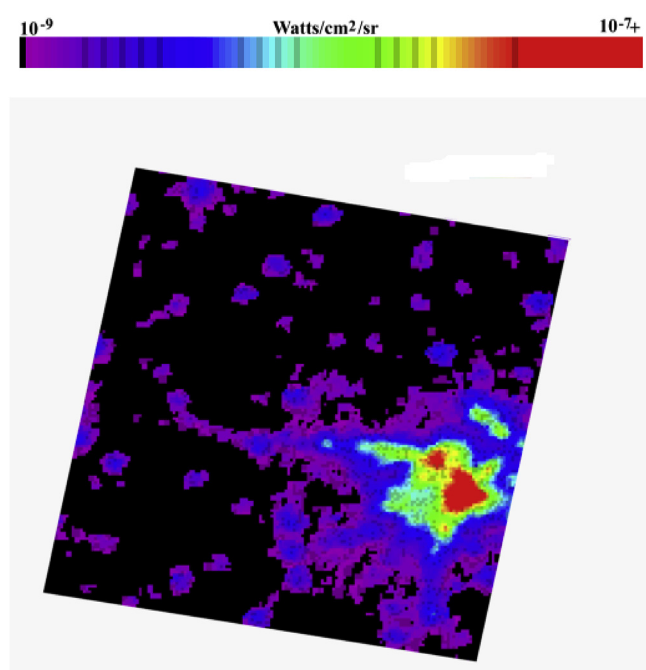

Fig. 10. DMSP radiance nighttime lights for St. Louis, Missouri.

Christopher Elvidge and his team NOAA-NGDC have led the development of the various annual products of DMSP/OLS (covering the years between 1992 and 2013), which have been widely used, and are freely accessible online athttps://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html. The two major 1 km global products of DMSP/OLS include average visible stable lights, and average lights × percentage, and are further described below (Baugh et al., 2010), however a host of other products have also been developed with time from DMSP/OLS data, including Global Radiance Calibrated Nighttime Lights, global impervious surface area (Elvidge et al., 2007a), global gas flare time series (Elvidge et al., 2009a), and more. By providing global time series of night lights, numerous papers have been published utilizing this unique source to study urbanization, socio-economic changes and threats to biodiversity (Bennett and Smith, 2017). False color composites of DMSP stable lights from different years have proven to be an effective way to visualize changes in artificial lighting and to follow patterns of urbanization, expansion of road networks, economic expansion or decline and damages to infrastructure as the result of armed conflicts (Fig. 11).

2.2.2. Landsat and nightsat

Environmental monitoring of the Earth has been dramatically boosted by the launch of the first Landsat satellite in 1972, and the ongoing continuation of Landsat missions (whose entire archives became free to the public in 2009), and other civilian governmental satellites, offering medium spatial resolutions between 5 and 100 m at various spectral and temporal resolutions (Lauer et al., 1997; Roy et al., 2014). While Landsat satellites do acquire night-time images, these are mostly useful for their thermal information, as the optical sensors onboard the TM and ETM + sensors were not designed for low light levels prevalent at night-time. However, the OLI sensor onboard Landsat 8, with its improved radiometric sensitivity, has been shown to be able to detect night-time lights from very bright areas such as gas flares and city centers (Levin and Phinn, 2016). Unfortunately, no sensor has been launched yet which offers operational multispectral monitoring of the Earth's night lights at medium spatial resolution. Nonetheless, the requirements of radiometric, spectral, spatial and temporal resolutions for such a sensor (termed NightSat) have been defined in a series of papers (Elvidge et al., 2007b; c, 2010), and are discussed in section 4.8 of this review paper. While two panchromatic sensors designed for observing night lights and offering a spatial resolution of about 300 m have been launched in joint missions of CONAE and NASA (the SAC-C HSTC in 2000, and the SAC-D HSC in 2011; Colomb et al., 2003; Sen et al., 2006), images from them are hardly available and few papers have utilized them (but see Levin and Duke, 2012).

2.2.3. Remote sensing of night lights from the International Space Station

2.2.3.1. Night-time astronauts photographs. Astronaut photography from various NASA missions, including the Space Shuttle missions and the International Space Station (ISS), have long been used for observing a variety of environmental phenomena from low Earth orbits (Stefanov et al., 2017). The database of these photos is extensive, includes both daytime and nighttime photos, and is freely accessible via the Gateway of Astronaut Photography of the Earth (https://eol.jsc.nasa.gov/). The very first human acquired images from the Earth at night that we know of were the images taken by the astronauts of the Space Shuttle during Hercules/MSI mission (Simi et al., 1995). For example a picture of Charlotte, US taken in 1993 was used to find the major sources of light at night, with the result of identifying vertical signs near the roads toward the airport that were lit on both sides with lights directed upwards to illuminate the signs.[1] This pioneer and other works were lost during the pre-internet era.

From 2001 until the present, the crew of the ISS has been taking images of Earth, space, and activities upon the station using digital single lens reflex (DSLR) cameras. Their nighttime images are the oldest multispectral images of the visible wavelengths emitted from the Earth at night. Most night-time ISS images of Earth and space were taken either for outreach purposes or for the astronaut's pleasure, offering a unique perspective on our planet (Fig. 12). Nevertheless, they comprise a unique and valuable dataset. Although there are technical challenges associated with radiometric calibration of such images (e.g. accounting for window extinction), work done at the Complutense University of Madrid over the last decade proves that calibration of ISS night light images is possible (Sánchez de Miguel et al., 2013a, 2013b, 2018; Sánchez de Miguel, 2015). One of the main problems of the astronaut photography is the motion blur produced by the orbital movement of the ISS. To solve this problem, astronaut Donald Pettit created a handmade device to compensate the movement of the ISS on the mission 006 (Pettit, 2009). Later, ESA created a special tripod called Nightpod (Sabbatini, 2014) used from the ISS030 to the ISS040 at least (precise date of decommissioning is unknown) (Fig. 13). While DSLR cameras can be modified and have their IR-filter removed, so as to measure incoming light also in the infrared band (which is useful both for astrophotography purposes and for monitoring artificial lights sources which emit light in the near infra-red; Andreić and Andreić, 2010), the vast majority of astronaut night-time photography of the Earth, was limited to the visible range alone.

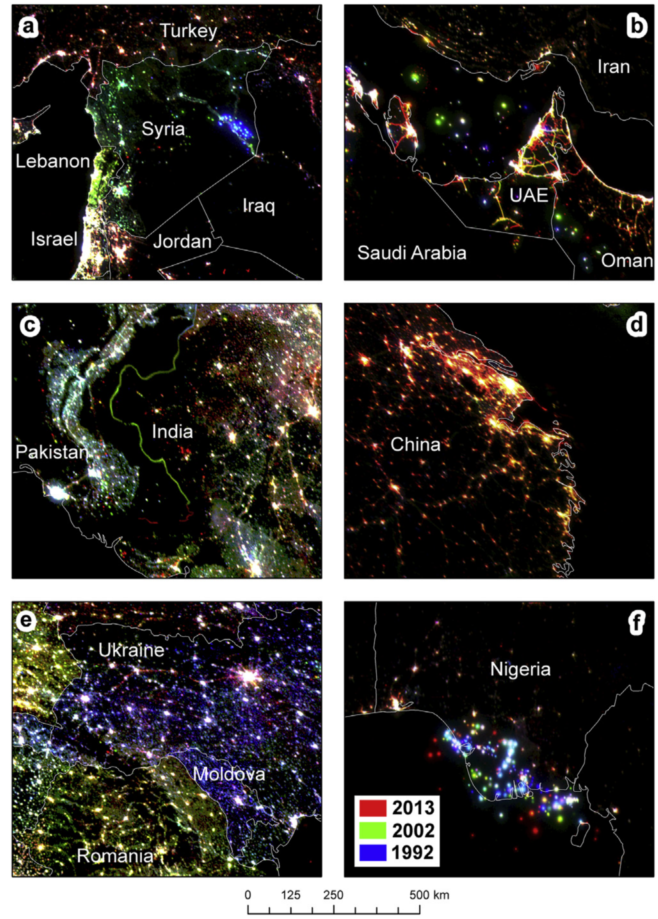

Fig. 11. False color composites of DMSP stable lights version 4, showing: (a) decrease in lights following the war in Syria; (b) expansion of roads in the United Arab Emirates (UAE); (c) the lit border between India and Pakistan; (d) urbanization in China; (e) economic decline in Ukraine and Moldova following the collapse of the Soviet Union; (f) temporal changes of gas flares from oil wells in Nigeria. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

[1] Private communication. William Howard, 12 Aug 2015.

Fig. 12. Night lights of the Levant, Astronaut photograph ISS053-E – 50422, taken on 28/9/2017, 00:10:11 GMT. At the bottom of the image the densely populated Delta of the Nile can be seen, while the center of the image covers Israel, the West Bank, Jordan and Lebanon. The consequences of the conflict in Syria are hinted in this photo, where Syria is mostly dark, in contrast with lit towns and cities in Turkey to the north.

images (Kyba et al., 2015a; ,Sánchez de Miguel et al., 2019b; Fig. 14), of hundreds of cities globally, albeit without any ordered acquisition program (Fig. 13). Various studies have shown the value of those photos for studying socio-economic properties of cities at finer spatial resolutions than available by the DMSP/OLS (e.g., Levin and Duke, 2012; Kotarba and Aleksandrowicz, 2016; Kuffer et al., 2018). Calibrated DSLR images from the ISS have been used for epidemiological studies (Garcia-Saenz et al., 2018), energy use and lighting technology studies (Kyba et al., 2015a,b), environmental impact studies (Pauwels et al., 2019) and ecological studies (Mazor et al., 2013). In some cases, researchers have used ISS images without using, or at least without explaining, a radiometric calibration; however, Sánchez de Miguel et al. (2013b) have developed a method to perform an absolute photometric calibration of ISS photos. Two companies currently provide calibration on demand of ISS images: www.noktosat.com and Eurosens. The "Cities at Night" project team has occasionally produced radiance calibrated images for scientific collaborations, and a project based at the University of Exeter is currently working on a data processing pipeline to produce a public database of calibrated images. The first mosaic of high resolution ISS images was made by Schmidt (2015), covering the administrative boundaries of the country of the Netherlands, and low resolution mosaics were made using time lapses by Sánchez de Miguel and Zamorano (2012), covering large parts of the US, Europe and middle-east.

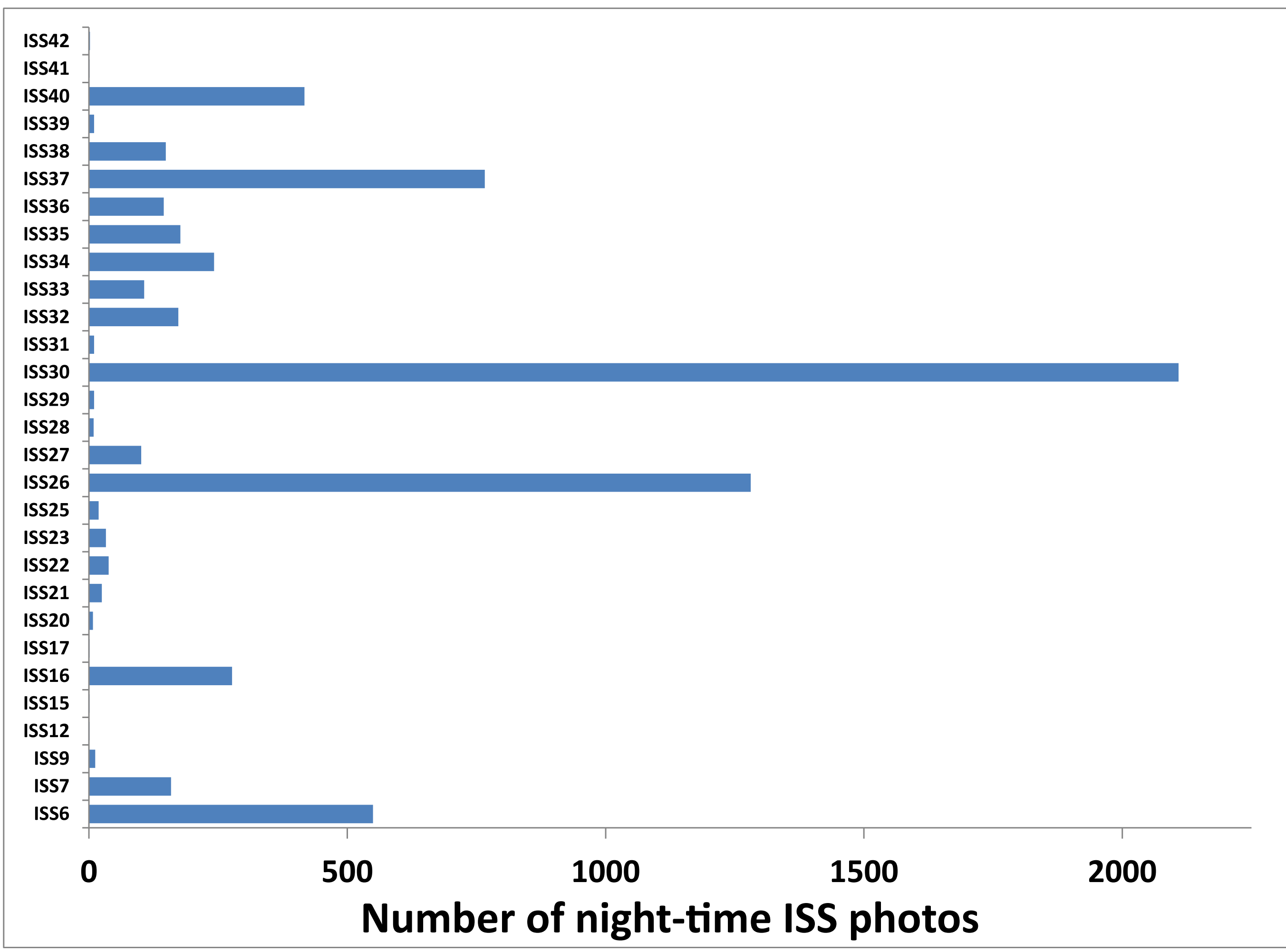

Fig. 13. The number of night-time ISS photos identified by the Cities at Night crowdsourcing project (http://citiesatnight.org/index.php/maps/). Note that in several ISS missions many night-time photos were taken, while in other missions hardly any night-time photos were taken. The data shown does not include the recent three years.

The greatest advantages of night-time astronaut photos over other sources, are in their moderate spatial resolution (often between 5 and 200 m), and in being the first to provide color space borne night-time

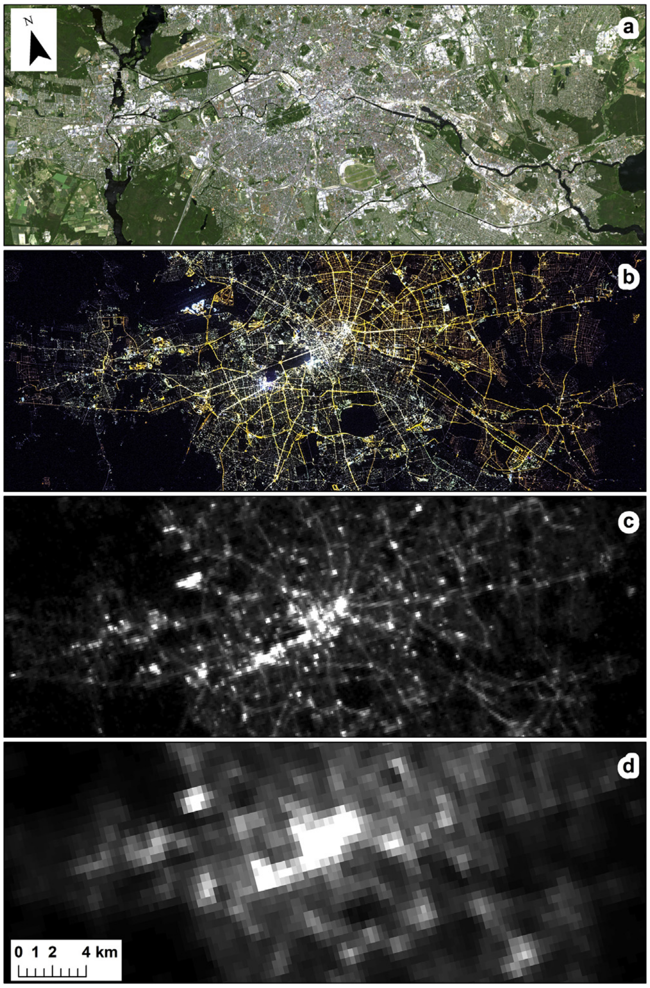

Fig. 14. Berlin at day and night: (a) Landsat 8 OLI, April 2017, true color daytime composite; (b) Astronaut photography from the International Space Station, ISS047-E – 29989, March 2016; (c) Luojia01 night-time image, August 25th, 2018; (d) VIIRS/DNB monthly composite, October 2016. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

2.2.3.2. Citizen science: cities at night. Currently, the astronaut photographs from the ISS are the largest online multispectral archive of night-time images of the Earth (https://eol.jsc.nasa.gov), with a unique potential for light pollution studies and to track changes in lighting technologies. However, these images lack precise location and georeferencing, and in addition, all the images of the Earth at night are mixed with images of astronomical and meteorological images, making it difficult to identify night-time images from the ISS, as they are often not tagged adequately. A citizen science program called "Cities at Night" was therefore launched with its major aim to provide an improved catalogue of night-time images from the ISS (Sánchez de Miguel et al., 2014). The project has three steps, classification/tagging to find the cities images called "Dark skies", location of the cities called "Lost at Night" and georeferencing called "Night cities". Thanks to the collaboration of more than 20,000 volunteers, the project has been able to tag more than 190,000 nocturnal images of mid and high spatial resolution (resolution from 5 to 200 m). The project was also able to locate more than 3000 images of cities with at least one control point and 700 images of cities with enough control points to be georeferenced (Sánchez de Miguel, 2015). A fourth app had been created as a gamified version of "Dark Skies" called "Night Knights" with all the unprocessed answers of the project available from the beginning, but also some products (a large processed tagged catalogue of images with low precise location and smaller sample precise located images) have been released and are available of the web page of the project (Sánchez de Miguel et al., 2018). The images located by the volunteers and the researchers have already been used on several papers concerning light pollution monitoring (Sánchez de Miguel. 2015), epidemiological studies (Garcia-Saenz et al., 2018) and ecological studies (Pauwels et al., 2019). Several groups have used the "Cities at Night" as training sample for computer vision proposes, including Minh Hieu (2016), Calegari et al. (2018) and Sadler (2018). Based on this catalogue it can be seen that ISS night-time photos are not representing all parts of the world, and are more common in the urban areas of North America, Europe, the Middle East, eastern China and Japan (Fig. 15a).

2.2.3.3. Additional night-time sensors on the ISS. Another source of images of the Earth at night from the ISS is dedicated instrumentation on the ISS. For example, the experiment LRO (Lightning and Sprites Observation) (Farges and Blanc, 2016) was able to produce around at least 100 night-time images of urban areas (see Figure S1 in Farges and Blanc, 2016); such imagery constituted the largest sample of medium spatial resolution (at about 400 m) images of Earth at night taken before the ISS026 mission. However, these images include sensitivity in the infrared regime, so they are difficult to compare to other images. Other instruments of similar science cases as ASIN recently arrived to the ISS might also be able to acquire some light pollution measurements. Since 2011, the Japanese Space Agency (JAXA) has been using a series of highly sensitive cameras on the ISS for the study of transient luminous event (TLEs) such as lightning of sprites, or other projects (Yair et al., 2013). In the first videos, the main goal was the detection of TLEs, but light emissions from the Earth were also obvious. The second generation of these cameras was installed in 2016, and there is currently an ongoing collaboration between the University of Exeter and JAXA to provide radiometric calibration of this data.

2.2.4. VIIRS/DNB

The two MODIS sensors, onboard the Terra and Aqua satellites (launched in 1999 and 2002, respectively), with their 36 spectral bands, have led to the development of dozens of global products at various spatial and temporal resolutions, for monitoring vegetation, snow, fires, surface temperature etc. (Justice et al., 2002). Providing continuity to MODIS, the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor onboard the Suomi NPP (Murphy et al., 2001) was launched in October 2011, and has been fitted with a specific panchromatic sensor designed for measuring night time lights – the Day and Night Band (DNB) (Miller et al., 2012, 2013). The VIIRS/DNB presents a significant improvement over the DMSP/OLS sensor, in data availability (with daily images provided for free), in its higher spatial resolution (740 m, instead of about 3 km for the DMSP), in providing radiometrically calibrated data which is sensitive to lower light levels and does not saturate in urban areas, and in the reduced overglow (Liao et al., 2013; Elvidge et al., 2013a, 2017, Fig. 12). Therefore, global nighttime lights product generation has switched over from DMSP to VIIRS data in 2012, with the last annual products of DMSP produced for the year 2013 (Elvidge et al., 2017). The first products made available based on VIIRS/DNB data provided global monthly composites of night lights, starting in April 2012 (available athttps://eogdata.mines.edu/download_dnb_composites.html), which have already allowed to advance our understanding on various topics, such as seasonal changes in night-time brightness (Levin, 2017), and detecting the negative impacts of military conflicts (Li et al., 2017). Raw VIIRS/DNB imagery are also freely available for downloading at a nightly basis (in contrast with DMSP/OLS data), and this has enabled to gain insights on the anisotropic characteristics of artificial lights (Li et al., 2019b). A novel product released in 2019, is NASA's Black Marble nighttime lights product suite (VNP46A1), at a spatial resolution of 500 m (Román et al., 2018). This product provides cloud-free, atmospheric-, terrain-, vegetation-, snow-, lunar-, and stray light-corrected radiances for estimating daily

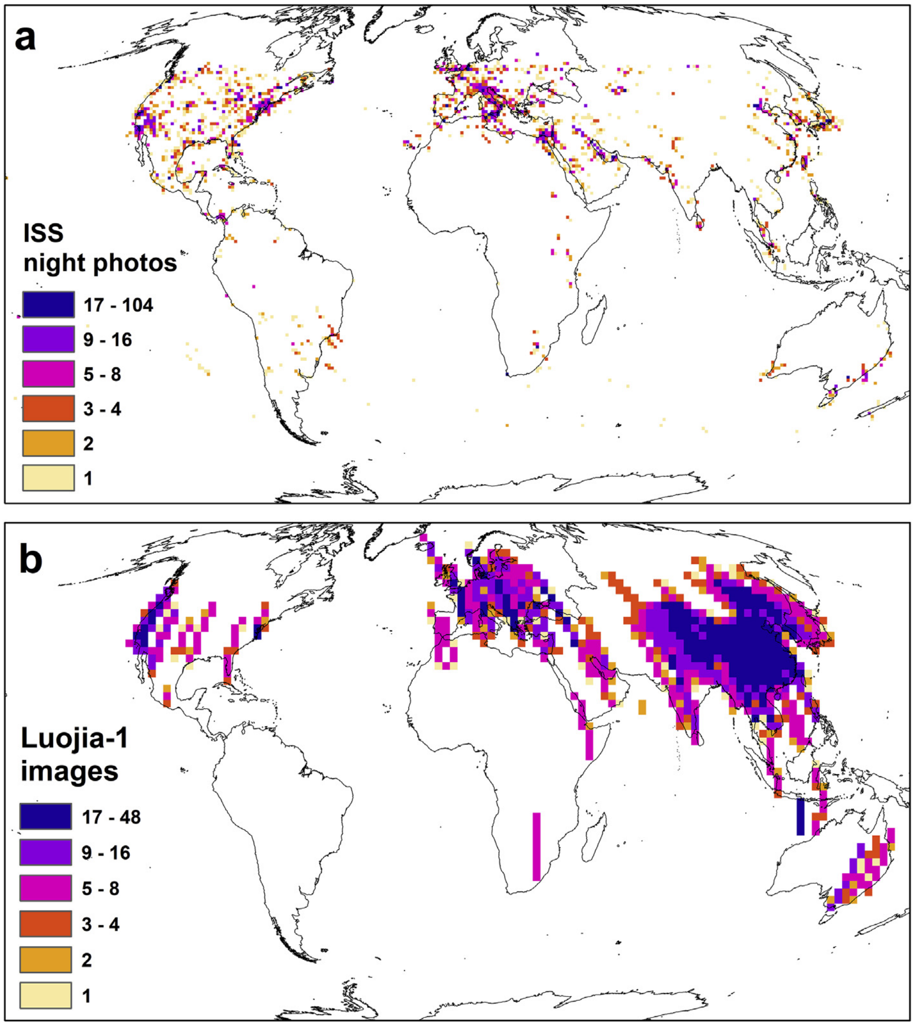

Fig. 15. (a) The number of night-time ISS photos identified by the Cities at Night crowdsourcing project (http://citiesatnight.org/index.php/maps/), within 100 × 100 km grid cells . (b) The number of all night-time Luojia-1 images acquired so far (n = 8675, May 2019), as received from Wuhan University, with 250 × 250 km grid cells.

nighttime lights (NTL) (Román et al., 2018), thus enabling fine tracking of conflict affected displaced populations, damages to the electricity grid following disasters, and identification of events when and where people congregate (Román and Stokes, 2015).

2.2.5. Commercial satellites and cubesats

A new phase in Earth observation from space ushered in 1999 with the launch of Ikonos – the world's first high spatial resolution commercial satellite, and the first to offer a 1 m panchromatic band from space (Belward and Skøien, 2015). Since then additional companies have joined in, and at present the state of the art Earth observation commercial satellites are Digital Globe's WorldView 3 and 4 (launched in 2014 and 2016, respectively), offering a panchromatic band of 31 cm, and 28 additional spectral bands at various spatial resolutions of 1.24 m, 3.7 m and 30 m. The first commercial satellite with high spatial resolution night-time capabilities (at 0.7 m), was the Israeli EROS-B satellite, which was launched in 2006, but only started offering night-time acquisition publicly in 2013 (Levin et al., 2014). The first commercial satellite to offer multispectral (red, green and blue) night-time lights images (at 0.92 m) was launched in 2017: the Chinese JL1-3B (Jilin-1) satellite (Zheng et al., 2018). Such high spatial resolution satellites enable to study urban land use in finer details (as in Katz and Levin, 2016) and possibly to start and classify lighting sources.

The current revolution in space borne remote sensing is that of using small satellite missions (Sandau, 2010). The first company offering global daily multispectral high spatial resolution (3 m) coverage of the entire Earth is Planet Labs, with its constellation of about 150 nano satellites (Strauss, 2017). In coming years, researchers may benefit from similar cubesats offering night-time capabilities (such as NITEsat, presented in Walczak et al., 2017). Various cubesats have been launched in recent years, such as the CUbesat MULtispectral Observing System (CUMULOS), and the multispectral AeroCube, demonstrating the capabilities these new sensors provide for night time imaging (Pack and Hardy, 2016; Pack et al., 2017, 2018, 2019). An example of a recently launched cubesat which publicly offers global images of many regions on Earth at night is LJ1-01 (Luojia-1). This satellite, Luojia-1, was built by Wuhan University and was launched in June 2018, providing night-time images at 130 m (Fig. 14; Jiang et al., 2018; Li et al., 2018b, 2019a,b,c; images can be downloaded freely from http://59.175.109.173:8888/app/login_en.html), with each image covering about 250 × 250 km. So far, the acquired Luojia-1 images (n = 8675, as of May 2019) provide a complete and frequent coverage of China, as well as some additional areas such as south-east Asia and Europe. Recent studies have shown that Luojia-1 images are capable to accurately map urban extent and to monitor the construction of infrastructure at a moderate spatial resolution (Li et al., 2018b, 2019a,b,c). Additional night-time sensors will also become available in coming years, such as TEMPO, a geostationary satellite which will offer two images per night

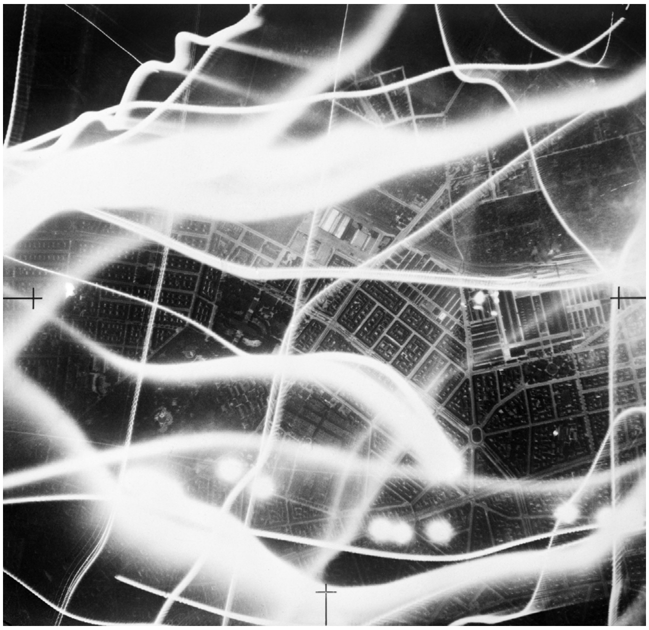

Fig. 16. A vertical aerial photograph taken during a raid on Berlin on the night of 2–3 September 1941. The broad wavy lines are the tracks of German searchlights and anti-aircraft fire. Also illuminated by the flash-bomb in the lower half of the photograph are the Friedrichshain gardens and sports stadium, St Georgs Kirchhof and Balten Platz.

over North America (Zoogman et al., 2017).

2.3. Airborne remote sensing of night lights

Topographic mapping using daytime aerial photos started back in World War I (Collier, 1994). The first aerial night-time photos we are aware of were taken during World War II, showing anti-aircraft searchlights, bombs exploding and incendiary fires (Fig. 16). In addition to space based observations, remote observation of night lights can be accomplished from aircraft, drone, and balloon-based platforms. However, proper imaging of city lights from aerial platforms began much later. Such platforms allow higher spatial resolutions, and do not require the intensive testing for use in space. While there were some efforts to map urban night-time lights at fine spatial resolutions using airborne sensors such as the hyperspectral AVIRIS (over Las Vegas; Kruse and Elvidge, 2011), a panchromatic camera (over Berlin, at 1 m; Kuechly et al., 2012), or using a multispectral camera (at 10 cm over Birmingham or 1 m over Ottawa; Hale et al., 2013; Xu et al., 2018), dedicated aerial campaigns cannot provide continuous global monitoring of urban areas. Another flight over Berlin with a multispectral camera was performed in 2014, but the radiometric calibration of the data is not yet complete (Kyba et al., 2015a, Sánchez de Miguel, 2015). Nighttime imagery from aircraft has been frequently taken, but less frequently published. For example, flights over London (Royé, 2018), Amsterdam, Friesland, and Deventer (http://nachtscan.nl/) have produced night imagery without leading to research publications. Aerial data from the state of Upper Austria is available online (https://doris.ooe.gv.at/themen/umwelt/lichtverschmutzung.aspx), but a report about the flight is available only in German (Ruhtz et al., 2015). In some cases, night light images have been acquired chiefly for artistic purposes (Laforet and Pettit, 2015), while in others, there is not sufficient information to allow radiometric calibration.

Few hyperspectral flights have been taken at night-time, perhaps because the instrumentation is much more complex. However, there have been a few cases, for example over Los Angeles (Stark et al., 2011) and Las Vegas (Metcalf, 2012), the ESA-Desirex and CM flights over Madrid performed by the Instituto Nacional de Técnica Aerospacial in 2008 (Moreno Burgos et al., 2010, Sobrino et al., 2009, Sánchez de Miguel, 2015), and the flights over Tarragona-Reus-La Bisbal de Falset (Cataluña, Spain) in 2009 (Tardá et al., 2011). The main limitation of these datasets is the low signal to noise that hyperspectral instruments produce in some areas of the city. Although the spatial resolution is limited compared to photography, it can reach up to 5 m. The most promising aspect of hyperspectral flights is the potential to unambiguously identify the light source technology. This has been demonstrated, for example, by Metcalf (2012).

Some experimental projects have made observations using drones (Sánchez de Miguel, 2015; Fiorentin et al., 2018; Regan, 2018), and new studies are starting to explore the potential of acquiring data on night time lights from drones, given the flexibility in deploying them at different times during the night, the ability to acquire multi-angular images (Kong et al., 2019), and their potential for providing some near-sensing validation to space borne measurements. To some extent, the limited use of drones for remote sensing of night lights may be due to regulations restricting the use of drones at night over urban areas. However, the potential of drones is clearly seen by their use in the film industry, for example in TV productions like “España a ras de cielo” (RTVE, 2013; http://www.rtve.es/alacarta/videos/espana-a-ras-de-cielo/espana-ras-cielo-espana-noche/4692661/) and “Bron/Broen” (SVT, 2011). Balloons offer a more flexible platform for night imagery, as the regulations are not as strict as for drones. Pioneering experiments were performed by the Daedalus team (Ocaña et al., 2016), where they combined detection of meteors with observation of night light emissions. These tests were mainly performed as technological demonstrations. The Far Horizons Project of the Adler planetarium of Chicago has also made several balloon flights. The purpose of these was to test the camera of a cubesat that will be launched in the future to monitor the conversion of street lamps in Chicago from sodium vapor lamps to white LEDs (Walczak et al., 2017).

2.4. Ground based measurements of night sky brightness

A major gap in the remote sensing of night lights, stretching back to the time that DMSP/OLS data first became available, has been the lack of field data to “ground truth” the observations. Most optical remote sensing is mainly obtained done during the day with very different illumination conditions, as the only light source is the Sun, and atmospheric corrections are performed to derive the surface reflectance of objects, which can be ground truthed using field or lab measurements using a spectrometer (Vermote et al., 1997). At night-time, we are not interested in surface reflectance but in the emission of artificial lights; however, there are many relevant light sources in the visible band that can be equally important under some conditions such as city lights, gas flares, volcanos, lightning, moonlight, starlights or airglow. In addition, the dynamic range of the phenomena observed goes from 0.01 nW/cm^2/sr to more than 1000 nW/cm^2/sr (for sensors with higher spatial resolutions sensors than VIIRS/DNB, the radiance from upward directed sources will be far larger). The factors that make observing night lights challenging (see Section 4) also complicate acquiring ground reference data. For example, changing lights and changing atmospheric factors such as aerosols and water vapor mean that even aerial data acquired several hours before or after a satellite overpass cannot be directly compared. One indirect solution to the problem has been to compare ground based night sky brightness measurements to either the light observed from space directly, or else to models of diffuse sky brightness based on night lights data (e.g., Wallner and Kocifaj, 2019).

The brightening of the night sky by artificial light emissions is referred to as “skyglow”, and is one of the most familiar forms of light pollution (Rosebrugh, 1935; Riegel, 1973; Kyba and Hölker, 2013; Aubé, 2015). Generally speaking, the artificially illuminated clear sky is brightest in the direction of nearby light sources, and darkest either at zenith or slightly displaced from zenith in the direction of undeveloped areas (Fig. 17). The main source of skyglow is light emitted towards the

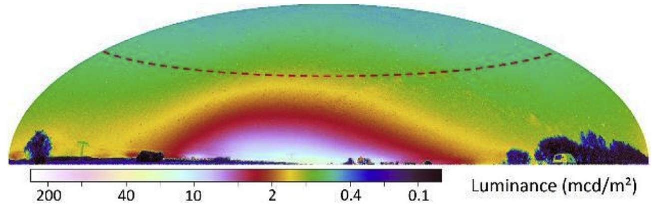

Fig. 17. All-sky luminance map based on a photograph taken 15 km outside of Berlin's city limits (30 km from the city center). Photograph and image processing by Andreas Jechow. The dashed line shows 40° from zenith (equivalently 50° elevation). A natural starlit sky has a luminance near 0.2–0.3 mcd/m^2 (Hänel et al., 2018).

horizon, because the path length to space is longest in this direction, greatly raising the scattering probability (Falchi et al., 2011). It is important to note that ground-based remote sensing measurements of night lights are usually done towards nadir, so these emissions are not generally imaged during night light observations (however see Kyba et al., 2013b). Observations of night sky brightness therefore complement remote sensing of night lights in two ways: first, they can be used as a ground truth, and second, they provide indirect information about light emissions at angles that are not directly imaged from space.

The influence of cloud cover on the surface light environment is important for understanding the ecological impacts of skyglow (Rich and Longcore, 2006; Kyba et al., 2011; Kyba and Hölker, 2013). In areas with little or no artificial lighting, clouds darken the night sky, while in areas with artificial lighting they make it considerably brighter. Some locations can experience both at once, in different viewing directions (Fig. 18, Jechow et al., 2018a). Atmospheric scattering is biased towards blue light on clear nights (Kocifaj et al., 2019), but clouds scatter at all wavelengths. For this reason, the artificially illuminated clear night sky is far bluer than the overcast night sky, or in other words the "amplification" of light caused by clouds is far stronger in the red (Kyba et al., 2012; Aubé et al., 2016). At the moment, understanding of the light environment on overcast and partly cloudy nights remains poor (Jechow et al., 2018a). While local models exist (e.g. Solano Lamphar and Kocifaj, 2016), global models of skyglow on overcast nights are not available, relatively few observations of cloudy sky radiance have been published, and local models of skyglow on overcast nights have not been validated with experimental data.

2.4.1. Current status of ground based observations of the artificially illuminated night sky

Hänel et al. (2018) recently reviewed the commonly used techniques for observing the night sky brightness and skyglow, so only a brief summary is provided here. There are three basic techniques: point observations with broadband radiometers (most common), multispectral all-sky photographic observations, and point observations with spectrometers (most rare). Of the three techniques, Hänel et al. (2018) concluded that all sky imaging techniques "provide the best relation between ease-of-use and wealth of obtainable information on the night sky" (see e.g. Jechow et al., 2017a,b, 2019a,b). However, Hänel et al. noted that a combination of the different techniques is ideal, as point observations can be used for long-term tracking, while being occasionally supplemented with all-sky photography. Note that both point observations taken in multiple directions (Zamorano et al., 2013) and image mosaicking (Duriscoe et al., 2007) can also be used to acquire information about the full sky dome.

In the past, night sky brightness observations were mainly performed by professional observatories and institutionally affiliated scientists (e.g. Walker, 1970; Zhang et al., 2015a). The recently introduction of low-cost night light radiometers, starting with the Sky Quality Meter (SQM), has greatly expanded the number of surveyed sites, and enabled the active participation of citizen scientists. The SQM instrument enables monitoring night-time brightness in a rapid fashion, either along transects while walking, biking (Katz and Levin, 2016) or attached to a car (Xu et al., 2018), or temporally, allowing to monitor temporal changes in night sky brightness (Pun et al., 2014; den Outer et al., 2011). In addition to instrumental observations, citizen scientists are able to make visual observations of night sky brightness by examining stellar visibility. The most widespread of these projects is "Globe at Night" (Walker et al., 2008), which has been running since 2006. While visual observations have lower precision than instrumental observations (Kyba et al., 2013a), they have the advantage of correctly accounting for spectral changes in night sky brightness due to changing lighting technology (Sánchez de Miguel et al., 2017, Kyba et al., 2018). Other instruments and methodologies such as the TESS-W photometers (which is growing to provide a global monitoring network, with freely available data via http://tess.stars4all.eu/; Zamorano et al., 2019), the Sky Quality Camera software, and the Loss of the Night app are further discussed by Hänel et al. (2018) and by Jechow et al. (2019b). The Sky Quality Camera software allows one to use a DSLR camera (which has been properly calibrated) with a fish-eye lens, to measure hemispherical night-time brightness (Jechow et al., 2018b, 2019a,b), to estimate cloud cover, and to create night sky brightness images with or without bright stars and the Milky Way (Fig. 18).

2.4.2. Direct comparison of night sky brightness observations to light observed from space

In many space-based night light images, it is possible to see a fuzzy haze that surrounds cities, extending into areas which are unlikely to contain lights (such as forests or offshore regions). This diffuse light in DMSP/OLS and VIIRS/DNB images has often been referred to as "blooming" (e.g. Amaral et al., 2005; Ou et al., 2015), likely due to its visual similarity to the phenomena of CCD blooming in digital photography. However, a recent study suggests that rather than being an instrumental error, it is likely that the instruments are actually correctly observing light scattered by the atmosphere, or in some cases light scattered by the atmosphere and then reflected from the ground.

When Kyba et al. (2013a) found that citizen science observations of skyglow were highly correlated with DMSP observations, they hypothesized that this correlation arises because the point spread function of the DMSP acts as a de facto approximate atmospheric radiative transfer model. A similar correlation between DMSP/OLS and night sky brightness was verified on a smaller spatial scale by Zamorano et al. (2016). However, using an intensive night sky brightness survey around the city of Madrid, Sánchez de Miguel (2015) demonstrated a strong correlation between diffuse light in space-based images from instruments with different intrinsic spatial resolutions. By comparing SQM ground based measurements using SQMs, with VIIRS/DNB imagery and ISS astronaut photos, Sánchez de Miguel et al. (2019a) have recently demonstrated that the diffuse light observed around cities is not an instrumental error, but is actually a direct observation of the component of urban skyglow that scatters upward, i.e., artificial sky brightness. Sánchez de Miguel et al. (2019a) also mentioned additional components of diffuse light in night-time imagery which remain to be quantified, such as albedo, natural airglow, sea fog, and real blooming.

2.4.3. Comparison of night sky brightness observations to radiative transfer models

Observations of night sky brightness can in principle be used to extract information about light emissions that are not available through direct observations. For example, there is considerable debate about what fraction of light from cities is emitted towards the horizon (Luginbuhl et al., 2009), which is difficult or impossible to directly observe from space (Kyba et al., 2013b), but may be inferred from night sky brightness data (Kocifaj, 2017). Falchi et al. (2016) produced models of night sky brightness under three different assumptions of the upward angular distribution function: Lambertian, emissions peaking at 30°, and strong emissions towards the horizon. Because light is additive, it is possible to fit for the linear combination of models that most closely

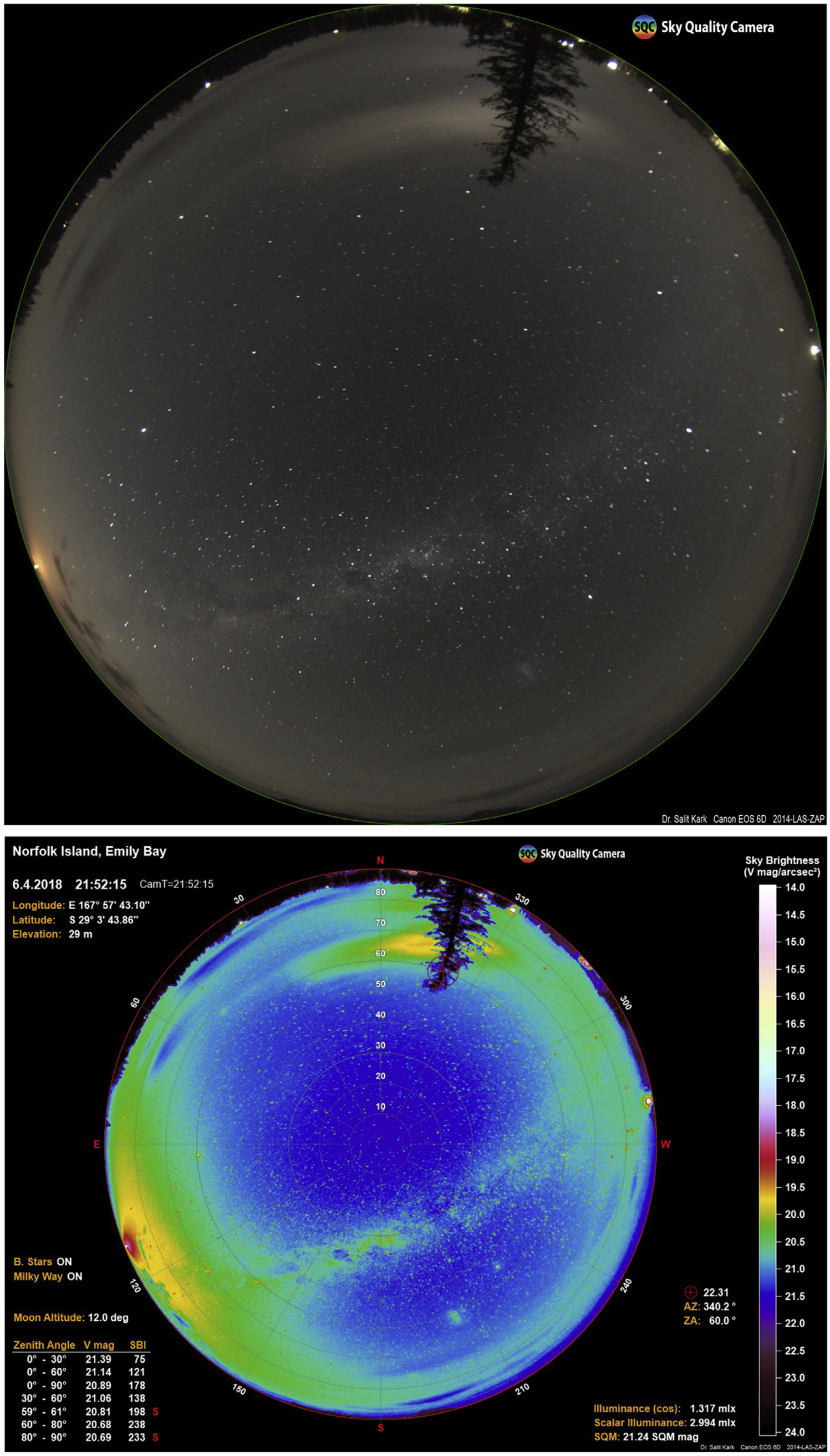

Fig. 18. Night-time hemispheric photo at Emily Bay, in the remote Norfolk Island, Australia (April 6th, 2018, 21:52 local time). The upper image shows the raw image, while the bottom image presents sky brightness as calculated by the Sky Quality Camera software. The bright light at the east (azimuth 112, left side of the image) is the moon rising over the horizon. Notice the difference between bright clouds (top-right side of the image) above artificial light sources, and the dark clouds (top-left side of the image) above dark areas. Photo taken by Noam Levin.

matches the data. In the case of Falchi et al. (2016), the data were SQM observations at zenith from a number of academically affiliated and citizen scientists, notably including Ribas (2016), Zamorano et al. (2016), and Globe at Night. A similar procedure could in principle be used with all-sky camera data.

The conditions under which skyglow models are accurate remains an open question. The global model of Falchi et al. (2016) does not consider shadowing by mountains, for example, so it is likely that errors are larger in mountainous regions. Ges et al. (2018) compared the predictions of Falchi et al. (2016) to SQM observations made along a transect from Barcelona out to sea. They found extremely good agreement with the model under atmospheric conditions similar to those upon which the model is based, but disagreement of up to 50% on a night with better optical conditions. In particular, they found that on a night with low aerosol load, the sky was darker than predicted near Barcelona, while far out to sea the sky was brighter than predicted.

There is a need for further comparison of models to observations, and direct comparisons of models to each other (e.g. Aubé and Kocifaj, 2012). As skyglow models are used to make lighting policy recommendations (e.g. Aubé et al., 2018), it is important to verify that their predictions are correct. Bará (2017) recently examined how dense observations should be in order to provide reliable data on zenith night sky brightness. He concluded that observations on a 1 km grid provide sufficient resolution for interpolation between the points to accurately represent night sky brightness. A major challenge for comparing models to observations occurs in areas where natural light sources such as airglow and stars are brighter than the artificial component of night sky brightness (Bará et al., 2015). Finally, the shifting spectrum of skyglow due to the change to LED technology poses a challenge for both observations and modeling, and is discussed in detail in section 4.5.

3. Applications of remote sensing of night lights

In this section, we aim to provide a brief overview of some of the most common applications of night lights data made using the existing and historical sensors. The aim is to demonstrate the breadth of existing studies, and to refer the reader to historical, key, and review papers about each topic. Readers should understand that for each topic, a considerably larger base of scholarship exists, and that not all applications of night lights are reviewed here. For example, we do not review studies on whether lighting benefits public safety (and/or the perception of safety), and on whether there is correspondence between higher night-time brightness, and decreased crime rates and car accidents (Painter, 1996; Marchant, 2004, 2017; Peña-García et al., 2015; Steinbach et al., 2015). Where relevant, we highlight some of the main challenges in the applications, and how these may be addressed with future sensors. These challenges and opportunities are then addressed in more detail in the following section.

3.1. Mapping urbanization processes

Our world has been rapidly urbanizing in recent decades. As of 2014, more than 54% of the global population live in urban areas, and by 2100, 70%–90% of the world's population, which is projected to increase by another three billion, will live in urban regions (United Nations, 2014). Due to broad impacts of the concentrated human activities and associated built environment, cities are now a major factor shaping the Earth system and are considered agents of global change (Mills, 2010). Cities worldwide now occupy only about 2% of the global land surface (Akbari et al., 2009), but produce more than 90% of the world gross domestic production (GDP) (Gutman, 2007), consuming more than 70% of the available energy (Nakićenović, 2012), and generating more than 71% of anthropogenic greenhouse gas emissions (Hoornweg et al., 2011). There is therefore an urgent need for timely and reliable information on the extent of urban areas to support sustainable urban development and management (Ban et al., 2015). Recent studies have highlighted the utility of NTL time-series data, alongside daytime land sensors and population censuses to help illuminate important aspects about the character of urbanization, and to identify growing informal settlements with inadequate infrastructure (Stokes and Seto 2019). Both capabilities are particularly useful for monitoring progress towards two of the United Nations Sustainable Development Goals under the Agenda 2030: Goal 7.1 (ensure universal access to affordable, reliable and modern energy services) and Goal 11.1 (ensure access for all to adequate, safe and affordable housing and basic services and upgrade slums).

Due to the fact that cities are brightly lit during the night, urban areas can be easily identified in nighttime light remote sensing data. Indeed, one of the first uses of NTL data from DMSP/OLS was to delineate urban extents, and DMSP/OLS data is one of the earliest datasets available for mapping our urbanizing planet (Zhu et al., 2019), and have been shown as useful for tracking electrification rates also in rural areas (Min et al., 2013; Min and Gaba, 2014). The panchromatic nature of DMSP/OLS NTL data first encouraged researchers to find an optimal threshold to separate urban areas from their backgrounds (e.g. Imhoff et al., 1997; Small et al., 2005). However, it turned out that it is not straightforward to find a single optimal threshold that can accurately delineate both large cities and small cities simultaneously (Zhou et al., 2015). While a larger threshold might be good for delineating large cities but tends to overlook small towns, a smaller threshold can bring back small towns but often leads to overestimating the extents of large cities. Such a situation becomes even more complicated due to the overglow effect in DMSP/OLS, and due to the use of different types of lighting together with different street lighting standards in different countries (Small, 2005). Optimal thresholds vary across space and a scheme of dynamic thresholds is required for large-scale and temporal dynamic urban extent mapping (Zhou et al., 2014; Elvidge et al. 1997b, 2009b; Imhoff et al., 1997; Small et al., 2005; Cao et al., 2009).

Due to the saturation of DMSP/OLS within urban areas, these images lack textural information, making it very hard to map urban patterns within cities. However, with the improved radiometric performance of VIIRS/DNB, new methods are being developed, demonstrating for example the ability to map local urban centers (Chen et al., 2017). The newer VIIRS/DNB nighttime light data is also better than DMSP/OLS data in mapping urban extents (Shi et al., 2014), and attention has been given to determine dynamic thresholds for mapping using ancillary information (He et al., 2006; Cao et al., 2009; Zhou et al., 2014; Liu et al., 2015). Recently, researchers have started to look into the potential of integrating DMSP/OLS with the Moderate Resolution Imaging Spectroradiometer (MODIS) (Guo et al., 2015; Lu and Weng, 2002; Zhang et al., 2013; Ouyang et al., 2019) or Landsat at a finer spatial resolution (Zhang et al., 2015b; Goldblatt et al., 2018), to improve the accuracy and performance of regional and global urban extent mapping, developing spectral indices such as the vegetation adjusted NTL urban index (VANUI) (Zhang et al., 2013).

The long historical archive of DMSP/OLS NTL data not only allows static urban extent mapping but also has high potential in characterizing urban extent dynamics at regional and global scales (Small and Elvidge, 2013). For example, Yi et al. (2014) utilized multitemporal DMSP/OLS NTL annual composites to study urbanization dynamics in Northeast China, Liu et al. (2012) and Ma et al. (2012, 2015) explored urbanization in all of China, Álvarez-Berríos et al. (2013) examined South America, Pandey et al. (2013) examined India, Zhang and Seto (2011) examined China, India, Japan and the conterminous United States, Castrence et al. (2014) studied Hanoi, Vietnam, and Zhang et al. (2016) did this for the entire globe. In a recent paper, Zhou et al. (2018) developed a new method to generate temporally and spatially consistent global urban mapping, finding that global urban area has increased from 0.23% in 1992 to 0.53% in 2013.

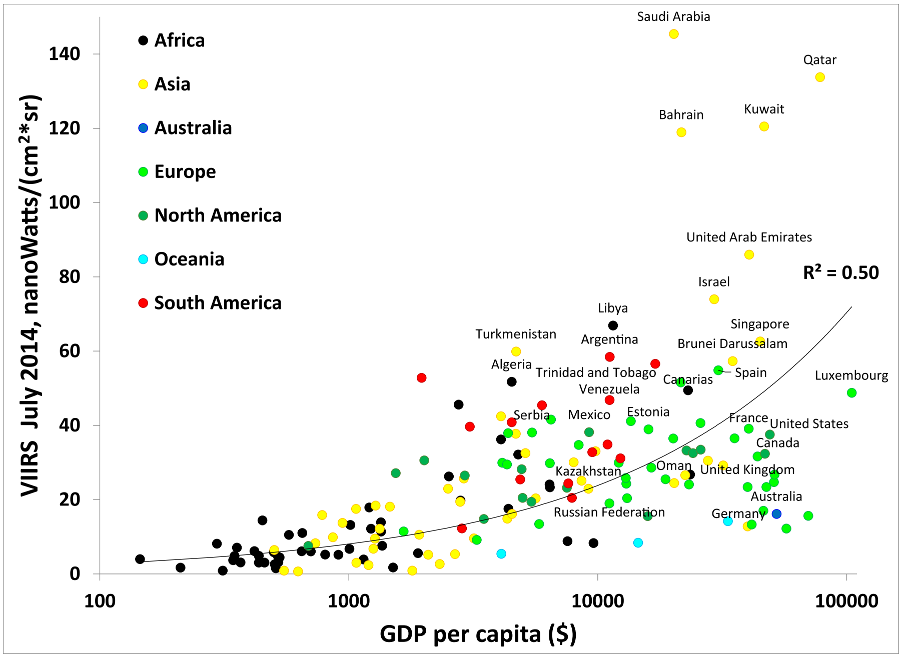

Fig. 19. Mean VIIRS radiance values in July 2014 at the country level (averaging all cities within a country), as a function of national GDP per capita. Based on data from Levin and Zhang (2017). Note that GDP on its own is not enough to explain night-time brightness differences of urban areas between countries. Additional variables include albedo, whether countries have natural gas and oil resources, and lighting standards, among other factors.

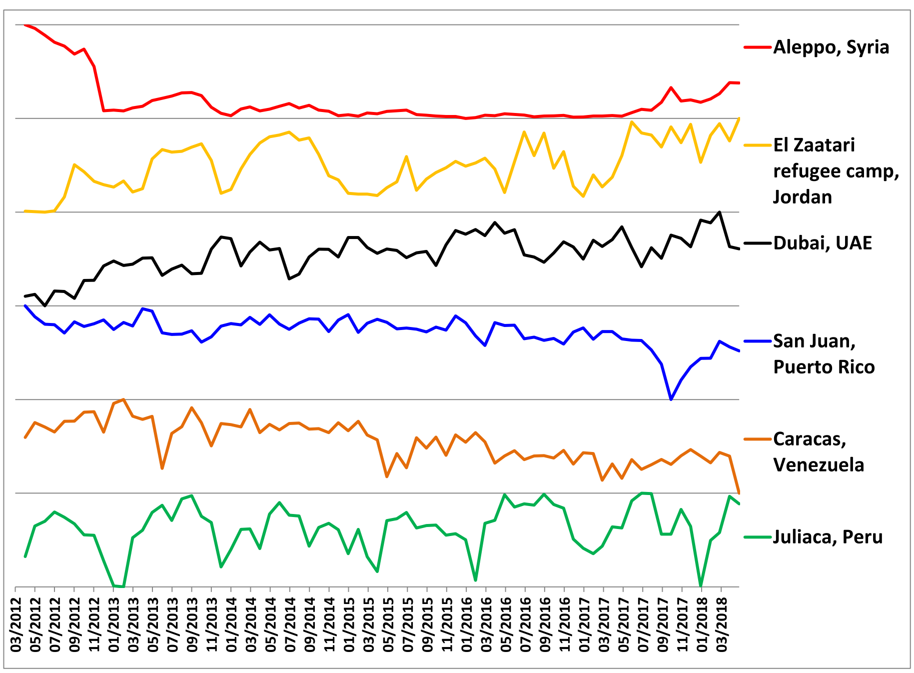

Fig. 20. Temporal changes in monthly VIIRS night-time brightness, demonstrating various patterns (each of the sites was normalized between its own minimum and maximum values). Aleppo, Syria: dramatic decrease in night-time lights due to the war in Syria. El Zaatari refugee camp, Jordan: influx of refugees from Syria makes this refugee camp one of the largest cities in Jordan. Dubai, UAE: A global city and a business hub in the Middle East, with a growing economy. San Juan, Puerto Rico: Hurricane Maria (September 20th, 2017) led to power outages throughout Puerto Rico. Caracas, Venezuela: In 2014 Venezuela entered an economic recession, with a decrease in its GDP, evident in a decrease of night lights in its capital city. Juliaca, Peru: A seasonal pattern is evident in night-time lights, commonly attributed to seasonal changes in albedo related to vegetation and snow cover.

3.2. Estimating GDP and mapping poverty

The connection between artificial lighting and urban areas described above has motivated many researchers to examine the possibility of using night lights data as an indicator of economic activity. Night-time light has been found to be positively correlated with Gross Domestic Product (GDP) or Gross Regional Product (GRP) at different spatial scales (Elvidge et al., 1997a,b; Forbes, 2013; Li et al., 2013a). However, there are also considerable differences in per capita light emissions observed for countries with similar GDP (e.g. Henderson et al., 2012; Kyba et al., 2017; Levin and Zhang, 2017, Fig. 19). The strength of incorporating night lights data into economic analyses is therefore in: (1) estimating GDP at finer levels of spatial resolution than are available through official statistics, (2) estimating GDP change (as opposed to levels) at high temporal frequency (e.g., in Bennie et al., 2014a,b, Fig. 20), and (3) estimating GDP in areas with poor or no reporting (Henderson et al., 2012).

An example of the first point above is disaggregating National GDP data to spatial grids. This was first carried out to produce 5 km resolution GDP map for 11 European Union countries and the United States (Doll et al., 2006), and it was further used, supported by ancillary data including a population density map (Landscan), to produce a global GDP map at 1 km resolution, showing that Singapore had the highest GDP density (Ghosh et al., 2010). Similarly, night-time lights can be used as a proxy of GDP for estimating wealth, allowing regional economic phenomenon such as inequality (Elvidge et al., 2012; Xu et al., 2015) and poverty to be mapped (Elvidge et al., 2009b; Wang et al., 2012; Yu et al., 2015; Jean et al., 2016). Henderson et al. (2016)

showed that physical geography (such as climate, biomes, topography, etc.) has a strong influence on the spatial distribution of economic activity, however, that there are differences between developed and developing countries in the relative importance of agriculture and trade variables, to explain spatial variability in night-time lights.

An example of an application of the third point above is in correcting the statistical GDP or GDP growth rate data for developing countries. This is based on econometric models which regard the real GDP (or GDP growth rate) as a linear combination of statistical GDP (or GDP growth rate) and estimated GDP (or GDP growth rate) derived from night-time light images (Chen and Nordhaus, 2011; Henderson et al. 2011, 2012). Based on this framework, economists have concluded for example that China's real GDP growth rate is higher that the values from official statistics (Clark et al., 2017).

3.3. Monitoring disasters

Disasters can affect night light emissions through damage to and interruption of electric utility services, and related power outages can be deteceted from space using night-time lights (Elvidge et al., 1998; Aubrecht et al., 2009). For example, tropical storms and hurricanes, heavy rains that cause flash or longer-term basin-wide flooding, damaging straight-line winds or tornadoes, widespread ice storms, fires, and earthquakes, frequently interrupt utility services for varying lengths of time. Outages can also occur from poorly maintained or damaged infrastructure, industrial accidents, or regional conflicts (see section 3.4). Disruptions can be on the order of hours for small, isolated events, to days, weeks, or even months, for particularly strong or long-lasting impacts such as those from major hurricanes (Román et al., 2018, 2019, Fig. 20) or earthquakes (Kohiyama et al., 2004). For meteorological events, lingering cloud cover can impact the ability to reliably detect changes following natural disasters (Zhao et al., 2018). Therefore, monitoring of nighttime lights is particularly well-suited to assessment of impacts from major events over longer-time scales, or for non-meteorological events (e.g. failed infrastructure, earthquakes) where cloud cover may be less prevalent.

Gillespie et al. (2014) demonstrated the use of DMSP/OLS annual to monitor the damage and recovery of areas affected by the December 2004 earthquake and the tsunami which followed it, in Sumatra, Indonesia. Such applications have expanded with the advantages of VIIRS/DNB night-time imagery. VIIRS/DNB has been used to capture power outage and recovery from severe storms, for example. False color composites of pre- and post-event lights were used by Department of Defense and other partners in their response to Hurricane Sandy (Molthan and Jedlovec, 2013). Cao et al. (2013) used comparisons of pre- and post-event emissions to identify loss and recovery of nighttime lights in Washington D.C. area from a derecho event (a wide-spread straight-line wind event), as well as following Hurricane Sandy, when Department of Energy utility reports were used as validation. Cole et al. (2017) combined nighttime light information, population data, and utility information to model likely future outages and affected populations, and documented outages and recovery following Hurricane Sandy in the northeastern states. Miller et al. (2018) used a long-term pre-event nighttime light composite and cloud-free scenes following Hurricane Matthew as a false color composite, in order to estimate outages. This work compared favorably to reported utility outages, and nighttime lights imagery also captured unique physical phenomena associated with the cyclone.

Zhao et al. (2018) investigated outages and recovery from earthquakes, major tropical cyclones, and floods with validation of outages against SAR-derived damage proxy estimates and flood mapping. They adopted the methodology of Cole et al. (2017) to derive a “percent of normal” condition as the ratio of a post-event scene to pre-event normal. For long-term outages in Puerto Rico following 2017's Hurricane Maria, Zhao et al. found a strong correlation between percent of normal light (low values) and reported outages ($R^2 = 0.94$), though obtaining cloud-free pre-event and post-event scenes were difficult. Finer-scale observations of nighttime lights and change have been developed from the NASA Black Marble Nighttime Light (NTL) composite and ancillary data layers (Zhang et al., 2015c; Wang et al., 2018), using spatial downscaling to estimate a 30 m product for changes on neighborhood scales (Roman et al., 2019, Fig. 21). These and other analyses demonstrate the utility of night lights in specifically examining impacts to electrical infrastructure, as opposed to other damage that may be more readily assessed via daytime sensing (e.g. flooding, structural damage).

3.4. Monitoring armed conflicts

In addition to the environmental disasters discussed above, human-caused disasters also have strong impacts on night light emissions. Remote sensing of night lights therefore provides an opportunity to monitor conflicts, where data is often scarce and governmental reports may be biased (Witmer, 2015). High spatial resolution daytime images have been proved effective to achieve this purpose (American Association for the Advancement of Science, 2013; Prins, 2007), but building a link between conflicts and these remote sensing images sometimes requires human skills of image interpretation. Since there is a direct link between night-time lights and a number of socioeconomic parameters, dramatic decreases in night-time brightness may serve as an indicator for damage to infrastructure caused by armed conflicts. In addition to reductions in population size and Gross Domestic Product (GDP), decreases in light emissions also provide a warning that civilians are likely lacking a stable electricity supply, which is essential for both basic living and operation of hospitals.

A pioneering study in this topic examined the war effect in Chechnya and Georgia by using monthly DMSP/OLS composites (Witmer and O'Loughlin, 2011), which were used to examine movement of refugees and burning oil fields caused by the wars. A more comprehensive examination of global conflicts was undertaken by Li et al. (2013b) using time series of annual DMSP/OLS composites. These authors used 159 countries as research samples, and found that wars lead to a sharp reduction of night-time lights, that peace agreements are followed by restoration of night-time brightness levels, and that war-torn countries have larger fluctuations of night-time lights than peaceful countries.

Since that time, night-time light images have been employed to evaluate the violent conflicts in Syria (Li and Li, 2014; Li et al., 2017, Fig. 11a), Iraq (Li et al. 2015, 2018a) and Yemen (Jiang et al., 2017) following the Arab Spring, showing that affected regions in these countries experienced dramatic reductions in light emissions after the conflict began (Fig. 20). Examining all Arab countries following the onset of the Arab Spring, Levin et al. (2018) found that reductions in night-time brightness correlated with decreases in the number of tourists (using Flickr photos as indicator of visitation), with increases in asylum seeker numbers, and with increases in the numbers of deaths from conflicts. Levin et al. (2019) have also suggested that reductions of night-time lights may serve as an indicator of risk to UNESCO World Heritage Sites from armed conflicts. As is the case with environmental disasters, the development of NASA's daily Black Marble product provides another step forward towards fine temporal monitoring of the effects of wars on internally displaced populations (Román et al., 2018).

3.5. Holiday and ornamental lights, and political, historical, and cultural differences in lighting

While disasters are evident from a temporal reduction in light emissions, lighting associated with holidays can result in a temporary increase. The uniformities and variations between nighttime light signatures can provide new insights into how energy behaviors, motivated by social incentives and economic activity, vary across national and cultural boundaries (Fig. 22). Temporal fluctuations in electricity

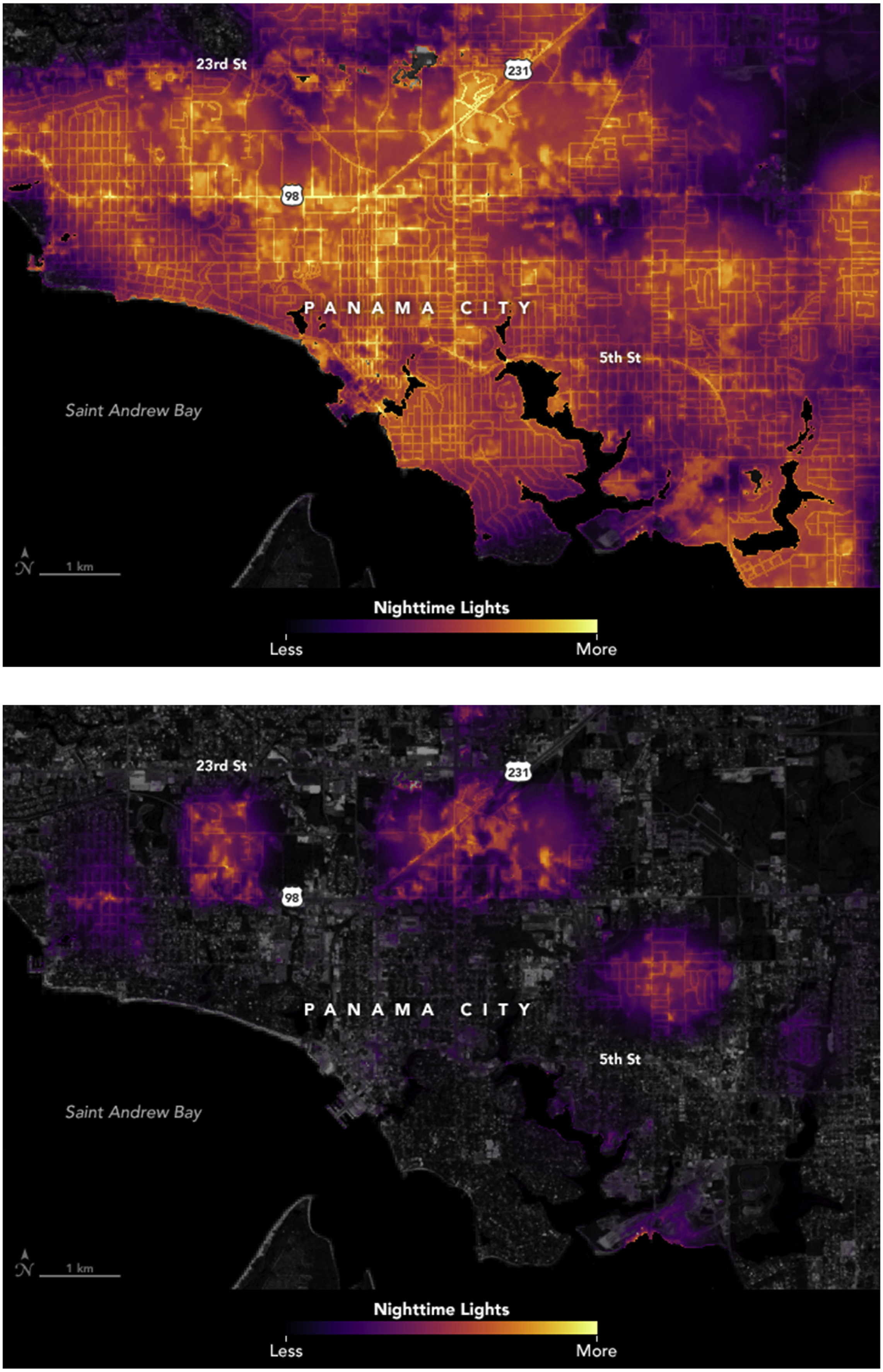

Fig. 21. After making landfall as a category 4 storm on October 10, 2018, Hurricane Michael knocked out power for at least 2.5 million customers in the southeastern United States, according to the Edison Electric Institute. The images show where lights went out in Panama City, Florida, comparing the night lights before (top) and after (bottom) the hurricane (October 6th and 12th, 2018, respectively).

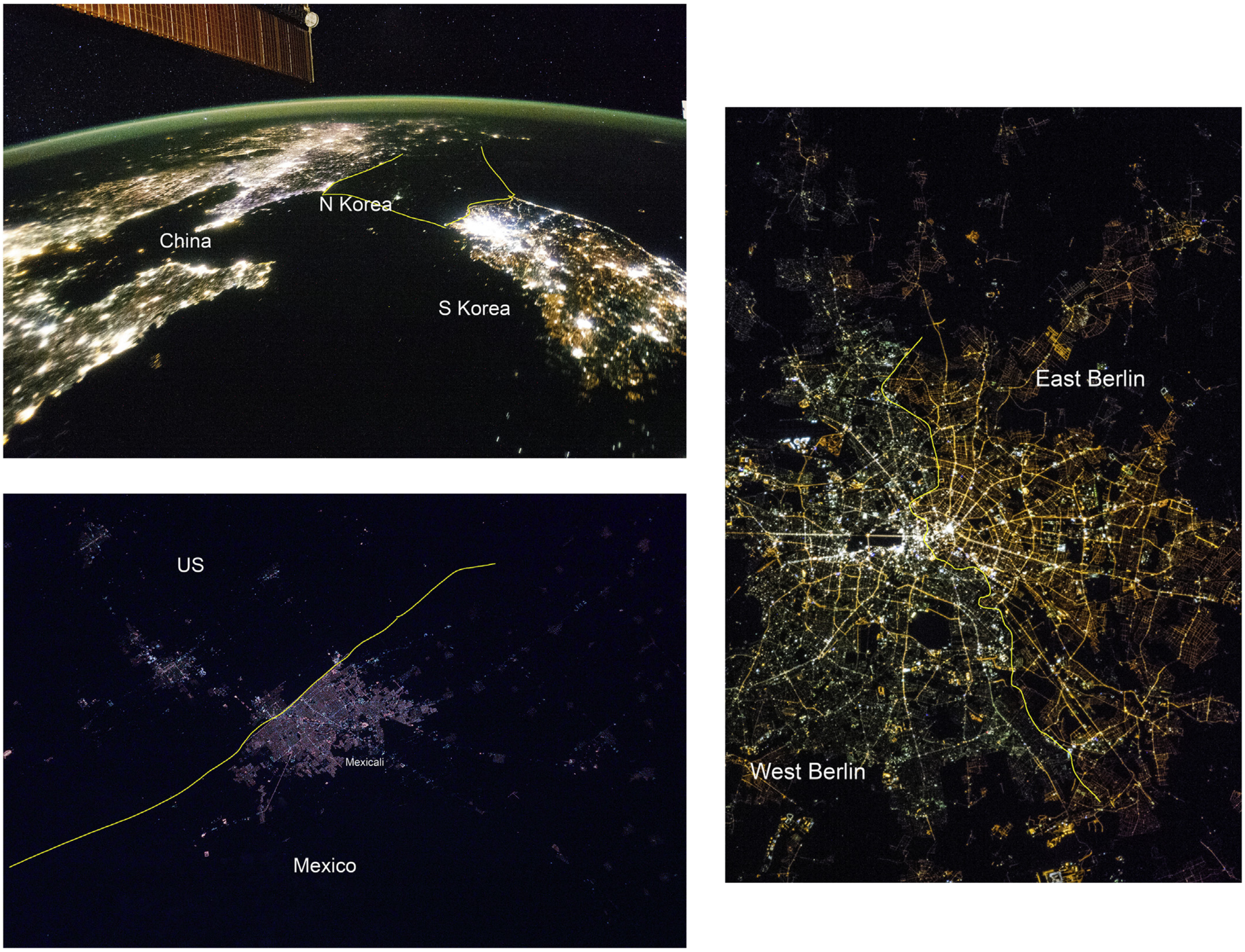

Fig. 22. Lighting differences between countries across borders, as seen from the ISS: China - North Korea - South Korea (ISS038-E – 38280), US - Mexico (ISS030-E – 213358), East and West Berlin (ISS035-E – 17202).

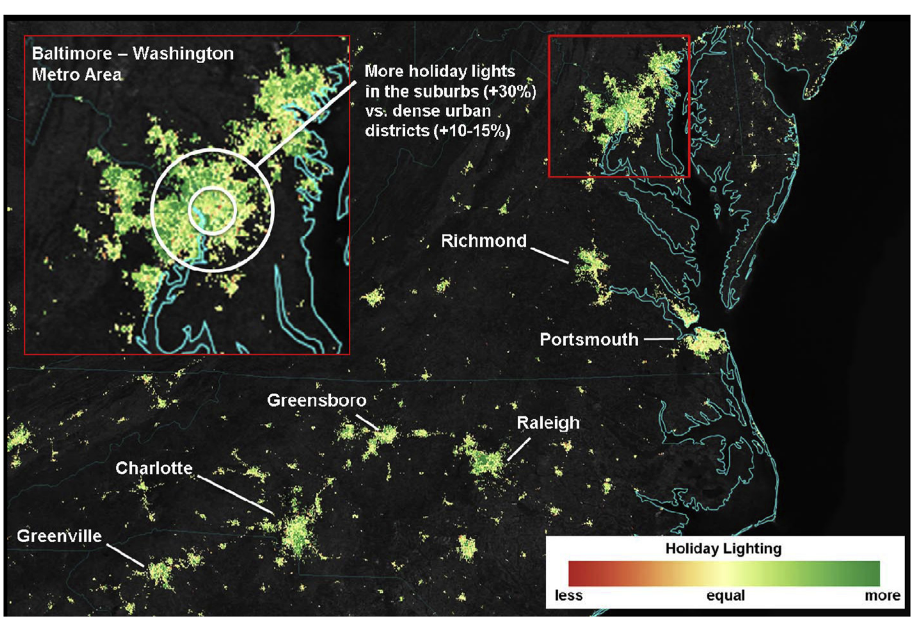

Fig. 23. City lights shine brighter during the holidays in the United States when compared with the rest of the year, as shown using a new analysis of daily nighttime data from the VIIRS instrument onboard the NASA/NOAA Suomi NPP satellite (Roman and Stokes, 2015). Dark green pixels are areas where lights are 30 percent brighter, or more, during December. Because snow reflects so much light, only snow-free cities were analyzed. Holiday activity is shown to peak in the suburbs and peri-urban areas of major Southern US cities, where Christmas lights are prevalent. In contrast, most central urban districts, with compact dwelling types affording less space for light displays, experience a slight decrease or no change in energy service demand. The calculation is based on the relative change in lights between the Christmas holiday vs. the rest of the year. It is a simple ratio between the latter vs the former. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

demand may represent changes in individual and macro-scale energy behaviors, for example during major cultural events such as Christmas, New Year, and the Holy month of Ramadan. During the Christmas and New Year holidays in the USA, the patterns of total lighting electricity usage (units of Watt · hr) derived from nighttime radiance were shown to uniformly increase across US cities with diverse ethnicity and religious backgrounds (Román and Stokes, 2015). Román and Stokes suggest that this shows that in addition of being a religious holiday, Christmas and New Year are also celebrated as a civic holiday across the US through holiday lighting (Fig. 23). Patterns of energy service demand observed through nightlight images during the Holy month of Ramadan can also indicate different religions as well as cultural observance practices. In the Middle East, cities with Muslim-majority population exhibit lighting peaks during and slightly after the 30 days of Ramadan compared to non-arab cities in Israel (Román and Stokes, 2015). Seasonal variations in nighttime lights have also been used to track patterns in ambient population (mainly tourists) in Greece (Stathakis and Baltas, 2018).

Lighting for cultural or celebratory purposes (such as light festivals; Giordano and Ong, 2017) may result in particularly bright emission signals compared to more functional lighting such as for streets and parking lots. For example, floodlighting of churches or other cultural objects often misses the facade, and can therefore be brightly visible on Suomi-NPP VIIRS/DNB images (eg. Kyba et al., 2018). Architectural lighting is often used to highlight significant buildings, and such lighting may only be on when special events are held or at certain times of the night (Meier, 2018). This may present a challenge for night lights analyses, with the inconsistent temporal pattern contributing to the variability of night lights datasets (Coesfeld et al., 2018).

Administrative borders offer the possibility to observe clear contrasts between different countries or regions, an area where the high resolution color photographs from the ISS can be quite useful (Fig. 22). The persistence of different lighting technologies in the former East and West Berlin and the extraordinary drop of light at the border between North and South Korea are well known examples. However, there are also large national differences between per capita light emissions in wealthy cities and countries (Kyba et al., 2015a, Sánchez de Miguel, 2015; Levin and Zhang, 2017). The root causes behind these differences are in some cases not well understood (and may be related to different lighting standards between countries), and night lights data may therefore play a useful role in some investigations based on the social sciences.

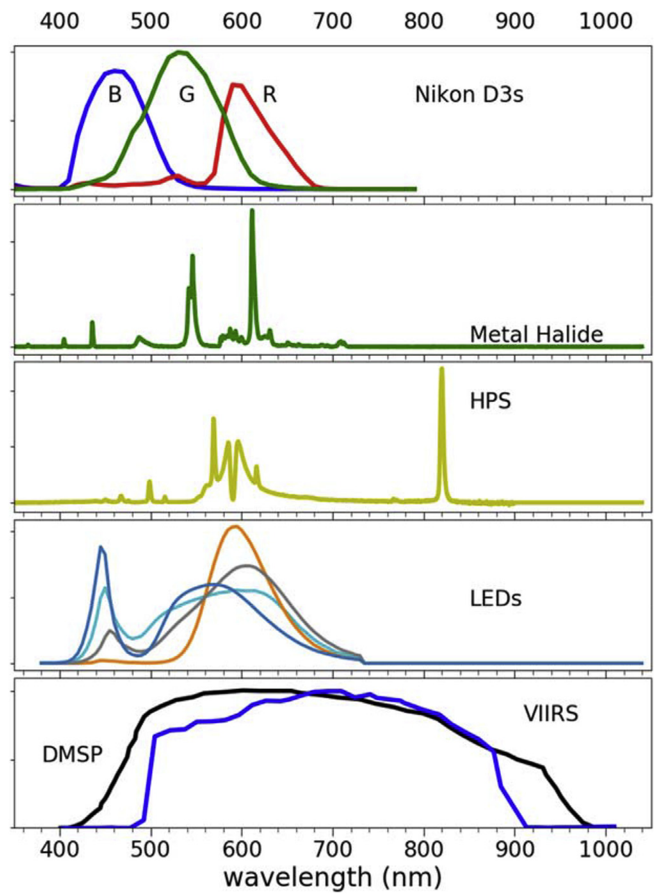

Fig. 24. Spectral response of the most popular sensors and most popular spectra, from top to bottom. (a) the spectral response of the Nikon D3s Cameras used by the astronauts at the ISS; (b) a typical spectra of a Metal Halide lamp, popular on architectural lights; (c) a High pressure sodium light, popular until 2014 on streelighting; (d) LEDs of 5000K (blue), 4000K (cyan), 2700K (grey) and PC-Amber(amber), popular on street lighting; (e) representative spectral response of DMSP/OLS(black) and SNPP/VIIRS/DNB(blue). Sources: Sánchez de Miguel (2015), Tapia Ayuga et al., (2015), Sánchez de Miguel et al., (2017), Elvidge. et al.,1999a,b,c and Liao et al., 2013. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

3.6. Astronomy

Astronomy is perhaps the oldest remote sensing discipline, with its goal to obtain information about objects at vast distances through observation of emitted, absorbed, scattered, or reflected light. Nearly all visible band astronomy is undertaken at night, because light scattered by sunlight in Earth's atmosphere outshines most celestial objects. The artificial light emitted by cities is similarly scattered by the atmosphere, and as a result one third of humans (including nearly 80% of North Americans) are no longer able to see the Milky Way from their homes (Falchi et al., 2016). This is an immense cultural loss (Gallaway, 2010). It also raises the cost of doing professional astronomy, as historically important and easily accessible sites such as Mount Wilson Observatory can no longer be used for research in the visible range (Teare, 2000), and even remote sites are increasingly threatened by light pollution (Krisciunas et al., 2010; Aubé et al., 2018). Studies of night sky brightness and its changes are therefore important for amateur and professional astronomy.

Remote observation of upward light emissions is crucial for the study of artificial night sky brightness on large scales. These data can be used with radiative transfer models to predict night sky brightness on clear nights (Cinzano et al., 2001; Falchi et al., 2016). Both satellite imagery and the derived night sky brightness maps are used by the public to find locations for astronomical tourism (Collison and Poe, 2013; Hiscoks and Kyba, 2017), and photometric indicators of visual night sky quality can be derived from ground based hemispherical photos (Duriscoe, 2016). The global spectral shift due to adoption of white LEDs is a major challenge for astronomy, both because the blue component of white light produces more skyglow (section 2.4), and because many current ground and space-based sensors are not sensitive to blue light (section 4.5, Fig. 24). Ground based observations of night sky brightness are therefore crucial for calibrating skyglow models, and are necessary for long-term monitoring due to changes in lighting practice (Kyba, 2018a; Hyde et al., 2019). A related topic is studies using ground based instruments to measure the impacts of cloud cover on night sky brightness (eg. Kyba et al., 2011, 2012; Jechow et al., 2017b, 2019a), but in this case the aim is usually to better understand the ecological impacts of this form of global environmental change (see next section).

3.7. Using night lights to estimate threats to ecosystems

Plants, animals, microorganisms, and entire ecological systems are affected by artificial light pollution, due to changes in behavior, physiology (including circadian rhythms), timing of activities, and disorientation, among many other reasons (Rich and Longcore, 2006; Navara and Nelson, 2007; Longcore et al., 2012; Gaston et al., 2013; Russart and Nelson, 2018). As this is a very active area of research in biology and ecology (Davies and Smyth, 2018), many researchers make use of night lights data. For example, several studies have used the mosaics of DMSP/OLS stable lights (as one of several variables), to globally map the human footprint in terrestrial areas (Sanderson et al., 2002; Venter et al., 2016) as well as to map the human impact in marine areas (Halpern et al., 2008, 2015). In a similar fashion, night lights were used to globally map impervious surface area (Elvidge et al., 2007a) and to estimate human population at fine spatial resolutions (Bhaduri et al., 2002), as both impervious surface and population density are known to negatively impact biodiversity.

Using a calibrated set of DMSP/OLS images (1992–2010), Gaston et al. (2015) demonstrated that protected areas were indeed darker (DN $<$ 5.5) than unprotected areas; however, they found that natural darkness has been eroding in many protected areas, and especially so in Europe, South and Central America, and in Asia, where there was a significant increase in mean nighttime lighting in 32–42% of all protected areas. In a following study, Koen et al. (2018) have found that areas with high species richness terrestrial and freshwater mammals, birds, reptiles, and amphibians, are suffering from encroachment of artificial lights. Marcantonio et al. (2015) used VIIRS/DNB data to show that a 10% reduction in light emissions near nature parks in Italy could lead to a 5–8% increase in the area suitable for high biodiversity. Social media (such as geotagged Flickr photos) has also been used in conjunction with night-time lights to estimate visitation of protected areas and the impact of human activity on them (Levin et al., 2015).

While most artificial lighting originates from land areas, marine ecosystems are not devoid of light pollution. As of 2010, based on DMSP/OLS data (as of 2010), about 22% of the world's coastlines (except Antarctica) were subjected to light pollution based on DMSP/OLS data, with 54% of Europe's coastlines under light pollution, followed by Asia (34%) and Africa (22%) (Davies et al., 2014). Field experiments using an underwater spectrometer in the Gulf of Aqaba have observed artificial light in the blue band down to a depth of 25 m near the coast, and up to 5 km from the coast at a depth of 5 m depth at 5 km from the coast (Tamir et al., 2017).

3.8. Using night lights to examine ecological light pollution

Studies which attempted to quantify the relationship between light pollution and presence or behaviour of species have mostly focused on specific organisms, such as sea turtles and birds (e.g. Van Doren et al., 2017). Using VIIRS/DNB data, La Sorte et al. (2017) showed that nocturnally migrating birds are attracted to urban lit areas, affecting their migration behaviour. In a follow-up study, Cabrera-Cruz et al. (2018) have shown that light pollution experienced by nocturnally migrating birds, is especially high during the migration season for species with smaller ranges. Recently, Horton et al. (2019) combined VIIRS/DNB with weather surveillance radar data to examine the exposure of migratory birds to light pollution, in order to provide data for targeted conservation actions. They found, for example, that over half of all migratory birds typically pass a single radar location within a single week, which suggests that targeted and relatively short term "lights out" campaigns for floodlit buildings could potentially greatly reduce the impact of light pollution on migratory birds.

Sea turtles represent one of the most studied groups, for which the negative impacts of artificial lights have been well known for decades (e.g. Witherington and Martin, 2000). Kamrowski et al. (2012, 2014) used DMSP/OLS imagery to identify which nesting sites of sea turtles along the Australian coastline are exposed to light pollution, and in which of these sites there was an increase in light pollution. Using finer spatial resolution imagery (ISS photographs and SAC-C), Mazor et al. (2013) have shown that nesting of sea turtles along the Mediterranean coast of Israel was negatively correlated with night-time brightness, and Weishampel et al. (2016) obtained similar results using DMSP data for nesting sea turtles in Florida, which was also confirmed by VIIRS data (Hu et al., 2018a). Given the differences between the light perceived by animals and humans (mostly horizontal light) and the light measured from space (mostly upwards reflected light; Katz and Levin, 2016), new ground based methods are developed to measure night-time brightness for ecological studies, e.g., using sky quality meters (Kelly et al., 2017) or hemispheric cameras (Pendoley et al., 2012). Jechow et al. (2019b) recently provided an overview of how a DSLR camera with a fisheye lens can be used for characterizing night time brightness over a full sphere, by taking two vertical plane photos. Such an approach is especially useful for studies on ecological light pollution, because the field of view of various species differs both in the horizontal as well as in the vertical plane.

Remote observations of night lights have also been used to examine the influence of light on bats, all of which are nocturnal, and many of which are extremely sensitive to artificial light. In a nationwide study of bats in France, Azam et al. (2016) combined VIIRS/DNB data with landcover data to examine the relative effects of impervious surface, intensive agriculture, and light emission. They found that agriculture had the strongest negative influence on all four species tested, and that light emission also had a negative influence on 3 of the 4 species tested, and in all cases had a stronger negative influence than impervious surface. Hale et al. (2015) used higher resolution (1 m) data from nighttime aerial photography and maps of tree cover together with observations of bats to examine how light modulates the impact of gaps in tree cover for bat flights. They found that the negative impact of light increases as crossing distance between trees increases. In a recent study, Straka et al. (2019) found that the lamp spectra also had important and species-dependent effects, using land cover data and a 1 m resolution map of light emission from Berlin (Kuechly et al., 2012) together with surveys of bat activity.

3.9. Epidemiology

In modern societies, exposure to artificial light is suspected as a contributing factor to some diseases (e.g. some cancers, obesity, and depression), through disruption of the circadian rhythm (Lunn et al., 2017) or sleep disturbance, as well as suppression of the hormone melatonin, which is related to ambient light intensities (Haim and Portnov, 2013; Cho et al., 2015). Space-based night light data allows studies of population exposures to artificial outdoor light, which can then be compared to data from either cohort studies or a set of patients and healthy controls. The "Light at Night hypothesis" for breast cancer was first proposed by Stevens (1987), who noted that if dim light is a risk factor, brightly lit communities could be expected to have higher levels of breast cancer. The first empirical analysis linking DMSP/OLS night lights data with breast cancer (BC) incidence was Kloog et al. (2008), which examined 147 urban localities in Israel. The study revealed a statistically significant association between ALAN and BC but not with lung cancer, which was used in the study as a negative control. Follow-up studies confirmed adverse effects of ALAN on BC and prostate cancer in worldwide cohorts (Kloog et al., 2009, 2010). Other studies investigated DSMP-derived ALAN data in conjunction with different health phenomena, including hormone-dependent cancers (Bauer et al., 2013; Hurley et al., 2014; Rybnikova et al., 2015, 2016b; Portnov et al., 2016; James et al., 2017; Kim et al., 2017; Rybnikova et al., 2018), obesity (Rybnikova et al., 2016a; Rybnikova and Portnov, 2016; Koo et al., 2016), and sleep quality (Koo et al., 2016). These studies, carried out in different regions and population cohorts, provide mutually complementing evidence about significant associations between ALAN and a wide of range of adverse health phenomena.

A major question for this research is the extent to which remote observations of light match individual exposures. Kyba and Aronson (2015) argued that if ALAN is a cause of disease (rather than a correlate), then estimated risk factors should increase with increasing spatial resolution of remotely sensed data. Rybnikova and Portnov (2017) then compared results obtained from DMSP and VIIRS-DNB satellite images, and detected a stronger ALAN-BC association when using the higher spatial resolution VIIRS/DNB images. Recent studies have used even higher resolution multi-spectral images taken from the ISS. Both Garcia-Saenz et al. (2018) and Rybnikova and Portnov (2018) used ISS image data to conclude that exposures to short wavelength (blue) ALAN appear to have stronger effects on hormone-dependent cancer incidence than exposures to green and red light spectra. This conclusion is consistent with results of laboratory and small cohort studies, which emphasize potential health risks associated with short wavelength illumination (Lunn et al., 2017). Keshet-Sitton et al., (2017) also demonstrated increased risk of breast cancer based on ground-level measurements rather than remote observations. Further work in this area will greatly benefit from improvements in resolution, coverage, and multispectral information from space-based sensors, as well as confirmation of the relevance of the data through ground-based measurements of a representative sample of individual exposures (Kyba and Spitschan, 2019).

3.10. Lighting technology

For some applications, identification of lighting technology as well as their dynamics on short time scales is desirable. To discriminate lamp types using airborne or spaceborn systems, high spatial and spectral resolution is necessary (Fig. 24). The ideal system would be to use a hyperspectral imaging spectrometer at low altitudes. Few studies with limited spatial coverage exist, such as the first ever performed over 1998 in Las Vegas, USA (Elvidge and Green, 2005; Alamús et al., 2017, see section 2.3 for more). Elvidge et al. (2010) showed that it was in principle possible to discriminate light sources with multispectral sensors, using detailed spectral field measurements and a modeling approach for the pre LED technologies. This was later demonstrated in practice with an aerial survey over Birmingham, UK. In that study, Hale et al. (2013) used a standard DSLR camera and supportive field measurements, and achieved a high success rate of distinguishing between different vapor lamps, although the technique used was fully phenomenological. Sensor requirements for satellite based surveys were proposed (Elvidge et al., 2007b,c) but few attempts have been performed. Using the hyperspectral data of a flight over Las Vegas Metcalf (2012) and Tardà et al. (2011) were able to determine different lighting technologies, Sánchez de Miguel (2015) used ISS images, and Zheng et al. (2018) were also able to distinguish high-pressure sodium (HPS) lamps from white LEDs using the new Jilin-1 satellite. However, there are fundamental limitations for multispectral sensors to distinguish between similar color light sources, like fluorescents/compact fluorescents and LEDs of same color temperature or HPS lamps and PC-Amber LEDs (Sánchez de Miguel et al., 2019b). It should also be noted that most of the research undertaken thus far has been done without radiometric calibrations of any kind or atmospheric corrections.

Ground-based measurements provide more freedom regarding temporal and spectral resolution (section 2.4). Several studies have used calibrated RGB cameras to track lighting remodelling from vapor lamps to LEDs (Kolláth et al., 2016; Barentine et al., 2018), or short term dynamics like the switching off of specific lights to assess their contribution to skyglow (Cleaver, 1943; Jechow et al., 2018b). Ground-based measurements can provide a wider temporal range than space based sensors (section 4.3), and also fill in the blind spot of the lack of sensitivity to blue light from LEDs (section 4.6, Kyba et al., 2017). High frequency data, for example as measured using ground based SQM, can be used to remotely sense the contributions of different lighting types (streetlights, vehicles, residential light) due to their differing temporal patterns (Bará et al., 2018). Systems used in urban science show promising results at the cross section to remote sensing as shown by the "pulse of the city" studies with ground-based measurements, using a hyperspectral camera by unraveling aggregate human behavior patterns (Dobler et al., 2015), lighting types (Dobler et al., 2016) or temporal profiles using RGB images (Meier, 2018). In addition, the combination of several remote sensing techniques (AstMON, SQM, ISS images and Hyperspectral spectrograph [SAND] plus energy statistics) was used to trace the temporal evolution and population of the lighting technologies used in Madrid for an average night (Sánchez de Miguel, 2015).

3.11. Mapping fires, gas flares, and greenhouse gas emissions

Wildfires are a major force shaping natural ecosystems, and their ignition and propagation are influenced by both natural and anthropogenic factors. Whereas during the industrial period the global fire regime has shifted from one driven primarily by rainfall, to one driven by human influence on fire (ignition and suppression), in the future climate change may play a decisive role in global fire regime (Pechony and Shindell, 2010). Fire management therefore requires mapping fire in space and in time. It has long been known that visible light data from DMSP had a capability to detect biomass burning and natural gas flaring (Croft, 1973, 1978, Fig. 6b). In the mid-1990s a nightly biomass burning algorithm was developed for DMSP low light imaging data and regionally implemented (Elvidge et al., 1996). This involved a lit pixel detection algorithm and masking of persistent lights from cities, towns and gas flares. Later on, as the distribution of DMSP/OLS data was lowered to 3 h, it was perceived that DMSP/OLS data can be used for operational fire monitoring (Elvidge et al., 2001b), and that active fire mapping using DMSP/OLS was able to detect more fires than MODIS (Chand et al., 2007).

A high correlation was identified between the total lit area of a country and total carbon dioxide (CO2) emissions (Doll et al., 2000), and even better results were obtained using the VIIRS/DNB (Ou et al., 2015). The first global satellite estimates of flared gas volumes came from DMSP, with flaring sites identified manually based on circular haloes of glow present in the DMSP annual cloud-free nighttime lights (Elvidge et al., 2009a). With the advent of VIIRS, these capabilities have been substantially enhanced based on the nighttime detection of fires and flares in three spectral ranges: near infrared (NIR), shortwave infrared (SWIR) and midwave infrared (MWIR). The VIIRS Nightfire (VNF) algorithm detects the presence of sub-pixel infrared emitters, such as fires and flares in six spectral bands and uses Planck curve fitting to derive temperature, source area, and radiant heat using physical laws (Elvidge et al., 2013b), which is an improvement over satellite fire products which use one or two spectral bands (Elvidge et al., 2013c). Daily VNF datasets are available for download from https://eogdata.mines.edu/download_viirs_fire.html. The VNF data has been successfully used to map and classify industrial heat sources (Liu et al., 2018), as well as to conduct annual surveys of natural gas flaring locations and estimate flared gas volumes (Elvidge et al., 2015a). The advantage of VNF over both DMSP and traditional MWIR fire products is the ability to calculate variables such as temperature using physical laws. However, Elvidge et al. (2019) recently showed that the VIIRS/DNB retains a capability to detect combustion sources too small to trigger detection in VNF. These results indicate that more complete compilations of IR emitters could be achieved by adding a DNB fire product to complement VNF and other satellite derived fire products, as recently reviewed by Chuvieco et al. (2019).

3.12. Monitoring fisheries

The earliest reporting on nighttime satellite detection of fishing boats using massive lighting to attract catch, traces back to DMSP data (Croft, 1978, Fig. 6c). From 2000 to 2012, NOAA provided regional near real time DMSP file transfer services to fishery agencies in Japan, Korea, Thailand, and Peru, where the boat detections were analyzed locally. However, an automatic algorithm for reporting boat locations was never developed for DMSP. The situation changed with VIIRS due to the large sizes of the images, making it impractical for most users to download the images for local analysis. In 2014, NOAA initiated the development of a VIIRS boat detection (VBD) algorithm. The initial algorithm was optimized for low moon conditions (Elvidge et al., 2015b) and produced high numbers of false detections from moonlit cloud and lunar glint features. This problem was resolved by adding a module which screens moonlit areas for lights found in DNB that are missing from the corresponding long wave infrared image based on a cross-correlation analysis. VBD is now produced globally with a nominal four-hour temporal latency, and is available online at https://eogdata.mines.edu/vbd/. In addition, NOAA provides near real time email and SMS alerts for VBD detections occurring in marine protected areas (MPAs) and fishery closures in Indonesia, Philippines and Thailand. The alerts now cover 989 individual areas, spanning 648,865 km^2, with 82,101 detections in 2017. VBD data have been successfully used to rate compliance levels in fishery closures in the Philippines and Vietnam (Elvidge et al., 2018), and to map core fishing areas in the Philippines (Geronimo et al., 2018).

4. Research challenges, limitations of current sensors, and outlook for the future

4.1. Challenges of night light sensing and the differences between day vs. night sensing in the visible band

There are many challenges associated with observations of visible band light at night, and the remote sensing of socioeconomic parameters on the basis of such data. The most obvious of these are the dramatically reduced radiance and extreme dynamic range of night scenes in comparison to daytime remote sensing. Consider the scene in Fig. 14. During daytime, the light source is the sun, shining from above the atmosphere. In a cloud free scene, rooftops, treetops, and open grassland or water areas are illuminated equally, and their radiance in the scene depends on their albedo. The typical dynamic range of the data is perhaps a factor of 50.

During the night, both celestial and artificial light sources are present. Areas appearing black in the night image are lit by natural sources like airglow and starlight, about 8 orders of magnitude fainter than direct sunlight. Streets are lit by reflected light from lamps, about 4 orders of magnitude fainter than direct sunlight (Hänel et al., 2018). Comparing the histograms of radiance over Berlin from a Landsat daytime image and a VIIRS/DNB night-time image, it can be observed that radiance at night was about 5 orders of magnitudes lower than at day time, and that the distribution at radiance at night-time is different, skewed towards dark areas, whereas during daytime it is distributed more normally (Fig. 25). Whereas within Landsat 8 night-time images of Berlin, Las Vegas and other cities, the brightest sources mostly emitted light within the visible bands, bright sources of gas flares also emitted significantly in bands 6 and 7 (in the short-wave infrared) of Landsat 8 (Levin and Phinn, 2016).

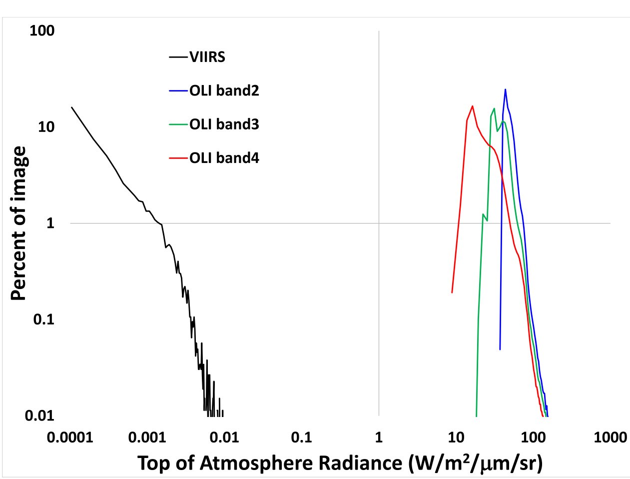

Fig. 25. Histograms of top of atmosphere radiance for the images of Berlin of VIIRS/DNB and day-time Landsat OLI shown in Fig. 14.

Some lamps (e.g., no cut-off or semi cut-off) radiate a portion of their light upwards without reflection (Cha et al., 2014), and can therefore have radiances approaching an order of magnitude of sunlight. Nighttime sensors that target to capture the radiance of all elements in an urban scene at high spatial resolution would therefore require an enormous instrumental dynamic range. In practice, this is never the case. At high spatial resolution, unlit areas are usually underexposed (as shown by Levin et al., 2014, using an EROS-B image), and lamps shining directly upward saturate the sensor. The problem of high dynamic range is reduced considerably at lower spatial resolution (as in Fig. 14), because even in urban areas, most of the scene consists of areas that are not artificially lit (e.g. rooftops and treetops).

In daytime scenes, radiances change throughout the day due to changing solar illumination, atmospheric conditions and viewing geometry between the sensor, the target and the sun: the Bidirectional Reflectance Distribution Function (BRDF; Schaaf et al., 2002). In most cases, surface radiances themselves are not of interest, but rather derived quantities like reflectance within a spectral window, surface emissivity or surface temperature. At night, in many cases it is the radiance itself that we are interested in, but this value can be highly variable. Coesfeld et al. (2018) discusses the sources of these radiance changes, and their discussion is summarized and expanded upon here.

We begin with a hypothetical scenario to demonstrate the complexity of the spatial distribution of night lights. Imagine a very long wall that is 30 m tall, with a single lamp mounted at 5 m height, 5 m away from the edge of the wall (Figure S1), which radiates in all directions. It can be immediately seen that when imaged from the left, the lamp is invisible, while when imaged from zenith or from the right, the lamp can be seen directly, as can the light reflected from the ground surface and the wall. If a space based instrument observes this scene on multiple days from multiple directions, the total radiance will change in an on-off fashion. Now consider the case where instead of radiating in all directions, the lamp shines all of its light directly on the wall (e.g. a well-directed floodlight). In this case, the radiance would go as $1\text{-}H(\theta\text{-}\pi/2)\cos\theta$, where θ is the angle between the observing direction and the normal of the wall, and H is the Heaviside step function. Viewed from the left, from directly above, or any view direction parallel with the wall's direction, the wall would appear to be black. When viewed from the right, the observed radiance would increase with both increasing nadir angle and increasing angular viewing distance from the wall's direction.

The scenarios described above were hypothetical, but are representative of two extremely common situations: first, screening (i.e. blocking) of artificial light by buildings, trees, or other objects, and second, radiation from vertical surfaces such as floodlit facades, light escaping windows, and illuminated signs. The imaging direction thus has a major impact on the radiance observed at night. Since this effect is determined by the local geometry, a general correction is not possible. At high spatial resolutions (Fig. 26), the effect is quite obvious. At low spatial resolutions, the effect may be minimized to some extent due to averaging many local conditions, surface geometries such as hillsides or long parallel streets which can make the effect visible even at a spatial resolution of 750 m (Li et al., 2019b).

Both DMSP/OLS and Suomi NPP/VIIRS DNB are wide-view sensors, with swath widths greater than 3000 km, which means they can accumulate angular observations varying in a large range. Angular observations sometimes are not preferred, because they often cause variation across geography that makes mosaicking or comparison over time a big challenge. However, angular information has been proved to carry valuable structural information and ironically is critical to normalize observations to the standard viewing-illuminating geometry, as

Fig. 26. Visibility of lit facades depends on perspective. The top image is a crop of an photograph taken from the South, so North facing facades are visible. The bottom image was taken from the North, so the South faces of buildings therefore appear dark. Photos taken by Alejandro Sanchez de Miguel and the Freie University"at Berlin during the EU COST Action ES1204 LoNNe. Figure and caption reproduced from Coesfeld et al. (2018), available under a Creative Commons Attribution license (CC-BY 4.0).

seen in MODIS (Schaaf et al., 2002) and MISR (Multi-angle Imaging SpectroRadiometer) (Diner et al., 1989). Due to the variation in street layout and building height, nighttime light is also expected to vary accordingly (Kyba et al., 2015a). Angular observations from both DMSP/OLS and VIIRS/DNB may thus provide structural and vertical information about urban areas, especially in the east-west direction, given the characteristic scanning geometry of sun-synchronous sensors. Such information still remains under-utilized up to date, however preliminary results indicate that measured radiance is lower at nadir and increases towards the edge of the scan (Bai et al., 2015). In a recent paper, Li et al. (2019b), have confirmed that the viewing angle of VIIRS/DNB affects the amount of measured night-time brightness, and that building height should be incorporated to understand the relationship between the satellite viewing zenith angle and emitted night-time lights. A different group (Li et al., 2019c) have approached the problem from the other direction, using ground based all-sky imagery from Google Street View to examine how much light can escape to space, and how this is affected by changes in vegetation. Future research is required to extract this invaluable information from both DMSP/OLS and Suomi NPP/VIIRS DNB, and to remove angular effects from night-time products.

4.2. Uncertainties due to moonlight, aerosol/cloud contamination, and seasonal vegetation effects

Uncertainties originating from angular, diurnal, and seasonal variations in atmospheric and surface optical properties are also a primary source of measurement error in the nighttime lights (NTL). As demonstrated by Román et al. (2018), characterizing these uncertainties is extremely crucial as a long-term record of NTL cannot be constrained directly from at-sensor top-of-atmosphere (TOA) radiances. The uncertainties can be separated into (1) environmental factors, such as moon light, cloud/aerosols, and surface albedo (interferes with the observed signal), and (2) errors stemming from seasonal variations in vegetation or in snow cover and associated surface properties, which can significantly affect estimates of seasonal and long-term trends (Fig. 20).

Key to characterizing these factors is an accurate estimation of the surface Bidirectional Reflectance Distribution Function (BRDF, or reflectance anisotropy), a quantity that is governed by the angle and intensity of illumination – whether that illumination be solar or lunar (e.g., Miller and Turner, 2009) or from airglow emissions – and by the structural complexity of the surface. Román et al. (2018) considered the semi-empirical RossThickLiSparse Reciprocal (RTLSR, or Ross-Li) BRDF model (Román et al., 2010; Roujean et al., 1992; Schaaf et al., 2002; Wang et al., 2018) to correct the effects of contamination through an external illumination in the NTL. This modeling approach is advantageous as it has been shown to capture a wide range of conditions affecting the VIIRS/DNB on a global basis. Similarly the RTLSR model also allows analytical inversion with a pixel-specific estimate of uncertainty in the model parameters and linear combinations thereof (Lucht and Roujean, 2000). Finally, the scheme is also flexible enough that other kernels can be easily adopted should any become available and should they be shown to be superior for a particular scenario.

Similar to day light sensing in visible band, NTL radiances also suffer from biases stemming from clouds and aerosols. A scene with opaque clouds can block the NTL radiance completely, whereas thinner and transparent or semi-transparent atmosphere blocks the radiance partially and scatters the light creating a fuzzy appearance (Elvidge et al., 2017). The vector radiative transfer modeling of the coupled atmosphere-surface system (Vermote and Kotchenova, 2008) can be used to compensate for aerosols, water vapor, and ozone impacts on the NTL radiances (Román et al., 2018). This correction mitigates errors stemming from poor-quality TOA retrievals, especially across regions with heavy aerosol loadings and at Moon/sensor geometries yielding stronger forward scatter contributions.

Seasonal variations such as those resulting from vegetation artifacts can also introduce challenges in the retrieval of satellite-derived NTL due to the canopy-level foliage along the ground-to-sensor geometry path. This effect occurs predominantly in urban areas where vegetation such as deciduous broadleaf canopies is present. The impact of this obstruction of surface light by the cyclical canopy results in reduction in the magnitude of NTL at city-wide scales (Levin, 2017; Levin and Zhang, 2017, Fig. 20). This occlusion effect has been shown to be directly proportional in magnitude to the density and vertical distribution pattern of the canopy. Román et al.(2018) proposed to use gap fraction to correct the vegetation effect. These seasonal changes may be viewed as a noise (when aiming to estimate socio-economic properties from NTL) or as a signal (when aiming to estimate light pollution from NTL).

4.3. Challenges related to temporal sampling

In addition to the seasonal changes mentioned above, night lights are dynamic throughout the course of individual nights (Figure S2). Observations of night sky brightness show typical decreases of typically around 5% per hour (Kyba et al., 2015b; Falchi et al., 2016), with larger decreases earlier at night. The decrease in light emission can also be seen through horizontal imaging (Dobler et al., 2015; Meier, 2018). Many municipalities intentionally dim or turn off street lights at late hours (Green et al., 2015), and these switch offs can produce very obvious signals in night sky brightness data (Puschnig et al., 2014, Sánchez de Miguel, 2015; Jechow et al., 2018b). The typical spectra of artificial light emissions also appears to shift as the night progresses (Kyba et al., 2012; Aubé et al., 2016). This is presumably due to changes in the fraction of lights coming from different types of lamps. Observations of low resolution ground spectra or sky spectra could therefore potentially be used to differentiate the relative contributions of light sources at different times (Bará et al., 2018).

Orbital platforms with a (relatively) fixed overpass time, such as DMSP (early evening) or VIIRS DNB (~ 1:30am) have limited ability to view such temporal changes. Depending on the application, this may be a disadvantage (they do not get the full picture of light use) or an advantage (the observed radiance values are more consistent). Platforms with a non-fixed orbital time can fill in the gaps to some extent (Kyba et al., 2015a), but such imagery is then taken on different dates. Only a geostationary platform could allow continuous, or at least repeated, tracking of radiance changes throughout the full night (e.g. Zoogman et al., 2017). With routine and growing numbers of observational passes from Suomi-NPP, JPSS-1 (now NOAA-20) and subsequent JPSS series of satellites, nighttime light observations will become even more frequent, providing opportunities for multiple cloud-free observations per night and greater temporal frequency to quantify the stability of light sources, their magnitude, and time to restoration following a disaster event.

Outside of the tropics, there is an important interaction between imaging time and the seasons in which an orbital platform can acquire data about artificial lights. This is of particular importance for many cities in Europe. In Berlin, for example, astronomical night does not occur in the period between May 19 and July 27. If the satellite overpass time is displaced from midnight, this period is even longer. For a satellite with a 21:00 overpass time, Berlin would be illuminated by twilight from early April until the start of September. Restricting the available night window to the period September–March means that nights with snow cover will make up a much larger fraction of the dataset, especially at higher latitudes or elevations. Annual products for high latitude countries (e.g. Canada, Sweden, Norway, Finland, Iceland) are therefore likely to be biased upwards due to snow cover if the satellite overpass time is too far from midnight (Elvidge et al., 2001a).

4.4. Long-term instability of some light sources

Many light sources in countries with stable electricity emit relatively similar amounts of light from night to night. Coesfeld et al. (2018) reported that the distribution of radiances in the DNB monthly composite data for urban and suburban locations and airports was near normal, with a standard deviation of about 13–19%, depending on whether all months or only autumn months were considered. Other light sources such as ship ports, stadiums, and power plants had larger variations, while some other light sources are much more dynamic (Coesfeld et al., 2018). Wildfires appear only during the time they are active, and oil flares are not stable from year to year (Coesfeld et al., 2018). Large construction sites may be brightly lit for relatively long periods (Kuechly et al., 2012), and eventually replaced by less brightly lit buildings. Greenhouses are among the brightest objects on Earth, but may only be lit during a portion of the year (Coesfeld et al., 2018). Special events such as large-scale outdoor concerts or light festivals (Figure S3) can also produce considerable light only for short periods. All these types of unstable lights pose a challenge for defining monthly and annual trends in light emissions.

4.5. Global spectral shift due to transitions to LEDs

The world is in the midst of a “lighting revolution” due to the development of light emitting diode (LED) technology (Pust et al., 2015). This is the fourth such revolution in the history of outdoor lighting: previous generations switched from oil to gas, gas to the first electric lights (arc lamps and incandescents), incandescent to high intensity discharge lamps (Riegel, 1973; Jakle, 2001; Isenstadt et al., 2014). Each new technology has not only allowed for an increase in light emission, but has also dramatically changed lighting spectra, and allowed new forms of illumination. The global transition to LED lights therefore has dramatic implications for remote sensing of night lights.

From a remote sensing perspective, there are two main consequences of the change towards LEDs. First, the “white” LEDs used for lighting outdoor areas have a broadband spectra, in dramatic contrast to the “line” type spectra of vapor lamps (Elvidge et al., 2010; Aubé et al., 2013, Fig. 24). Much of the world was lit by orange colored high pressure sodium lamps at the start of the 21st century, and existing broadband monitoring instruments designed for 20th century lights can therefore easily mistake a change in spectrum for a decrease in emitted light (Kyba et al., 2015a,b; Sánchez de Miguel et al., 2017). For similar reasons, the spectral change affects the perception of artificial lights by animals, and therefore the ecological impacts of such light (Longcore et al., 2018). Future research should be thus directed on examining the impacts of the transition of artificial lighting to LEDs on various topics, including ecological light pollution, human health, crime and car accidents, preferably using a before-after-control-impact (BACI) design, as in Plummer et al. (2016) and Manfrin et al. (2017).

The second major consequence of the introduction of LEDs is a change in illumination practices. For example, LEDs are more easily dimmed than vapor lamps, so lighting may become more temporally dynamic. Streetlights based on LEDs are less likely to directly emit light into the atmosphere, and may potentially result in less total emissions through more careful direction of the light (Kinzey et al., 2017). The most important change, however, may turn out to be a shift in the “typical” source of light observed from space, away from street lighting and towards lights emitted for advertising or artistic purposes (Kyba, 2018b). This spectral shift will likely affect the ability to existing sensors such as VIIRS/DNB to quantify artificial lights from space, given that it is not measuring incoming light in the blue band (Fig. 24). Modelling work recently done by Bará et al. (2019) indicates that for certain transition scenarios (from HPS to LED), the VIIRS may detect reduction in artificial zenithal sky brightness, even if sky brightness in reality increases, due to the loss of the HPS line in the near-infra red, and the inability of the VIIRS to detect blue light. The emission of blue light from LED sources therefore requires future night-time sensos to include the blue channel (which is not covered by DMSP/OLS, VIIRS/DNB or Luojia-1), however blue light is scattered more (Kocifaj et al., 2019), and thus atmospheric haze removal techniques should be developed for night-time imagery, for future products.

4.6. Challenges in calibrating ground and space borne measurements

While night light remote sensing has benefited various applications, there are certain research gaps that need to be overcome in order to transform this data to be more quantitative. While in traditional optical remote sensing satellite images are atmospherically corrected to derive their reflectance values (Clark and Roush, 1984), it is not so clear which units should be used in night light imagery. The DMSP/OLS imagery products are distributed as stable lights or average lights x percent (DN values between 0 and 63). Often these products are used to calculate the total lit area or the total lights, however, these data are not in luminance units. Photometry is the measurement of the intensity of electromagnetic radiation in photometric units, like lumen/lux/etc, or magnitudes. Radiometry is the measurement of optical radiation, with some of the many typical units encountered are Watts/m^2 and photons/sec/steradian. The main difference between photometry and radiometry is that photometry is limited to the visible spectra as defined by the response of the human eye (Teikari, 2007). Of relevance for such measurements, are the photopic and scotopic bands. Human photopic vision which allows color vision, takes place under daytime conditions as well as under artificial illumination, and is based on the properties of cone photoreceptors in the human retina. Human scotopic vision on the other hand, takes place under dark conditions, using the retinal rods alone, when humans perceive the world in “grey scale”; in comparison to photopic vision, scotopic vision is shifted towards shorter wavelengths, mostly between 454 and 549 nm (Elvidge et al., 2007b).

In recent years there have been some attempts to calibrate fine spatial resolution images to photometric units. Hale et al. (2013) used ground measurements of incident lux along linear transects to calibrate their aerial night light images into illuminance units. A different approach has been used by Cao and Bai (2014), who examined the temporal variability in light as measured by the VIIRS/DNB from various features which they expected to emit uniformly in different nights. Another approach for field mapping of night lights that can be used for calibrating aerial or space borne night light imagery is using ground networks of instruments such as the Sky Quality Meter (SQM, manufactured by Unihedron, measuring the brightness of the night sky in magnitudes per square arc second;http://www.unihedron.com/projects/darksky/), however ground networks aimed at monitoring light pollution are fairly recent (den Outer et al., 2011; Pun and So, 2012; Zamorano et al., 2019). In an interesting study using Extech EasyView 30 light meters to map night brightness along a 10-m sampling grid on the Virginia Tech campus, brightness was measured twice: First with the light meter pointing upward to catch direct light from the light fixtures at 30 cm from the ground, then with the light meter pointing down to measure reflected light (Kim, 2012). Most ground networks of SQM are directed to measure zenith night sky brightness. In a study comparing the correspondence between an EROS-B night-time image, and ground measurements done with SQMs in three directions (downwards, horizontally and upwards), Katz and Levin (2016) have shown that the lowest correspondence was with ground measurements directed upwards (representing sky glow), whereas the strongest correspondence was found with ground measurements directed downwards (representing street light reflected by the surface). Thus, in addition to the inconsistency in the photometric units used for calibrating aerial night lights images, there is a gap with regards to how should one measure light on the ground so that it best corresponds with what an airborne or a space-borne captures.

4.7. Consistent nightlight time series across different platforms and sensors

Although the signal of change in the DMSP/OLS NTL time series is larger than the error signal and also large enough to render the error signal (noise) unimportant (Zhang and Seto, 2011), to facilitate accurate change analysis with NTL time series it is necessary to calibrate first to minimize differences caused mainly by satellite shift (Zhang et al., 2016). The challenge to achieve successful radiometric calibration of remote sensing imagery obtained at different times is to find invariant ground targets that can be used as references for reliable comparison over time. As the first attempt, Sicily, Italy was chosen as the reference site to calibrate the reference image F121999 and other images individually (Elvidge et al., 2009a,b,c). These models were then applied to calibrate the entire DMSP/OLS time series from 1992 to 2008. This method successfully reduced differences caused by satellite shift to some order. However, models derived in Sicily might not be generalized to cover the entire globe, since noises introduced by various sources might not be geographically homogenous (Pandey et al., 2017). To address this problem, researchers studying regional urbanization dynamics have chosen local reference sites to derive their models so that they better fit their specific regions (Liu et al., 2012; Nagendra et al., 2012; Pandey et al., 2013). In an attempt to produce more generalized models for the entire globe, Wu et al. (2013) extended the Elvidge et al. (2009a,b,c) method by selecting more reference sites, including Mauritius, Puerto Rico, and Okinawa, Japan in addition to Sicily, Italy. Despite that the Wu et al. (2013) method achieved improvement, the way they chose invariant regions was not essentially different than that applied by Elvidge et al. (2009a,b,c) and also suffers from the limitation of subjectively choosing areas.

Li et al. (2013a,b) designed an automatic method to find invariant pixels in Beijing, China to avoid subjective errors. This automatic method can minimize the bias introduced by subjective selection of invariant regions and has the potential to be extended to the entire globe. However, since the region of Beijing experienced dramatic changes in the past decades, this method might lead to overcorrection to the NTL time series. Furthermore, the iterative procedure to identify stable pixels is very computation intensive and thus cannot be directly implemented at the global scale, considering the gigantic amount of pixels. Zhang et al. (2016) designed a ridge sampling and regression method to calibrate the NTL time series over the entire globe. This method is based on a novel sampling strategy to identify pseudo-invariant features. Data points along a ridgeline-the densest part of a density plot generated between the reference image and the target image-were first identified and those data points were then used to derive calibration models to minimize inconsistencies in the NTL time series. In this way, only 63 pairs of data points were used to run a regression model for calibrating each target image, significantly reducing computation load. Since only the F152000 image was used as the reference image, target images close to the two ends of the time series might be over corrected due to the increased time intervals. Li and Zhou (2017) proposed a stepwise calibration approach to address that issue. They first reduced temporal inconsistency within each satellite segment and then systematically moved each satellite segment up or down to generate a temporally consistent NTL time series from 1992 to 2013, by making full use of the temporally neighbored image as a reference for calibration.

Each of the methods mentioned above has its strengths and shortages. A framework to assess and choose a right method for a specific application was proposed by Pandey et al. (2017). Future efforts are still needed to design better NTL calibrating methods. Furthermore, there is a huge gap between DMSP/OLS and VIIRS/DNB. A temporally consistent NTL time series extending from DMSP/OLS to VIIRS/DNB is highly desirable, yet still a huge challenge, due to differences in passing time, onboard calibration, spatial resolution, and other considerations (see Li et al., 2017, as well as Zheng et al., 2019, for examples of inter-calibration between DMSP/OLS and VIIRS/DNB). Ground-based stable and radiometrically calibrated light sources may offer a useful approach for inter-calibration between night-time lights sensors, as well as for validating the performance of these sensors, as attempted by Hu et al. (2018b) and Ryan et al. (2019).

4.8. Outlook for the future

4.8.1. The need for geostationary platforms

Despite the benefits of its unique information content, a significant limitation of current VIIRS/DNB measurements is infrequent revisits, and hence poor temporal resolution across the night. The low earth-orbiting (LEO) satellite platform offers only 1–2 passes per night at low to mid-latitudes, meaning that the VIIRS/DNB information must be used in 'snapshot mode.' With the addition of NOAA-20 in November 2017 to the same orbital plane as Suomi, there is now a 50-min update around 01:30 local time.

This second observation provides some information on the changing environment, but still cannot resolve parameter evolution or the diurnal cycle. For this, a geostationary-based (GEO) version of the DNB would be needed in order to overcome this principal limitation. Having a sensor that can provide low-light visible sensitivity from GEO would represent a significant advance over current nighttime imaging capabilities represented by the VIIRS/DNB. A pioneering study on the temporal dynamics of urban lights was done by Dobler et al. (2015), using horizontal images from a fixed camera, every 10s over 22 nights, demonstrating the type of information which can be derived from continuous monitoring of artificial lights throughout the night. Frequent monitoring of the Earth at night from sunset to sunrise will allow researchers to uncover circadian patterns of human activity, not only to quantify temporal changes in light pollution, but also to better inform us on changes in ambient population during night-time, e.g., people working at night, or attending various night-time events.

Such a GEO platform would allow stare and thereby attain signal-to-noise on par or better (by a factor of 10) than the VIIRS/DNB. Dual proposing a nighttime GEO instrument as a star tracker, and conducting multiple intermittent read-outs over the ~20s sampling interval, would further allow the instrument to achieve the necessary navigation and stability requirements for this measurement to attain 700 m resolution. It would be very useful, but not required, to coordinate nighttime GEO operations with a contemporary geostationary sensor (e.g., the Advanced Baseline Imager on GOES-R) to leverage additional spectral information from those sensors. As noted in Miller et al. (2013), combining the visible band with near infrared (conventional) and thermal

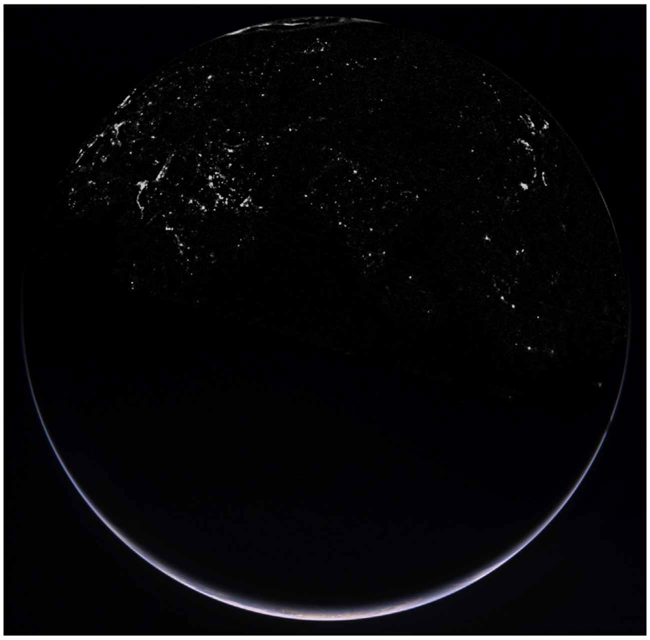

Fig. 27. OSIRIS view of Earth by night. This is a composite of four images combined to show the illuminated crescent of Earth and the cities of the northern hemisphere. The images were acquired with the OSIRIS Wide Angle Camera (WAC) during Rosetta's second Earth swing-by on 13 November, 2007. This image showing islands of light created by human habitation (from the Nile River on the upper left side, to eastern China on the upper right side) was taken with the OSIRIS WAC at 19:45 CET, about 2 h before the closest approach of the spacecraft to Earth. At the time, Rosetta was about 80 000 km above the Indian Ocean where the local time approached midnight. The image was taken with a five-second exposure of the WAC with the red filter. This image showing Earth's illuminated crescent was taken with the WAC at 20:05 CET as Rosetta was about 75 000 km from Earth. The crescent seen is around Antarctica. The image is a colour composite combining images obtained at various wavelengths. Source: http://www.esa.int/spaceinimages/Images/2007/11/OSIRIS_view_of_Earth_by_night. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

bands would further expand the utility of the low-light observations. For instance, a geostationary lowlight visible sensor, combined with shortwave and thermal infrared bands from co-located ABI observations, would be able to retrieve both cloud optical depth and effective particle size via moonlight, leading to improved estimates of cloud water path.

So far, the only occasion that a sensor acquired a full night-time image of the entire hemisphere (as a geostationary satellite would be able to do) showing artificial lights was in the ESA - Rosetta mission. In three occasions the probe ESA - Rosetta made flybys over the Earth to get the gravitational assistance it needed to change direction to its main scientific goal, the comet 67P/Churiumov-Guerasimenko. The team took images of the Earth during these flybys, and currently these images are still the only images of the Earth at night taken from a position where it is possible to see the full earth at night (other images available are renders or mosaics of individual images or scans). These images were taken with the camera OSIRIS (Keller et al., 2007) on the filters “Blue”, “Green”, “Orange”. Unfortunately, these images are only available on the raw format and Level 3 calibration. The difficulty of their reduction and georeferencing have therefore limited their use in peer review publications, although they are freely available at the ESA archive (https://archives.esac.esa.int/psa/) (Fig. 27).

4.8.2. Spectral information

Artificial lighting sources vary in their emission spectra from the sun's emission and from each other (Aubé et al., 2013, Fig. 24). To better estimate the negative effects of light pollution, various spectral indices have been proposed, including the Melatonin Suppression Index (MSI), the Induced Photosynthesis Index (IPI) and the Star Light Index (SLI) (Aubé et al., 2013), which also allow to compare the impacts of different lamp types on different species based on their spectral response curves (Longcore et al., 2018). With hyperspectral data, the major types of artificial lighting sources can be separated (Dobler et al., 2016). However, the majority of available space borne sensors are panchromatic, with only ISS photos and the new Jilin-1 satellite offering RGB color images, allowing the calculation of such indices (Sánchez de Miguel et al., 2019b; Table 1). As noted above, the panchromatic channel on the DMSP/OLS and VIIRS/DNB does not cover the blue light, thereby important spectral information is missing, which will become even more crucial as more cities change their street lighting technology to LED (Kyba et al., 2015a). Future night-time sensors designed for monitoring artificial lights should therefore include the blue band, and offer several spectral bands in the VIS-NIR range, so as to enable the identification of lighting types, and so as to fit human scotopic and photopic vision (Elvidge et al., 2007b). Investigating the optimal spectral band combination, Elvidge et al. (2010) concluded that the best set of spectral bands (in terms of cost and efficiency) would include at least four bands: the blue, green, red and NIR (as on Landsat). Such a combination of bands which will enable the identification of major types of lighting, and will also allow the estimation of the luminous efficacy of radiation, and the correlated color temperature, but not will enable to estimate other properties, such as the color rendering index (Elvidge et al., 2010). With the transition to LEDs, we are facing the global challenge of how to reduce light pollution, in spite of this new technology which allows to light up more areas at lower costs. One direction can be the application of light pollution metrics (such as developed by Aubé et al., 2013 and by Longcore et al., 2018) which will be placed on packages of bulbs, to better inform consumers on possible light pollution impacts, similar to information provided on food packages concerning their ingredients, allergens, and dietary information (Tangari and Smith, 2012).

4.8.3. Spatial resolution

Numerous studies have made great use of available night-time sensors (mostly DMSP/OLS and VIIRS/DNB) to study the spatial and temporal patterns of artificial light at night, and the anthropogenic and physical variables explaining it, at global, regional and national levels. However, most studies of night lights were not able to examine spatial patterns at the neighborhood or street level due to the lack of sensors with fine spatial resolution (Table 1). The spatial resolution of the majority of night-time space borne sensors is below 100 m, and freely available images of cities at spatial resolution which is better than 100 m are only available from astronaut photographs taken from the ISS. However, these images are not taken regularly, and are of varying radiometric and spatial quality. Night-time images with high spatial resolution (< 5 m) have been shown to enable the mapping and classification of individual lighting sources (e.g., Metcalf, 2012; Hale et al., 2013), and can enable us to better understand the nightscape as experience by animals within urban areas (Bennie et al., 2014b). However, high spatial resolution such as offered now by commercial satellites (such as EROS-B and Jilin-1) may not be needed for all applications. Indeed, several papers have shown that high spatial resolution of night time images did not improve our ability to explain spatial patterns of light pollution, and that better correlations were obtained at spatial resolutions of 50–100 m (Katz and Levin, 2016) or even at coarser spatial resolutions (e.g., Anderson et al., 2010). This result may relate to the combined artefact of night-time images becoming darker and with greater contrast between dark and bright areas with increasing spatial resolution (Kyba et al., 2015a; Katz and Levin, 2016). At high spatial resolutions there may also be greater differences between ground measurements of night-time brightness in the horizontal direction, and space borne measurements of night-time brightness, which only capture upward emissions of artificial lights (Katz and Levin, 2016). Indeed, in their evaluation of the required spatial resolution of a concept mission termed as NightSat, Elvidge et al. (2007b) estimated that a sensor with a spatial resolution of 50–100 m would suffice to present the major night-time features which are common to urban and rural areas. Such medium spatial resolution will also enable global monitoring of the Earth at night at a frequent revisit time, without requiring a constellation with too many satellites. The rise in launch and use of cubesats (such as Planet Labs; Strauss, 2017), and the recent launch of the Luojia-1 cubesat (Jiang et al., 2018), may offer a relatively cheap approach for providing global coverage of the Earth at night, at finer spatial resolutions than currently available. An additional research challenge, which relates to the need to better quantify the exposure to light pollution, requires us to develop methods to quantify and understand the differences between human exposure to night-time brightness both indoors (based on ground based sensors or on smart wearable technology, mobile device platforms or embedded platforms; Ko et al., 2015) vs. the exposure to night-time brightness outdoors (as measured by satellites).

5. Conclusions

Images of artificial lights at night directly observe human activity from space, and therefore enable a number of remote sensing applications either unique to night light sensing (e.g. monitoring illegal fishing, remotely sensing lighting technologies) or strongly complementing other types of remote sensing (e.g. evaluating the impacts of armed conflicts and disasters and the recovery from them, quantifying temporary and seasonal changes in population, studying urban change). The field of remote sensing of night lights has greatly expanded since the early 2000s, thanks to an increase in the number and quality of space and ground based sensors able to measure low levels of light in the visible band. This development has also had a major impact on the study of light pollution, which has grown in parallel with remote sensing of night lights. Nevertheless, despite the demonstrated value of night lights data, the sensors, algorithms, and products for night lights still lag far behind the state of the art in remote sensing based on reflected daylight, or in other spectral ranges. In particular, night lights data are generally taken at lower resolutions, lack temporal coverage, and most importantly lack multi- or hyperspectral data. This is of particular concern at the moment, because of the global shift in the night lights spectra due to the adoption of LED lights.

New and improved sensors and algorithms will not only allow a host of new remote sensing applications based on night lights data; they will also have a dramatic influence on our understanding of human influence on one of the most threatened environments on Earth's land surface: the night. In stark contrast to many other environmental stressors such as climate change due to greenhouse gasses or chemical pollution, reductions in light emissions reduce the degree of light pollution and its environmental impact immediately. Whereas reducing greenhouse gas levels requires coordinated global action, light pollution depends overwhelmingly on local actors. Many of the transitions needed to achieve a sustainable society, such as emissions free transportation, are difficult problems that still require considerable research and likely changes in behavior. Methods to eliminate waste light, on the other hand, are already well known (e.g. Falchi et al., 2011); lights must simply be directed more carefully (which LEDs can help with), in many cases overall light levels must be reduced, and in other cases, lights can simply be turned off. Fortunately, it has been demonstrated that reductions in overall light emission can be accomplished while actually improving vision over current practice (e.g. Narendran et al., 2016).

The main challenge facing the transition to sustainable lighting is one of awareness. Future night lights data will play a key role in this regard. The data will be used to visualize changes in light emission and light pollution, identify and quantify emissions from specific polluters, and evaluate the effectiveness of light pollution mitigation strategies.

Acknowledgements

CCMK acknowledges funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 689443 via project GEOEssential, and funding from the Helmholtz Association Initiative and Networking Fund under grant ERC-RA-0031. Some aspects of this manuscript were based upon work from COST Action ES1204 LoNNe (Loss of the Night Network), supported by COST (European Cooperation in Science and Technology). ASdM acknowledges funding from the EMISS@N project (NERC grant NE/P01156X/1) and the Cities at Night project. QLZ acknowledges funding from the One Hundred Talents Program of the Chinese Academy of Science ([2015], No. 70). AJ is supported by the Leibniz Association, Germany within the ILES (SAW-2015-IGB-1) and CONNECT (SAW-K45/2017) projects and by the IGB Leibniz Institute through the Frontiers in Freshwater Science project (IGB Frontiers 2017). Black Marble product suite data created at NASA's Goddard Space Flight Center with support from the NASA's Earth Observing System Data and Information System, Terrestrial Ecology, and Group on Earth Observations programs under grants NNH16ZDA001N-GEO-0055 and NNH17ZDA001N-TASNPP-0007. We thank the anonymous reviewers for their constructive comments on previous versions of this manuscript. Finally, we would like to pay our respects to Abraham Haim, who passed away this January. Abraham was a leader in the field of ecological and health impacts of artificial light, and was involved in a number of studies relating remotely sensed night lights data to human health impacts.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rse.2019.111443.

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